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Is Mild Really Mild?: Generating Longitudinal Profiles of Stroke Survivor Impairment and Impact Using Unsupervised Machine Learning

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Abstract: The National Institute of Health Stroke Scale (NIHSS) is used worldwide to classify stroke severity as 'mild', 'moderate', or 'severe' based on neurological impairment. Yet, stroke survivors argue that the classification of 'mild' does not represent the holistic experience and impact of stroke on their daily lives. In this observational cohort study, we aimed to identify different types of impairment profiles among stroke survivors classified as 'mild'. We used survivors of mild stroke' data from the START longitudinal stroke cohort (n = 73), with measures related to sensorimotor, cognition, depression, functional disability, physical activity, work, and social adjustment over 12 months. Given the multisource, multigranular, and unlabeled nature of the data, we utilized a structure-adapting, unsupervised machine learning approach, the growing self-organizing map (GSOM) algorithm, to generate distinct clinical profiles. These diverse impairment profiles revealed that survivors of mild stroke experience varying degrees of impairment and impact (cognitive, depression, physical activity, work/social adjustment) at different time points, despite the uniformity implied by their NIHSS-classified 'mild' stroke. This emphasizes the necessity of creating a holistic and more comprehensive representation of survivors of mild stroke' needs over the first year after stroke to improve rehabilitation and poststroke care.

Keywords: mild stroke; artificial intelligence; patient profiling; unsupervised learning; personalized healthcare

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1. Introduction

Despite the largely preventable nature of stroke, it remains the second leading cause of death and disability in 2019, which is likely to continue [1]. Stroke is a complex condition with variable impairments and severity, yet stroke patients are often classified in an overall sense as 'mild', 'moderate', or 'severe' [2]. This categorization is typically established using the National Institutes of Health Stroke Scale [NIHSS], which is a widely used assessment tool designed to measure neurological impairments in stroke survivors [2]. The NIHSS is used to screen for neurological impairment across multiple domains, such as consciousness,

movement, and language using 11 items and was designed for use primarily in the acute phase after stroke [3]. The overall score is interpreted as a score of neurological stroke severity according to the following groupings: 0–4 as mild stroke, 5–15 as moderate stroke, 16–20 as moderate to severe stroke, and 21–42 as severe stroke [4]. This classification often remains with the stroke survivor in the later stages of recovery.

Yet, 'mild' stroke survivors often argue the classification of 'mild' does not correspond with their daily experiences, as they report depression and difficulties in advanced physical and social activities, leading to a diminished quality of life [5,6]. Moreover, studies show that persons with mild stroke struggle to cope with the consequences of stroke, experience difficulties in everyday life [7], and may undergo persistent disability and difficulty with complex activities [8]. While it is recognized that the NIHSS is a valid and reliable screening measure, it has been reported that many acute stroke survivors with mild classification by NIHSS could have been overlooked for intensive rehabilitation therapy [9].

Given the complexity of the physical, psychological, and social burdens associated with stroke, it is important to measure the holistic impact of impairment and recovery following stroke to achieve targeted and personalized care [10,11]. This is particularly important for stroke survivors classified as 'mild', as survivors of mild stroke may be investigated less due to the assumption that they are expected to regain their premorbid functionality with minimal or no intervention. This is despite evidence that even mild symptoms can impact the ability to perform daily activities and household chores [12]. Given the physical, social, emotional, and functional burden experienced by persons with mild stroke and considering the common practice of using only the NIHSS to classify stroke severity, further investigation of the latent impairments associated with 'mild' stroke survivorship is required, thus leading to the question, 'Is mild really mild?'

In this study, our objective was to identify various patterns in mild stroke recovery to facilitate tailored and personalized poststroke care. We aim to detect groupings of survivors of mild stroke based on their cognitive, mood, social, and physical abilities, as well as quality of life, analyzing variations in their poststroke experiences beyond the NIHSS-scale-based categorization. For this purpose, we utilized a variety of outcome measures developed to evaluate various aspects of stroke, including motor skills, sensory perception, cognitive function, mood, functional disability, physical capacity, and social interactions among survivors. This more comprehensive profile allows us to better understand the poststroke experiences of survivors and thus improve their quality of life.

These multiple stroke impairment metrics are characterized as multisource and multigranular data, represented as unlabeled data, making these data less amenable to investigation using traditional statistical or supervised machine learning techniques that typically rely on datasets annotated by human experts. Therefore, we utilized a structure-adapting unsupervised machine learning approach, the growing self-organizing map (GSOM) algorithm [13], to automatically generate profiles of impairments in survivors classified as 'mild' by the NIHSS.

We used data from the Stroke Imaging Prevention and Treatment (START) [14] longitudinal cohort study, which consist of multiple test scores of stroke survivors at three time points [3–7 days; 3 months; 12 months after stroke] in their stroke journey. These time points align with commonly defined phases of recovery: 3–7 days, within the acute phase; 3 months, end of the early subacute phase; and 12 months, within the chronic phase [15]. Specifically, we processed survivors of mild stroke' data at these time points to generate GSOM representations at each point in time. By examining the representation captured by the GSOM, we aimed to distinguish unique profiles among 'mild' stroke survivors at each time point. These profiles of impairments across multiple domains, including cognition, mood, physical activity and social functioning provide new insights, all without the need for prior knowledge or human annotation.

2. Materials and Methods

2.1. Data Availability

The participants in this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of this research, supporting data are not available.

2.2. Study Design

The START study [14] was a prospective, longitudinal cohort study of 200 stroke survivors who were investigated at baseline [admission], 24 h, 3–7 days, 3 months, and 12 months after stroke [14]. Inclusion criteria included participants diagnosed with ischemic stroke, aged ≥18 years, and with no prior disability [modified Rankin scale ≤ 2 points] [16]. Participants who adhered to these criteria were recruited from participating hospitals throughout Australia and New Zealand, all of which had specialized stroke units, between June 2010 and April 2013. Prior to data collection, informed consent for participation was obtained from the patient or family member or legally responsible person. After enrolment, all participants were contacted again at each assessment time point to continue participating in the study. Ethics approval was obtained by the ethics committees responsible for each recruiting hospital site and the tertiary institution involved. Approval was also obtained for the use of the collected data in subsequent analyses in related research by the research team (HREC/17/Austin/281).

This longitudinal study aimed at assessing participants at different time points for their stroke severity, depression, cognitive abilities, functional outcomes, physical activity, and lifestyle at the 3–7 days, 3-month, and 12-month time points. These assessments were administered by a stroke specialist or healthcare professional trained in their administration and blinded to study design. The neurological stroke severity was classified according to The National Institute of Health Stroke Scale (NIHSS) at baseline as 'mild', 'moderate', or 'severe'.

2.2.1. Participants and Study Size

The current study included only the stroke survivors who were classified as 'mild' according to the NIHSS at baseline (i.e., (NIHSS ≤ 5 points). There were 107 survivors of mild stroke in the START dataset according to the baseline NIHSS; however, after data processing, it was noted that only 73 had complete information over one year due to health conditions, missed participation, and consent withdrawal. After eliminating incomplete data, there was a study cohort of 73 stroke survivors for the current study.

2.2.2. Quantitative Measures

The START dataset consists of outcomes based on multiple tests that are used to measure impairment across distinct domains following stroke [14]. In this study, in addition to the NIHSS, we analyzed data from 6 other measures across different domains: cognition, emotional health (depression), disability, physical activity, work and social adjustment, and health-related quality of life (Figure 1).

The following section provides a description of each test with the corresponding measurement criteria.

National Institute of Health Stroke Scale (NIHSS)

The National Institute of Health Stroke Scale (NIHSS) is an 11-item assessment used to evaluate the severity of neurological deficits with stroke, including consciousness, language, neglect, visual-field loss, extraocular movement, motor strength, ataxia, dysarthria, and sensory loss [17]. The potential NIHSS scores range from 0 to 42; higher scores represent more severe stroke deficits.

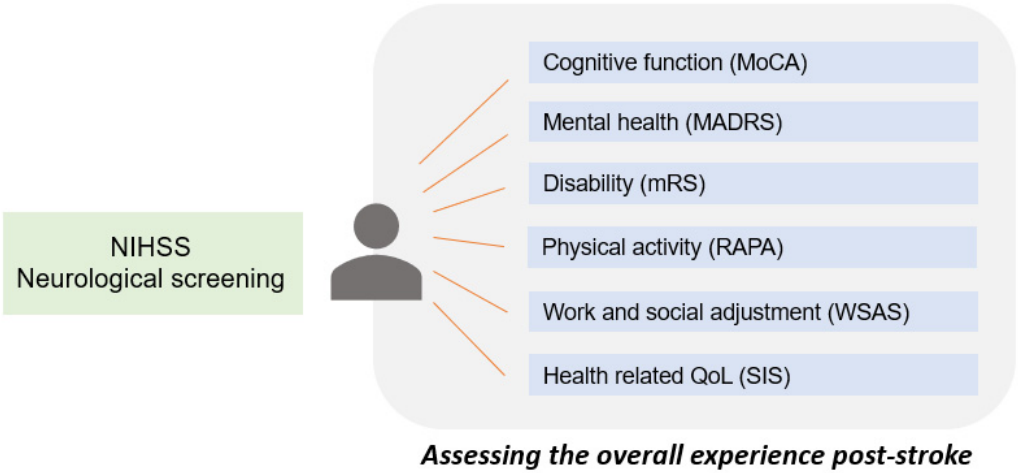

Figure 1. Measures used to assess the overall experience of survivors of 'mild' stroke.

Montreal Cognitive Assessment (MoCA)

The Montreal Cognitive Assessment (MoCA) is a sensitive and widely used screening tool to detect poststroke vascular cognitive impairment [18,19]. The MoCA assesses diverse cognitive domains, including visuospatial and executive functions, attention, memory, language, conceptual thinking, and orientation. The total MoCA score is 30, with higher scores indicating better cognitive function. An extra 1 point is added to the total score if a person has less than 12 years of formal education.

Montgomery–Åsberg Depression Rating Scale (MADRS)

The Montgomery–Åsberg Depression Rating Scale (MADRS) measures a person's depressive symptoms [20]. Using a structured interview, the MADRS was found to have excellent inter-rater reliability [20]. The MADRS has 10 items rated on a 6-point Likert scale (0–6). The total MADRS score is 60; a higher score indicates more severe depressive symptoms. A score of 18 or greater is suggestive of major depression [21].

Modified Ranking Scale (mRS)

The modified Rankin Scale (mRS) is a widely used functional outcome measure in stroke. The mRS assesses an individual's degree of disability or dependence in daily activities after stroke through a structured interview [15]. Six levels are defined in the mRS scoring from 0 to 6: 0 for no symptoms at all, 5 for total dependence, and 6 for dead.

Rapid Assessment of Physical Activity (RAPA) Questionnaire

The Rapid Assessment of Physical Activity (RAPA) is an easy-to-use, valid outcome measure that assesses levels of physical activity, and hence lifestyle, among adults [22]. The RAPA has 9 items, including 7 items for aerobic activities and 2 items for strength training and flexibility.

Work and Social Adjustment Questionnaire (WSAS)

The Work and Social Adjustment Scale (WSAS) is a 5-item self-report scale of functional impairment resulting from a health problem [23]. The five WSAS items determine functional impairment according to the following dimensions: (1) work; (2) home management; (3) social leisure activities; (4) private leisure activities; and (5) relationships with others. Each item is rated on a 0 to 8 scale: 0 indicates no impairment at all and 8 indicates very severe impairment. The maximum total score on the WSAS is 40. Good reliability and validity have been reported for the WSAS [23,24].

Stroke Impact Scale (SIS)

The Stroke Impact Scale (SIS) is a disease-specific, self-report questionnaire that evaluates self-perceived disability and health-related quality of life after stroke [24]. The SIS assesses the subjective impact of stroke in eight domains: strength, memory and thinking, emotion, communication, (instrumental) activities of daily living (ADL/IADL), mobility, hand function, and participation. All items within each domain are scored on a 1- to 5-point Likert scale. The total scores of each domain range from 0 to 100. Higher item scores indicate a lower level of difficulty experienced. The reliability and validity of the SIS are excellent [25,26].

These measures were selected as preferred scales to cover a range of impairments often experienced after stroke but missed as part of the NIHSS tool (e.g., cognition, MoCA; depression, MADRS), as they are commonly used in practice and/or research (NIHSS, mRS, SIS), are modifiable outcomes (RAPA, WSAS), and have sound foundations [14]. The rationale for our specific measures is provided in our protocol paper [14].

2.3. Methodology

Stroke survivors undergo multiple assessments to determine their function and ability in various domains. These assessments are conducted independently. In this study, we aimed to conduct a fusion of the scores across multiple assessments to understand different variants of impairments within the survivors of mild stroke. This is particularly important to enable the distinguishing of poor-performing aspects and nonimpaired aspects of each individual.

To achieve this objective, we utilized an AI framework that could combine multisource, granular data to create a latent representation of stroke survivor data. The high-level architecture of this framework consisted of a data processing module; an AI module comprising the GSOM [14], which is an unsupervised machine learning approach; and a visualization module to analyze the outcomes. This approach is presented in Figure 2. We designed this framework to accommodate the selected participants' data from the START longitudinal study.

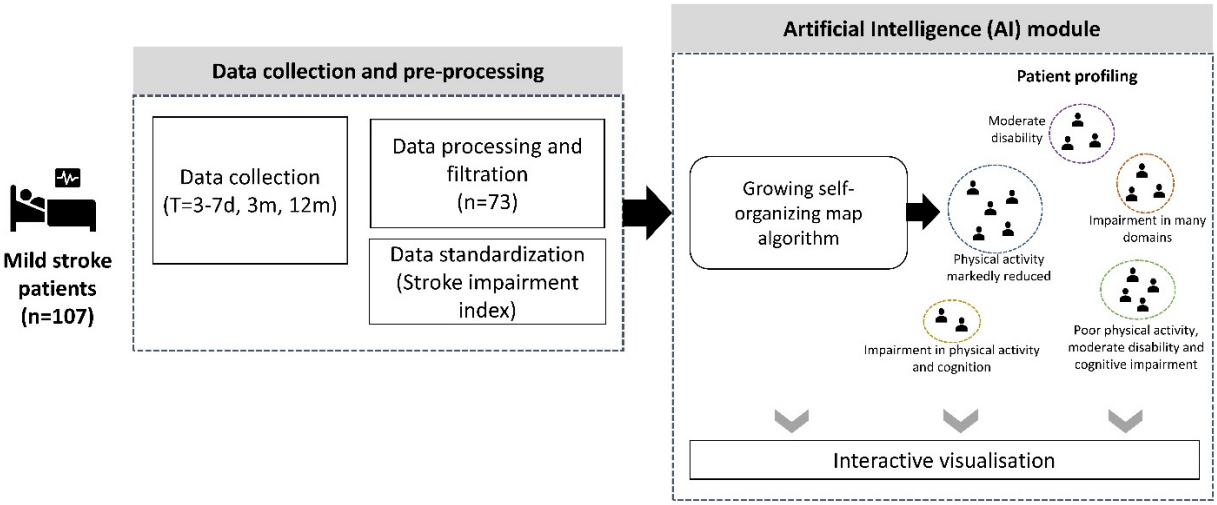

Figure 2. The proposed framework with the growing self-organizing map (GSOM) algorithm to identify impairment profiles.

2.3.1. Data Preprocessing

The first module of the proposed framework was used to preprocess the data to explore missing values and anomalies and transform them into comparable and computable information across all the selected tests. As the first step of data processing, we filtered the START patient data sample based on the completeness of the data. We evaluated the missing data for demographic details and selected the assessment data for analysis. As pre-

viously noted, the selected tests were the NIHSS, Montreal Cognitive Assessment (MoCA), Montgomery–Åsberg Depression Rating Scale (MADRS), modified Rankin scale (mRS), Rapid Assessment of Physical Activity (RAPA), Work and Social Adjustment Scale (WSAS), and Stroke Impact Scale (SIS). As per the inclusion criterion, participants' records that did not contain data for these tests were removed from the dataset since the objective was to find stroke survivor groupings considering all aspects of stroke impairment and impact.

2.3.2. Data Standardization—Creating a Stroke Impairment Index

The filtered dataset was then processed to achieve standardization across all the tests, as different tests have different scales measuring impairment and impact. For example, the MoCA assessment uses a scale of 0–30, while the SIS assessment uses a scale of 0–100. In order to standardize the data fed into the machine learning algorithm, it was necessary to ensure that all features adhered to the same scale. Therefore, the data normalization step was carried out using MinMax Scaler to transform assessment scores, so that all values were between 0 and 1, which served as the impairment index. On this scale, zero indicated no impairment, and one indicated severe impairment. The standardized data of each assessment were used as the input feature vector for the artificial intelligence (AI) algorithm.

2.3.3. Growing Self-Organizing Maps to Detect Variants of Impairment

The AI module of the proposed framework uses a self-structuring version of the self-organizing map (SOM) algorithm called the growing SOM (GSOM) [11]. This algorithm has a map topography that self-structures by adapting its size and shape based on the attributes and variations of the input data without being dependent on a fixed structure. The GSOM can handle the outliers and noise in data, therefore establishing its applicability for conducting unsupervised data exploration, anomaly detection, data mining, and profiling applications in multiple domains [27].

We selected GSOM for the AI module considering three major features that aligned well with the requirements of this study. Firstly, the unsupervised learning capability of the GSOM was important due to the exploratory nature of the analysis, aiming to discover previously unknown patterns. Compared to clustering algorithms, which need a predefined number of clusters, the GSOM has the benefit of not requiring prior knowledge of the input data. Secondly, the GSOM can not only generate clusters based on similar groupings of assessment outcomes but also capture the topological relationships among the clusters with neighborhood-preserving mappings. The self-structuring ability of the GSOM has been shown to generate clusters that better preserve the relationships in the input variables compared to the SOM [28]; therefore, GSOM was more suited for this study as we used inputs from multiple assessments. Thirdly, the GSOM 'grows' nodes starting from an initial 4-node network and, as such, is better suited for studies where multiple maps are visualized and compared. The unsupervised clustering of multiple dimensions of participant data was formed using an improved variant [29,30] of the GSOM, with a transience mechanism facilitating the encapsulation of plasticity in the GSOM. This enabled the algorithm to discard outdated information and overfitting knowledge in its knowledge acquisition, without the loss of stability of the algorithm.

In the GSOM, as input data are presented, nodes of the network compete with each other for ownership of the input, and the winners strengthen their relationships with this input. The competitive learning process is repeated for the complete dataset for several cycles that ultimately the maps associated output nodes with the patterns in the input dataset. The growth of the GSOM is determined by the number of dimensions in the input space and the spread factor (SF), which controls the spread of the neural network structure independent of the dimensionality (features) of the dataset [12]. To select the best hyperparameters, such as the spread factor and learning rate, a randomized approach was employed to determine the optimal values. For the spread factor, a range of 0.3 to 0.9 was evaluated, while for the learning rate, a range of 0.01 to 0.5 was considered. Using

the GridSearch method, the optimal values were identified as a spread factor of 0.8 and a learning rate of 0.3 for this study. In this work, we utilized the Python implementation of the GSOM. As the inputs to the GSOM, we used the standardized scores of the assessments for survivors of mild stroke.

2.3.4. Identification of Impairment Profiles

The GSOM generates a two-dimensional grid of nodes, with each node denoting a group of similar data patterns. Nodes located in closer proximity to each other on the map are indicative of clusters. As a result, creating GSOM maps enables the automatic detection of data point clusters (participants) through iterative analysis of participant data within each node. This process unveils unique patterns that differentiate these clusters from the larger population. Consequently, by visually inspecting the map, we can identify regions where nodes are densely clustered, as these areas generally correspond to clusters of similar patterns. Therefore, the framework enables the automatic identification of prominent clusters by computing the intracluster similarity using the patient data of each cluster. The GSOM algorithm was used for this task with a 0.8 spread factor, while the Euclidean distance [31] was used as the distance measure to calculate the difference in input data between two participants. This resulted in marked regions that indicated different subgroupings (profiles) of survivors of mild stroke.

The analysis was conducted to identify the following:

(a) Profiles (subgroupings) within NIHSS assessment on day 3–7 after stroke;
(b) Profiles across measures on day 3–7 after stroke;
(c) Profiles across measures at 3 months after stroke;
(d) Profiles across measures at 12 months after stroke.

In this study, we created an interactive visualization tool using the GSOM maps that can be used by clinicians to monitor each participant's impairment profiles over time. Appendix A presents screen captures of the developed tool.

2.3.5. Statistical Analysis

After identifying the impairment profiles through the GSOM, we computed the mean for each assessment. Afterward, t-tests were used to compare the mean of each assessment in the identified profiles with other participants' data [32]. A significance value of 0.05 was used to reject the null hypothesis and conclude that there was a statistically significant difference in the mean of the assessment scores between the identified profile and other participants.

3. Results

3.1. Demographic and Clinical Characteristics of Stroke Sample

Seventy-three survivors of stroke met the inclusion criteria for mild stroke with available data and were included in this study's sample. The demographic and background clinical information of the participants is presented in Table 1. The clinical and functional outcome characteristics of the sample are summarized in Table 2 for each of the main variables included in the analysis, i.e., NIHSS, MoCA, MADRS, mRS, RAPA, WSAS ,and SIS, at day 3–7, 3 months, and 12 months after stroke.

Table 1. Demographic characteristics of 'mild' stroke survivors included in this study (n = 73).

	n (%)
Sex	
Male	51 (69.9%)
Female	22 (30.1%)
Age group	
Mean (years)	71.45
Standard deviation (years)	11.37

Table 1. *Cont.*

	n (%)
Ethnicity	
Asian	4 (5.5%)
Australian or New Zealander	46 (63.0%)
European	17 (23.3%)
Other	6 (8.2%)
Marital Status	
Divorced	13 (17.8%)
Married/de facto	51 (69.9%)
Other	2 (2.7%)
Single	2 (2.7%)
Widowed	5 (6.8%)
Employment	
Employed for wages	18 (24.7%)
Homemaker	1 (1.4%)
Out of work for <1 year	2 (2.7%)
Retired	44 (60.3%)
Self-employed	7 (9.6%)
Unable to work	1 (1.4%)

Table 2. Clinical characteristics and functional outcomes of survivors of 'mild' stroke at day 3–7, 3 months, and 12 months after stroke.

Time after Stroke	*Median*	*IQR*	*Q1*	*Q3*
Day 3–7				
NIHSS	2.00	2.25	1.00	3.25
MoCA	26.00	5.25	22.75	28.00
MADRS	3.00	5.25	0.75	6.00
3 months				
NIHSS	0.00	1.00	0.00	1.00
MoCA	27.00	4.00	25.00	29.00
MADRS	4.00	8.00	1.00	9.00
mRS	1.00	1.00	1.00	2.00
RAPA	5.00	3.00	4.00	7.00
WSAS	2.00	10.00	0.00	10.00
SIS	93.06	9.21	87.55	96.76
12 months				
NIHSS	0.00	1.00	0.00	1.00
MoCA	27.00	4.00	24.00	28.00
MADRS	3.00	8.00	0.00	8.00
mRS	1.00	2.00	0.00	2.00
RAPA	5.00	4.00	3.00	7.00
WSAS	2.00	8.00	0.00	8.00
SIS	93.58	11.39	86.21	97.60

NIHSS (National Institute of Health Stroke Scale; 0 to 42); MADRS (Montgomery–Åsberg Depression Rating Scale; scale range 0 to 60); MoCA (Montreal Cognitive Assessment; 0 to 30); mRS (modified Rankin scale; 0 to 6); SIS (Stroke Impact Scale; 0 to 100); RAPA (Rapid Assessment of Physical Activity; 0 to 10); WSAS (Work and Social Adjustment Scale; 0 to 40).

3.2. Stroke Survivor Clusters Based on the NIH Stroke Scale

The NIHSS consists of 11 items that focus on different neurological aspects such as level of consciousness, horizontal eye movement, visual field test, facial palsy, motor arm, motor leg, sensory, speech, language, and attention. The scores for each question item are aggregated to form the final NIHSS score, which is used for stroke severity classification. However, this aggregated score fails to capture the aspects that are more impaired or not. Therefore, we used the AI framework on the baseline NIHSS item scores, on day 3–7 after stroke, to detect different impairment groupings (annotated regions) that can be derived solely from the NIHSS.

This analysis results in five different profiles pertaining to different impairments, as shown in Figure 3 and Table 3. The scores of the participants in such groupings were compared with the rest of the population using t-tests to determine if there was any significant difference. Participants in nonannotated regions did not exhibit patterns that could be differentiated, meaning they had mixed NIHSS item-score attributes that were not significant.

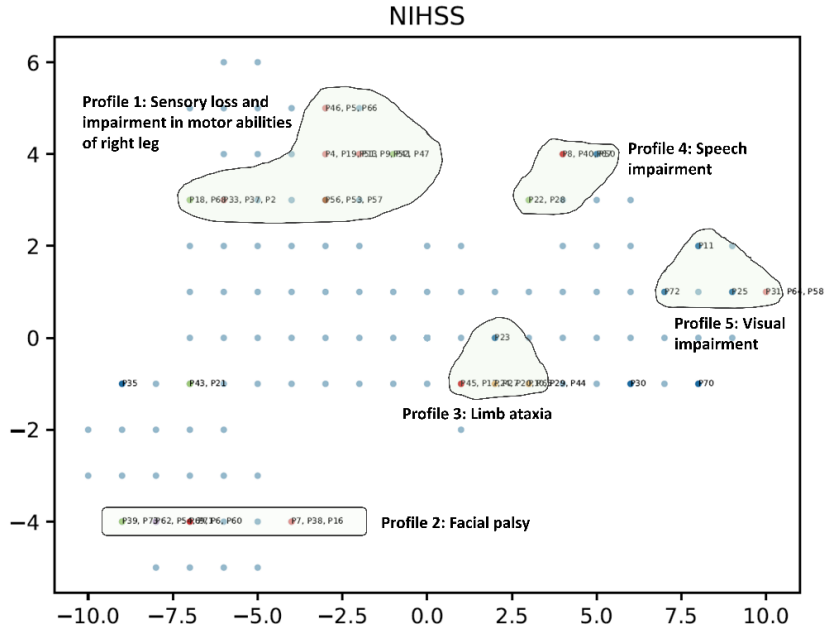

Figure 3. Impairment profiles identified using the outcomes of the NIHSS.

Profile 1 participants (19.2%) showcased mild to moderate somatosensory loss and impairment of motor abilities in the right leg. The impairment scores given to sensory loss (sensory loss mean: profile 1 = 0.571, other participants = 0.068, $p < 0.05$) and difficulty with motor abilities in the right leg (motor leg right mean: profile 1 = 0.5, other participants = 0.017, $p < 0.05$) in this profile were significantly higher than those for the other participants. They did not show a remarkable difference in the other attributes.

Profile 2 participants (15.06%) were separated from the other participants due to their increased impairment scores for facial palsy. Profile 2 participants showcased higher impairment scores (facial palsy mean: profile 2 = 1.72, other participants = 0.27, $p < 0.05$) as the majority were suffering more from partial paralysis of the lower face compared to other survivors of mild stroke.

Profile 3 participants (13.7%) showed increased scores for limb ataxia compared to other participants. All the participants in this profile had ataxia present in either one or two limbs (limb ataxia mean: profile 3 = 1.6, other participants = 0.111, $p < 0.05$).

Profile 4 participants (8.2%) were differentiated from the rest due to their impairments in speech. All the participants in this profile had mild to moderate aphasia, indicating some obvious loss of fluency or facility of comprehension without significant limitations on ideas expressed (best language mean: profile 4 = 1.33, other participants = 0.07, $p < 0.05$). Moreover, all the participants had mild to moderate dysarthria, where patients slur at least some words and at worst can be understood with some level of difficulty (dysarthria mean: profile 4 = 1, other participants = 0.313, $p < 0.05$).

Profile 5 participants (8.2%) showed an increased level of visual impairment compared to the other participants. All the participants in this profile had partial or complete hemianopia, indicating visual impairment (visual field test mean: profile 5 = 1.5, other participants = 0.044, $p < 0.05$).

Table 3. Comparison of impairment profiles identified within NIHSS.

Profile 1: Sensory Loss and Impairment in Motor Abilities of the Right Leg		
Sensory Loss	**Profile 1**	**Other Participants**
Mean	0.571	0.068
Variance	0.264	0.064
Observations	14 (19.2%)	59 (80.8%)
	$p = 0.001$	
Motor leg (right)		
Mean	0.500	0.017
Variance	0.423	0.017
Observations	14 (19.2%)	59 (80.8%)
	$p = 0.008$	
Profile 2: Facial Palsy		
	Profile 2	**Other Participants**
Mean	1.727	0.274
Variance	0.618	0.202
Observations	11 (15.06%)	62 (84.93%)
	$p = 0.000$	
Profile 3: Limb Ataxia		
	Profile 3	**Other Participants**
Mean	1.600	0.111
Variance	0.267	0.100
Observations	10.000	63.000
	$p = 0.000$	
Profile 4: Speech Impairment		
Best Language	**Profile 4**	**Other Participants**
Mean	1.333	0.075
Variance	0.267	0.070
Observations	6.000	67.000
	$p = 0.001$	
Dysarthria		
Mean	1.000	0.313
Variance	0.000	0.249
Observations	6.000	67.000
	$p = 0.000$	
Profile 5: Visual Impairment		
Visual Field Test	**Profile 5**	**Other Participants**
Mean	1.500	0.045
Variance	0.300	0.074
Observations	6.000	67.000
	$p = 0.000$	

This analysis of the NIHSS attributes showcased different subgroupings of impairments among survivors of mild stroke that enabled the creation of another layer of granularity for survivors identified as mild.

3.3. Profiles across Measures

The performance on each of the six domain assessments was mapped for each individual classified as mild. The GSOM generated a latent representation with the six impairment profiles, as shown in Figure 4 for two individuals. As illustrated, different individuals exhibit impairment in different domains, consistent with their varied poststroke experiences. This provides valuable insights into identifying individual needs that can be considered in the delivery of personalized rehabilitation care.

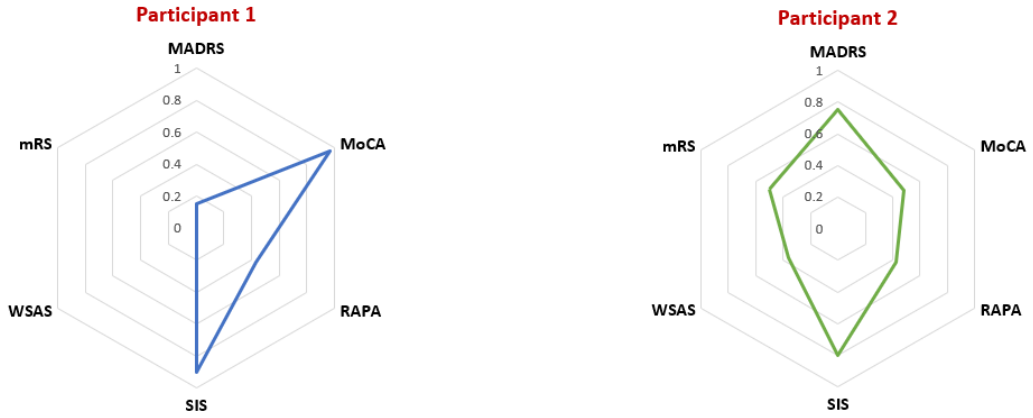

Figure 4. Illustration of assessment scores across domains in two survivors of mild stroke. NIHSS (National Institute of Health Stroke Scale; 0 to 42); MADRS (Montgomery–Åsberg Depression Rating Scale; scale range 0 to 60); MoCA (Montreal Cognitive Assessment; 0 to 30); mRS (modified Rankin scale; 0 to 6); SIS (Stroke Impact Scale; 0 to 100); RAPA (Rapid Assessment of Physical Activity; 0 to 10); WSAS (Work and Social Adjustment Scale; 0 to 40).

3.4. Different Profiles of Survivors of Mild Stroke at Different Time Points of Their Recovery Trajectories

The START study obtained measures for participants at day 3–7, 3 months, and 12 months after stroke, which permitted a longitudinal study of stroke impairment and impact. The selected measures, NIHSS, MoCA, MADRS, mRS, RAPA, WSAS, and SIS, were used to assess stroke impairment and impact across several different domains. The GSOM algorithm was applied to participant data at these three time points separately to infer the different profiles of survivors of mild stroke over time. An example is shown in Figure 5.

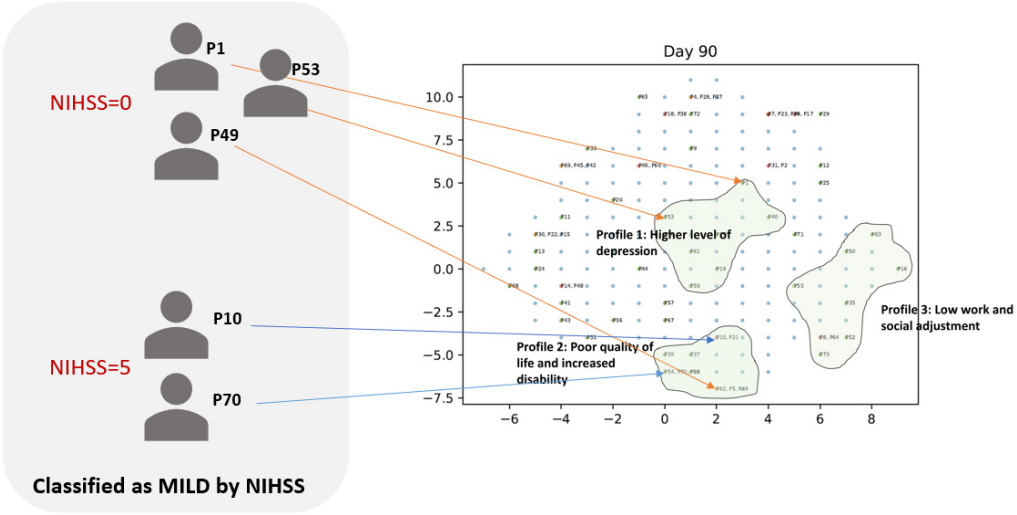

Figure 5. Illustration of variations in survivors of mild stroke.

3.4.1. Profiling at Day 3–7 after Stroke

At day 3–7 after stroke, only the MADRS and MoCA assessment outcomes were reported in addition to the NIHSS. Based on these data, the AI module separated the participants into two significant profiles indicating clear impairments in these outcomes compared to the other participants, as shown in Figure 6 and Table 4. Based on the analysis, 35.6% of the participants reported significant impairments in cognition or depression compared to others.

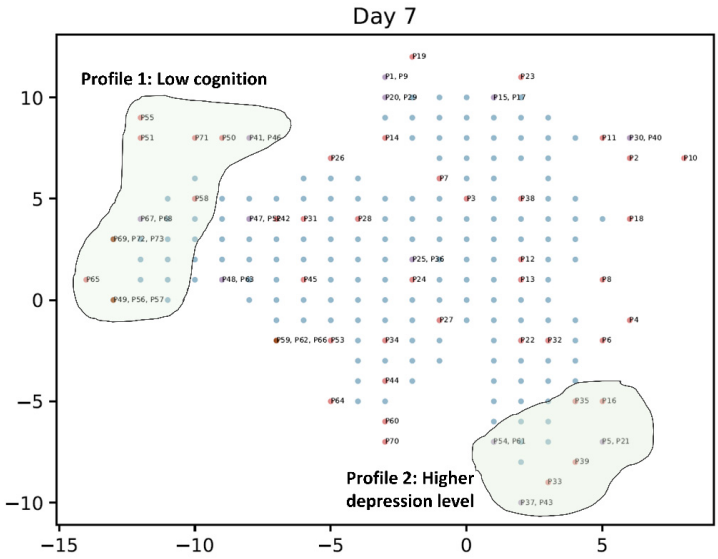

Figure 6. Impairment profiles on day 3–7 after stroke.

Table 4. Comparison of impairment profiles on day 3–7 after stroke.

Profile 1: Low Cognition		
Day 3–7 MOCA Score	**Profile 1**	**Other Participants**
Mean	19.000	25.767
Variance	13.500	8.250
Observations	13 (17.8%)	60 (82.2%)
	$p = 0.0000$	
Profile 2: Higher Depression Level		
Day 3–7 MADRS Score	**Profile 2**	**Other Participants**
Mean	16.500	3.238
Variance	9.833	9.217
Observations	13 (17.8%)	60 (82.2%)
	$p = 0.0000$	

Profile 1 participants scored lower on the MoCA assessment, indicating lower cognition abilities compared to the other participants (MoCA mean: profile 1 = 19, other participants = 25.77, $p < 0.05$). They did not show significant impairments in the other domains.

Another grouping exhibited higher levels of depression as they scored higher on the MADRS assessment on day 3–7 after stroke compared to other participants, as shown in Profile 2 (MADRS mean: profile 2 = 16.5, other participants = 3.2, $p < 0.05$). Participants in the non-annotated regions did not exhibit significant variations in their assessment scores compared with other participants.

Thus, the two identified profiles provided evidence of subgroupings of impairment in cognition or depression on day 3–7 after stroke among stroke survivors who had been classified as mild.

3.4.2. Profiling at 3 Months after Stroke

At 3 months after stroke, the MoCA, MADRS, mRS, RAPA WSAS and SIS scores were reported. Based on these data, the AI module generated three significant profiles indicating different impairments among 35.6% of mild stroke patients, as shown in Figure 7 and Table 5.

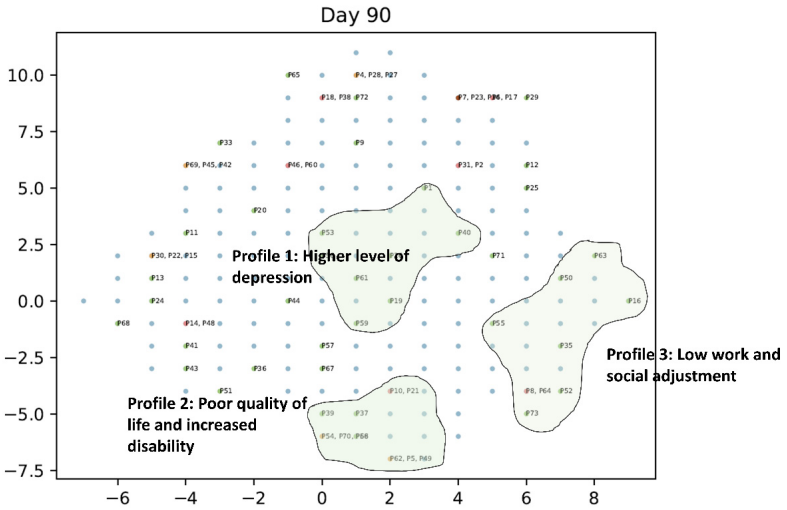

Figure 7. Impairment profiles at 3 months after stroke.

Table 5. Comparison of impairment profiles at 3 months after stroke.

Profile 1: Higher Depression Level		
MADRS	**Profile 1**	**Other Participants**
Mean	12.714	5.469
Variance	49.238	48.855
Observations	7 (9.6%)	66 (90.4%)
	$p = 0.017$	
Profile 2: Increased Disability and Poor Quality of Life		
mRS	**Profile 2**	**Other Participants**
Mean	1.667	0.859
Variance	0.500	0.535
Observations	9 (12.3%)	64 (87.7%)
	$p = 0.004$	
SIS	**Profile 2**	**Other Participants**
Mean	68.444	84.328
Variance	289.528	266.414
Observations	9 (12.3%)	64 (87.7%)
	$p = 0.012$	
Profile 3: Low Work and Social Adjustment		
WSAS	**Profile 3**	**Other Participants**
Mean	15.150	3.794
Variance	88.781	32.183
Observations	10 (13.7%)	63 (86.3%)
	$p = 0.002$	

Participants in profile 1 (9.6%) demonstrated a higher level of depression based on their scores for the MADRS assessment (MADRS mean: profile 1 = 12.71, other participants = 5.47, $p < 0.05$). Apart from their higher level of depression, they did not exhibit significant impairment in other assessments.

Another notable exemption is profile 2 (12.3%,) where participants recorded higher scores for the mRS assessment (mRS mean: profile 2 = 1.66, other participants = 0.85, $p < 0.05$), which evaluates the degree of disability following stroke. Participants in this cluster also showed comparatively lower scores on the SIS, which assesses the other dimensions of health-related quality of life: emotion, communication, memory and thinking, and social role function (SIS mean: profile 2 = 64.44, other participants = 84.32, $p < 0.05$). It could be determined that in contrast to the other groupings among survivors of mild stroke

at 3 months after stroke, profile 2 participants displayed more impairment and impact due to their increased disability and poor quality of life.

The AI algorithm separated another group of participants in profile 3 (13.7%), who scored higher on the WSAS assessment (WSAS mean: profile 3 = 15.15, other participants = 3.79, $p < 0.05$), which indicates low work and social adjustment in daily life. These participants did not show a significant difference in the other assessments.

3.4.3. Profiling at 12 Months after Stroke

At 12 months after stroke, the MoCA, MADRS, mRS, RAPA, WSAS, and SIS scores were used for the profiling. Among participants at 12 months after stroke, 43.9% showed at least one impairment with greater frequency than that of participants with impairment at day 3–7 or at 3 months after stroke. The participants were grouped into identified profiles by the AI algorithm, as shown in Figure 8 and Table 6. Four distinct impairment profiles were identified at this time point.

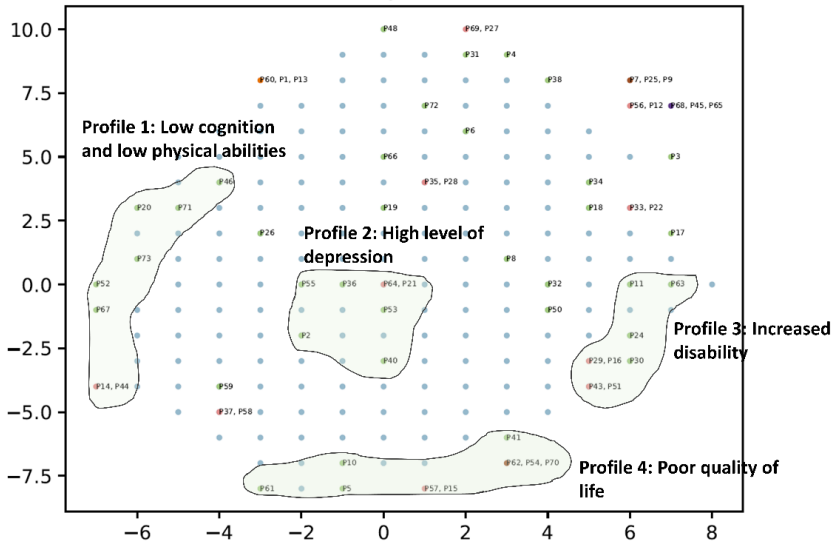

Figure 8. Impairment profiles at 12 months after stroke.

Among the survivors of mild stroke at 12 months after stroke, a group of participants showed lowered cognitive abilities and low engagement in physical activities. These participants, highlighted in profile 1 (11%), scored less on the MoCA assessment (MoCA mean: profile 1 = 21.12, other participants = 26.59, $p < 0.05$), measuring their cognitive abilities, and on the RAPA assessment (RAPA mean: profile 1 = 2.62, other participants = 4.2, $p < 0.05$), which evaluated their level of physical activity.

Another group of participants shown as profile 2 (9.6%) demonstrated an increased level of depression compared to other participants as they scored higher on the MADRS assessment for depression (MADRS mean: profile 2 = 9.71, other participants = 4.88, $p < 0.05$). It is noteworthy that higher levels of depression among this group of participants were seen at all three time points.

Profile 3 (11%) participants were separated from the rest given their increased level of functional disability. This group exhibited higher scores on the mRS assessment, which evaluates disability in stroke survivors for recovery and continued disability. All participants with this profile had disability symptoms, while a few reported moderate disability (mRS mean: profile 3 = 1.5, other participants = 0.75, $p < 0.05$).

In profile 4 (12.3%), participants indicated a poor quality of life, as indicated by their low scores on the SIS assessment, which evaluates disability and health-related quality of life after stroke. Their SIS assessment outcomes were significantly lower compared to those of the other participants (SIS Mean: profile 4 = 70.55, other participants = 87.67, $p < 0.05$).

Table 6. Comparison of impairment profiles at 12 months after stroke.

Profile 1: Low Cognition and Low Physical Abilities		
MoCA	**Profile 1**	**Other Participants**
Mean	21.125	26.585
Variance	18.125	9.809
Observations	8 (11%)	65 (89%)
	$p = 0.003$	
RAPA	**Profile 1**	**Other Participants**
Mean	2.625	4.200
Variance	3.411	3.819
Observations	8 (11%)	65 (89%)
	$p = 0.025$	
Profile 2: Higher Level of Depression		
MADRS	**Profile 2**	**Other Participants**
Mean	9.714	4.879
Variance	30.238	39.770
Observations	7 (9.6%)	66 (90.4%)
	$p = 0.030$	
Profile 3: Increased Disability		
mRS	**Profile 3**	**Other Participants**
Mean	1.500	0.754
Variance	0.571	0.657
Observations	8 (11%)	65 (89%)
	$p = 0.014$	
Profile 4: Poor Quality Of Life		
SIS	**Profile 4**	**Other Participants**
Mean	70.556	87.672
Variance	190.278	169.113
Observations	9 (12.3%)	64 (87.7%)
	$p = 0.002$	

3.5. Capturing Individual Patient Trajectories

Using the GSOM algorithm, we generated patient recovery pathways from the data collected at the day 3–7, 3 month, and 12 month time points, as shown in Figure 9. The selected subgroup of patients, categorized as 'mild' based on their NIHSS overall scores, display varying trajectories despite their initial categorization.

At the 3 month (90-day) period, it can be observed that a cluster of patients present similar patterns of characteristics, with only minor differences in cognitive abilities and work and social adjustment. In comparison, these individuals at day 3-7 show differences in cognitive abilities, as indicated by the MoCA score. Notably, one patient (represented by the orange pathway) exhibited lower cognitive ability and a higher mRS score by 12 months post-stroke. Thus, while the patients exhibited dissimilarities initially, by 3 months their recovery pathways converge, highlighting the dynamic nature of individual recovery trajectories over time.

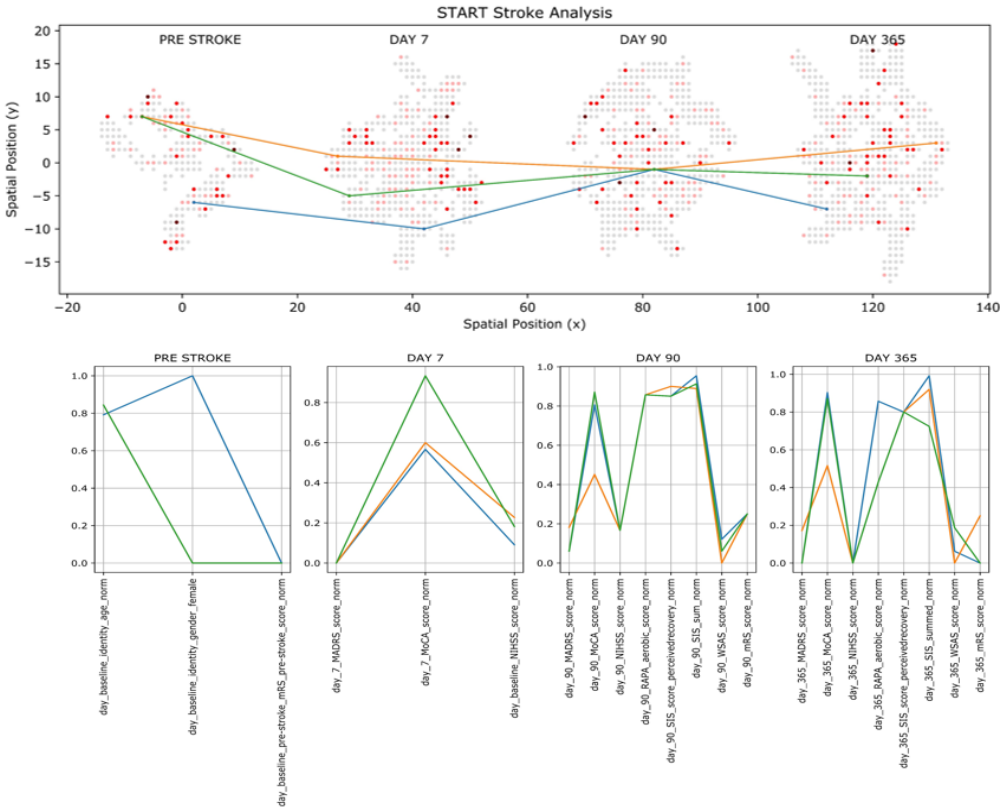

Figure 9. Individual recovery trajectories at different time points. Different lines represent different individuals.

4. Discussion

Although NIHSS screening is used to provide a measurement of 'mild' stroke severity, we examined if individual experiences varied based on other poststroke factors such as their cognition, mood, physical ability, and work and social adjustment. Our findings revealed different groupings (profiles) of survivors of mild stroke based on the GSOM maps. By examining the representation captured by the GSOM, we were able to distinguish distinctive profiles among survivors of 'mild' stroke at each time point. These profiles revealed impairments in various domains, including cognition, mood, physical activity, and social functioning, and all without the need for prior knowledge or human annotation. Incorporating such factors from multiple domains adds value to the current NIHSS screening, with potential to better deliver a personalized care plan for survivors of stroke.

The identification of distinct clusters of impairments highlights the need to incorporate a comprehensive assessment of survivors of mild stroke that encompasses evaluations from multiple domains, in addition to the NIHSS screening, to improve personalized care. Acknowledging a range of impairments across various domains can assist clinicians in gaining a better understanding of the diverse clinical profiles associated with 'mild' stroke survivorship. This approach can be used to add value to the current neurological screening of stroke, to enhance the quality of life and support planning of home-based rehabilitation programs. This is essential for survivors of mild stroke who experience additional impairments, as they could be omitted from comprehensive rehabilitation care due to the initial screening of stroke severity.

Our findings, using a structure adapting unsupervised machine learning approach, provide new insights into understanding poststroke impairment and recovery for those presenting with 'mild' stroke according to the NIHSS during the first week after stroke. First, the investigation of the clustering of impairment across items of the NIHSS revealed that despite the 'mild' classification, variations in impairments could be observed. In this analysis of the NIHSS, five such distinct clusters emerged based on patterns of motor

disabilities, somatosensory impairment, speech impairment, visual impairment, and facial palsy, highlighting the necessity of providing individualized rehabilitation and care for survivors of mild stroke. We believe that this study is one of the pioneering studies to use an unsupervised machine learning approach to automatically detect different impairment variations in survivors of mild stroke using the assessment outcomes of the NIHSS.

Second, we used additional measures of mood, cognition, and functional outcomes at key recovery time points [15] to explore variations in the impairment in survivors of mild stroke over time. At day 3–7 after stroke, distinct clusters were defined by the presence of depressive symptoms (based on MADRS) and cognitive impairment (based on MoCA). These findings support the use of mood and cognitive measures at this time as an adjunct to the NIHSS screening.

The granular level of analysis at 3 months after stroke enabled the detection of the three groupings of survivors of mild stroke: a group with higher levels of depression, a group with poorer quality of life coupled with increased disability, and the third group with low work and social adjustment. Among these profiles, special attention should be provided to survivors who have reported poor quality of life and increased disability as this imposes a burden on their daily lives.

At 12 months after stroke, survivors of mild stroke continued to show impairment across different domains despite zero or low scores on the NIHSS. The number of survivors with impairment was higher at 12 months than at previous time points, a potentially unexpected finding [33]. At this stage, four clusters were detected with significant impairment across multiple domains. One profile reported lower cognition and markedly reduced physical activity. This is consistent with recent reports on deterioration in cognition over time after stroke [34]. Given the value of physical activity and cognition on quality of life, it is recommended that health professionals continue to monitor and address these outcomes even in those without notable impairment. Another profile showed a higher level of depression. Depression was noted as a key issue in survivors of mild stroke, as all three time points had groups of participants with a significant level of depression based on the MADRS assessment. At 12 months after stroke, profiles 3 and 4 exhibited increased disability and poor quality of life, respectively. Together, these findings emphasize the presence of ongoing impairment and poor functional outcomes across a constellation of domains even at 12 months after stroke in those classified as having a 'mild' stroke early after stroke. These impairment profiles at 12 months after stroke highlight the burden carried by survivors of mild stroke across different domains despite their initial classification as mild.

Capturing personalized longitudinal pathways is crucial for tailoring treatment plans to individual patient needs. By monitoring recovery trajectories over time, healthcare providers can identify specific patterns and variations in patient progress that might otherwise be unnoticed. This detailed insight allows for the customization of interventions based on individual recovery rates, cognitive abilities, and overall health status. Personalizing treatment plans based on longitudinal data ensures that each patient receives the most effective care, improving outcomes and optimizing resource utilization. Moreover, understanding these unique pathways can lead to better-informed clinical decisions, ultimately enhancing the quality of life of patients through more precise and responsive healthcare strategies.

The presence of impairment across multiple domains advocates for survivors of stroke classified as 'mild' in the first week after stroke being closely monitored, at least over the first year after stroke, and/or be offered bursts of rehabilitation to prevent or address these ongoing impairments. Our findings also provide strong evidence supporting the voice of people classified as having a mild stroke that 'mild' is not really mild, based on their lived experience.

Given the fact that stroke affects the physical, cognitive and mood functionality of a person, it is imperative to identify and understand these complexities [35]. Wide variability in quality-of-life ratings (0.45 to 0.95 on a scale from 0 to 1) was reported even in those with mild stroke [35]. Yet, it was established that vague measures aimed at determining the

quality of life following stroke impede clinician decision making [36] as survivors of mild stroke report an abundance of issues associated with return to meaningful activities and life satisfaction [7,8]. These findings, together with the current findings, suggest that the NIHSS screening alone does not adequately capture the underlying reality of survivors of stroke. Rather, it suggests the value of a profile of outcomes to provide a more meaningful and comprehensive view of stroke survivorship and quality of life.

Several implications for clinicians arise from this study. First, we provide evidence to showcase different profiles of impairment that exist among survivors of 'mild' stroke at different times in the first year after stroke. The fusion of data from multiple assessments enabled the generation of an overview for each person, which is otherwise challenging to assess using conventional means. This new approach permitted the illustration of different profiles of stroke survivors despite the single 'mild' classification by the NIHSS. The evidence presented in this paper relating to various groupings of survivors of mild stroke confirms that the stroke severity classification should not rely only on neurological functions but would benefit from incorporating cognition, mood, functional disability, physical, and social activity measures and self-perceived impact. Based on our results, we propose that an optimal approach for assessing stroke recovery would integrate multiple existing scales to provide a more comprehensive view of a patient's recovery process. While each scale mentioned in our manuscript—including the Montreal Cognitive Assessment (MoCA), Montgomery–Åsberg Depression Rating Scale (MADRS), modified Rankin scale (mRS), Rapid Assessment of Physical Activity (RAPA), Work and Social Adjustment Scale (WSAS), and Stroke Impact Scale (SIS)—effectively measures specific aspects of poststroke impairment, none captures the entire recovery spectrum alone.

Our findings suggest that combining these scales allows for a more nuanced profiling of stroke survivors. Furthermore, our findings indicate that at different time points, different scales were distinctive in the profiling, e.g., MoCA and MADRS on day 3–7; MADRS, mRS/SIS, and WSAS at 3 months; and MoCA/RAPA, MADRS, mRS, and SIS at 12 months. By clustering and analyzing the combined outputs of these diverse scales, we can better identify patient profiles and tailor interventions accordingly. New insights from and use of the AI clustering approach now makes profiling across multiple scales feasible for clinicians. Alternatively, this integrated approach could lead to the development of a new, comprehensive stroke assessment tool that more holistically evaluates cognitive, emotional, physical, and social recovery aspects. Such a tool could significantly enhance personalized care plans and improve overall patient outcomes. Our approach enables widening the scope of the monitoring of stroke survivors and demonstrates the value of incorporating multiple domains in the characterization of survivors of stroke. This is significant in the medium to longer term, when survivors of stroke continue to experience impairments and impact despite being classified as 'mild'.

Second, the identification of distinct profiles of impairment and impact at different times enables the provision of personalized and targeted care and rehabilitation to survivors of stroke focusing on the domain and profile of impairment. For example, the identification of cognitive impairment and depression in survivors of 'mild' stroke may initiate treatments related to emotional health, cognition, and quality of life. This could promote intervention therapies, as the early detection of survivors of stroke with similar levels of depression could facilitate counselling and evidence-based care at early stages. Such need-based care and precautions would in turn enrich the poststroke quality of life of survivors of 'mild' stroke, thereby improving the current rehabilitation and person-centered care.

Third, we suggest the plausibility of integrating AI-enabled insights for decision making and designing strategies for rehabilitation that are associated with improving function and the quality of life in survivors of stroke. Using the framework presented in this paper, clinicians can input data related to different stroke assessments to visualize distinct subgroupings of stroke survivors, as shown in Appendix A. The framework is scalable to accommodate data from many patients and operate on a larger scale. While this serves as a cost-effective decision-making platform, it also categorizes stroke survivors based on

the similarity of their impairments, permitting clinicians and therapists to strategically design treatment and rehabilitation programs for survivors of stroke who have similar disabilities. Using this approach in healthcare institutions to analyze poststroke patient data has practical implications: The interactive visualization tool puts the approach and resources into the hands of clinicians. It can help identify where an individual is positioned in relation to the clustering of impairments that may impact the recovery trajectory, allowing therapists to personalize care plans more effectively.

As limitations of this study, we acknowledge that the portion of participants with missing data could be improved. This occurred primarily due to patients not performing all the tests planned in the study. Furthermore, information from survivors categorized as having moderate and severe severity could also be used as additional information for comparison purposes.

5. Conclusions

While presenting the potential of using AI in clinical settings, we believe that conventional means of assessing stroke severity should be revisited to incorporate impairment from different domains. This is important, particularly as the prevalence of mild stroke appears to have seen a substantial increase in recent years [37]. Survivors of mild stroke should be investigated at a granular level to determine if the categorization of mild 'is really mild'. The discovery of different profiles for survivors of stroke will systematically empower person-centered precision rehabilitation based on individual treatment needs, thereby advancing the survivorship and care of those previously classified as 'mild'.

Author Contributions: Conceptualization, A.A., R.N., D.D.S., D.A. and L.M.C.; data curation, A.W.; formal analysis, A.A., R.N., D.L.C., A.W., and L.M.C.; investigation, A.A., R.N., D.L.C., C.B., S.D., G.A.D., D.A. and L.M.C.; methodology, A.A., R.N., D.D.S., D.A. and L.M.C.; software, A.W.; supervision, D.D.S., C.B., S.D., G.A.D., D.A. and L.M.C.; writing—original draft, A.A., R.N., D.D.S., D.A. and L.M.C.; writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Ethics approval for the original study was obtained from the Austin Health Human Research Ethics Committee (H2010/03588, approved 06 January 2010), Melbourne Health Human Research Ethics Committee (2009.079, approved 13 January 2010), ethics committees responsible for each recruiting hospital site and the tertiary institution involved. Approval was also obtained for use of collected data in subsequent analyses of related research by the research team (HREC/17/Austin/281, approved 04 September 2017).

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The participants in this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research, supporting data are not available.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The outcomes of the study were integrated into an interactive visualization platform which enabled investigation and visualization of data in a systematic way. The platform pro-

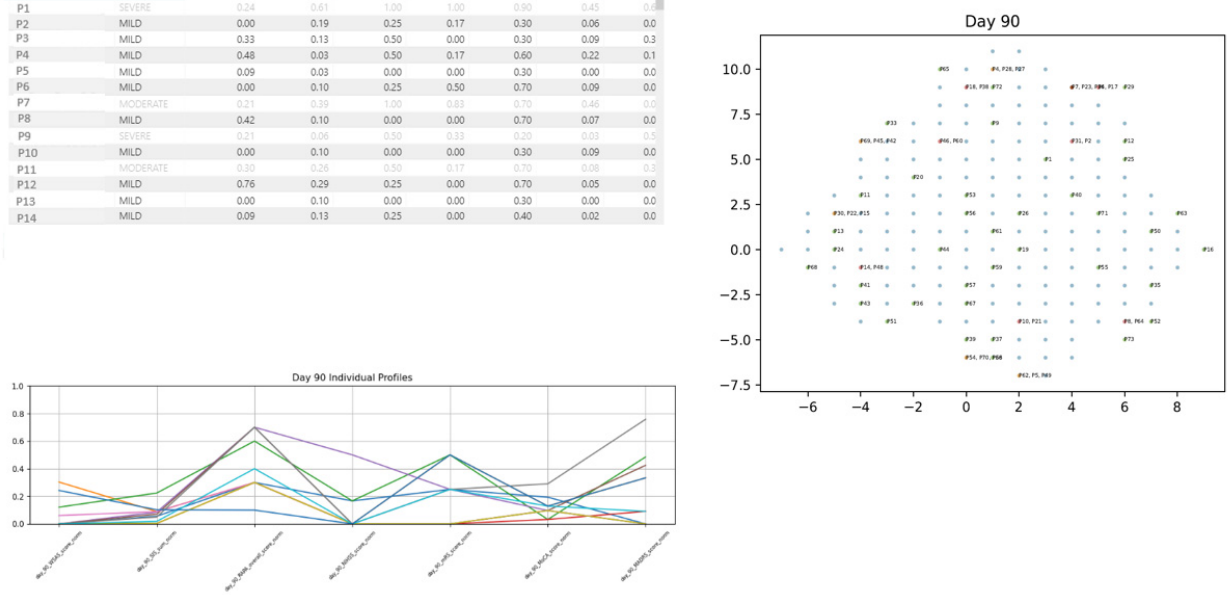
vides a detailed investigation into patient trajectories over time as well as offers interactive data visualisation via filtering capabilities.

Figure A1A shows the aggregated demographic details. Figure A1B shows a snapshot of outcomes of the GSOM based on the START data. These visuals can be filtered per person or by different test groups for data exploration.

id_code	day_baseline_identity_age	day_baseline_identity_gender_female	day_7_severity_NIHSS
P1	79	0	SEVERE
P2	78	0	MILD
P3	54	0	MILD
P4	54	0	MILD
P5	59	1	MILD
P6	90	0	MILD
P7	86	1	MODERATE
P8	86	0	MILD
P9	32	0	SEVERE
P10	50	1	MILD
P11	80	0	MODERATE
P12	52	0	MILD
P13	75	0	MILD
P14	73	1	MILD

(**A**)

id_code	day_7_severity_NIHSS	day_90_MADRS_score_norm	day_90_MoCA_score_norm	day_90_mRS_score_norm	day_90_NIHSS_score_norm	day_90_RAPA_overall_score_norm	day_90_SIS_sum_norm	day_90_WSAS_score_norm
P1	SEVERE	0.24	0.61	1.00	1.00	0.90	0.45	0.6
P2	MILD	0.00	0.19	0.25	0.17	0.30	0.06	0.0
P3	MILD	0.33	0.13	0.50	0.00	0.30	0.09	0.3
P4	MILD	0.48	0.03	0.50	0.17	0.60	0.22	0.1
P5	MILD	0.09	0.03	0.00	0.00	0.30	0.00	0.0
P6	MILD	0.00	0.10	0.25	0.50	0.70	0.09	0.0
P7	MODERATE	0.21	0.39	1.00	0.83	0.70	0.46	0.0
P8	MILD	0.42	0.10	0.00	0.00	0.70	0.07	0.0
P9	SEVERE	0.21	0.06	0.50	0.33	0.20	0.03	0.5
P10	MILD	0.00	0.10	0.00	0.00	0.30	0.09	0.0
P11	MODERATE	0.30	0.26	0.50	0.17	0.70	0.08	0.3
P12	MILD	0.76	0.29	0.25	0.00	0.70	0.05	0.0
P13	MILD	0.00	0.10	0.00	0.00	0.30	0.00	0.0
P14	MILD	0.09	0.13	0.25	0.00	0.40	0.02	0.0



(**B**)

Figure A1. (**A**) Visualization of demographic details of patients. (**B**) Visualization of the GSOM profiles and patients' assessment scores.

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