

Towards Early Detection of Mild Cognitive Impairment: Predictive Analytics Using the Oculo-Cognitive Addition Test (OCAT)

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Abstract: Mild cognitive impairment (MCI) is often challenging to diagnose. The Oculo-Cognitive Addition Test (OCAT) is a rapid, objective tool that measures eye movement and time-based features during mental addition tasks in under one minute. This study aims to develop predictive machine learning algorithms for early detection of those at greater risk for mild cognitive impairment, helping warrant further testing. OCAT testing with integrated eye tracking was completed by 250 patients. Time-related and eye movement features were extracted from raw gaze data. Feature selection was performed using machine learning methods, including random forest and univariate decision trees, to identify predictors of Dementia Rating Scale (DRS) outcomes. Supervised models—logistic regression (LR) and K-nearest neighbors (KNN)—were trained to classify MCI. Class imbalance was addressed using the Synthetic Minority Over-sampling Technique. LR models achieved the highest performance using the combined time and eye movement features, with an accuracy of 0.97, recall of 0.91, and the area under the precision-recall curve (AUPRC) of 0.95. This study demonstrates that machine learning models trained on OCAT-derived features can reliably predict DRS outcomes (PASS/FAIL), offering a promising approach for early identification of MCI.

1 INTRODUCTION

Mild Cognitive Impairment (MCI) is a condition that represents a transitional state between normal aging and dementia, particularly Alzheimer's Disease (AD) (Anderson, 2019; Chen et al., 2021; Petersen et al., 1999), though some cases stem from reversible causes such as concussion, metabolic pathologies, and psychiatric disorders (Petersen et al., 2018). According to the 2018 American Academy of Neurology guidelines, individuals with MCI exhibit cognitive deficits while maintaining functional independence in activities of daily living (Petersen et al., 2018). Diagnostic criteria for MCI have evolved over time – from initially emphasizing memory loss (Petersen et al., 1999) to including impairments in other domains such as language, visuospatial processing, or executive skills (Chen et al., 2021;

Petersen, 2004) – reflecting the heterogeneity of its clinical presentation.

When cognitive decline or MCI is suspected, a comprehensive neuropsychological assessment remains the gold standard for diagnosis (Aarsland et al., 2009; Matteau et al., 2011). However, due to testing time, rigor, clinical availability, and insurance coverage, not all patients can undergo full testing. As a validated alternative, the Mattis Dementia Rating Scale (DRS) is frequently used to measure general cognitive function (Matteau et al., 2011; Porto et al., 2007). The DRS has also been validated as a short-form test for MCI screening (Matteau et al., 2011). Even so, this test can take as few as 15-20 minutes with an alert, healthy individual, but can take close to an hour for a person with advanced impairment (Marson et al., 1997; Matteau et al., 2011).

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Given the time and resource demands of comprehensive neuropsychological assessment, there is a clinical need for a brief, objective screening tool to predict a patient's relative risk for MCI, ensuring that those at greatest need are prioritized for further assessment. It has been shown that patients with a score lower than 140 on the DRS are at greater likelihood of having MCI (Harvey & Mohs, 2001; Mattis, 1976; Montgomery, 1982; Schmidt et al., 1994). Note this cutoff is much higher than the clinical psychometric threshold of 123 (Mattis, 1988). Many neurological diseases lead to changes in eye movements, also termed oculometrics, and these changes have been identified as early biomarkers of Alzheimer's disease and related dementias (Laguna et al., 2011; Mosimann et al., 2005). Studies have shown that cognitive impairment can be identified by quantifying changes in oculometric patterns such as fixation duration, saccadic velocity, blinks, and pupillary response (Pradhan et al., 2019; Pradhan et al., 2018; Pradhan et al., 2022). The Oculo-Cognitive Addition Test (OCAT) (Pradhan et al., 2024) was designed to efficiently (< 2 minutes) assess cognitive function (Pradhan et al., 2022) by capturing eye movements and associated time parameters during verbally administered mental addition tasks. Participants are instructed to complete, as rapidly as possible, 12 trials of summing three consecutive numbers shown separately on three consecutive blank screens in seemingly random positions categorized by low, medium, and high cognitive workload, respectively. While the location of the numbers may appear random to the subject, OCAT consists of a structured "infinity loop" pattern of 24 symmetrical positions in which the numbers appear (Figure 1). By utilizing this "infinity loop" pattern, OCAT is inherently structured, allowing for measurement and quantification of eye movements in horizontal, vertical, and diagonal directions, using integrated eye-tracking hardware, while modulating cognitive demand through verbal addition tasks, to engage brain areas associated with attention, working memory, numerical representation, and oculometric coordination (Pradhan et al., 2022). Eye movement features measured include saccades, fixations, blinks, and pupil dilations, which have a variety of functions with multiple voluntary and reflexive factors (Kang et al., 2023; Purves et al., 2001). Time-based features recorded—such as total test time, the average time to complete each three-number addition task (where each number is associated with the low, medium, or high cognitive load), and response time of following the number on the screen also reflect cognitive processes like attention, processing speed, and

working memory. In a proof of concept study, OCAT demonstrated increased saccadic latency and fixation time in a hypoxic population (Pradhan et al., 2022), supporting its sensitivity to cognitive load.

The objective of this study was to develop predictive machine learning models for possible mild cognitive impairment (PMCI) identification using the combined eye movement and time-based features extracted from the raw gaze data during the OCAT testing. OCAT was performed the same day as, but prior to, neuropsychological testing which included the DRS. It is hypothesized that with the optimal model, the features derived from OCAT will reliably and accurately predict DRS outcomes (PASS/FAIL). This study represents the foundational work toward establishing OCAT as a rapid, objective screening tool for neurological function, with the potential to guide further neuropsychological assessment.

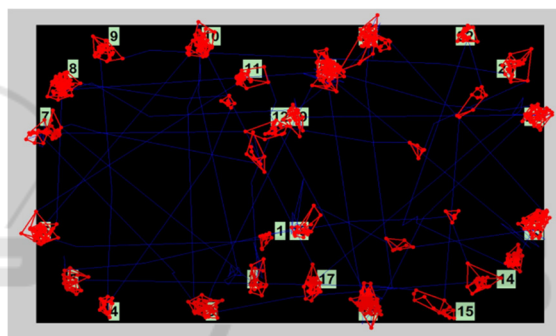


Figure 1: Eye tracking data during OCAT showing the fixations (in red) and saccadic movement (in blue).

2 METHODOLOGY

2.1 Participants

250 participants who underwent neuropsychological testing were enrolled in this study protocol, which was approved by the Institutional Review Board (IRB). Subjects between 21 and 99 years of age with normal vision (including those with correction), no clinically significant visual impairment, and the ability to provide consent themselves were enrolled. Informed consent was obtained from all participants before enrolment. All tested participants were categorized into Cognitive Normal (CN) and Possible Mild Cognitive Impairment (PMCI) groups, including those with mild dementia, based on their DRS score during clinical neuropsychological assessment. As per the clinical standards, participants with a DRS score of 140 or above were labelled as CN, and those with less than 140 scores were labelled

as PMCI (Harvey & Mohs, 2001). A portion of the data was used to train and optimize supervised machine learning models, while remaining data was reserved for independent validation. Model performance was evaluated by assessing recall, specificity, precision, and accuracy in classifying patients with DRS scores indicative of MCI, based on established diagnostic thresholds (Harvey & Mohs, 2001). Participants whose eye-tracking data during OCAT testing did not meet the predefined “tracking ratio” threshold of 80% due to excessive signal loss, poor eye-tracking calibration, or unstable gaze recordings were excluded from further analysis to ensure the reliability and validity of gaze-based cognitive performance measurements during the OCAT. The final distributed dataset included the OCAT data of 206 participants, with 166 categorized as CN class and 40 as PMCI class.

2.2 Equipment and Procedures

The OCAT testing was conducted in a quiet, climate-controlled room. The ambient light levels were at stable luminance and consistent throughout the data collection. The OCAT software was installed on the 14” EyeOn Elite Windows 10 Pro tablet (EyeTech Digital Systems, Tempe, Arizona, USA) with an integrated eye tracking device (8MP Eye Gaze Camera) to track eye gaze during the OCAT testing. The resolution of the tablet screen was 1920 x 1080. The raw eye-gaze data was collected at a sampling rate of 120 Hz. During the study, participants were seated facing the tablet and positioned to maintain a viewing distance of 60 cm, a distance within the recommended reading range. The session began with a 5-point calibration to optimize eye-tracking accuracy. Calibration quality was verified, and recalibration was performed if necessary to maintain a calibration error below 0.5 degrees. To control potential task novelty effects, a structured preview and practice phase were incorporated before data acquisition. Participants first received standardized instructions and observed a demonstration of the task. Subsequently, an initial practice session was conducted, during which participants completed a full OCAT trial that allowed for task familiarization and reduction of learning-related variability. The subsequent OCAT trial was considered the formal test, and only data from this test were analyzed. The OCAT testing session was performed before any scheduled neuropsychological testing for the Neurology appointment to avoid any fatigue effects.

2.3 Data Processing and Feature Extraction

The time-related features described in Table 1 were measured during the OCAT for overall task completion time and for each addition sequence.

Addition sequences had varying cognitive workloads (low, medium, and high in the form of first, second, and third number, respectively). The raw gaze data obtained during the OCAT were pre-processed to extract eye movement-related features. Pre-processing involved cleaning artifacts using filtering techniques followed by applying fixation and saccade classification algorithms based on dispersion thresholds (Pradhan et al., 2018). From the processed data streams, the features related to saccades and fixations, along with blinks and pupillary dynamics, were computed to characterize participants’ cognitive and oculomotor performance (Table 1). The features listed in Table 1 were computed for each OCAT test performed by every participant. The features exhibiting significant deviation from a normal distribution (skewness outside the range of -1 to 1) were subjected to logarithmic transformation during the data preprocessing stage. This transformation aimed to reduce skewness and stabilize variance, thereby improving the performance of the classification model and predictive accuracy. It is worth noting that, in addition to the 31 features listed in Table 1, the age of the participants was also included as an additional feature in the predictive modelling.

To develop and evaluate the performance of the machine learning models to predict the possible mild cognitive impairment, the OCAT dataset was randomly split into training and testing sets, with 80% of the data used for training and the remaining 20% reserved for testing. This stratified split ensured that the class distribution between CN and PMCI was preserved across both subsets, as summarized in Table 2. To address the issue of class imbalance in the training data, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE generates synthetic samples for the minority class (in this case, PMCI class) by interpolating between existing minority class instances, thereby improving the model’s ability to learn discriminative patterns and reducing bias toward the majority class. Table 3 shows the class distribution of training and testing data after applying SMOTE.

Table 1: Description of OCAT features categorized into time and eye-movement related features.

Time-related Features	
1.	Total Test Time (s)
2.	Mean Time for Number 1 (low cognitive workload) (s)
3.	Mean Time for Number 2 (medium cognitive workload) (s)
4.	Mean Time for Number 3 (high cognitive workload) (s)
5.	(Log-) Mean Latency Time (ms)
6.	(Log-) Standard Deviation of Latency Time (ms)
Eye Movement-related Features	
Fixations:	
7.	Mean Fixation Time for Number 1 (ms)
8.	(Log-) Standard Deviation of Fixation Time for Number 1 (ms)
9.	Mean Fixation Size for Number 1 (mm)
10.	(Log-) Standard Deviation of Fixation Size for Number 1 (mm)
11.	Mean Fixation Area for Number 1 (mm ²)
12.	(Log-) Standard Deviation of Fixation Area for Number 1 (mm ²)
13.	Mean Fixation Time for Number 2 (ms)
14.	(Log-) Standard Deviation of Fixation Time for Number 2 (ms)
15.	Mean Fixation Size for Number 2 (mm)
16.	(Log-) Standard Deviation of Fixation Size for Number 2 (mm)
17.	Mean Fixation Area for Number 2 (mm ²)
18.	(Log-) Standard Deviation of Fixation Area for Number 2 (mm ²)
19.	Mean Fixation Time for Number 3 (ms)
20.	(Log-) Standard Deviation of Fixation Time for Number 3 (ms)
21.	Mean Fixation Size for Number 3 (mm)
22.	(Log-) Standard Deviation of Fixation Size for Number 3 (mm)
23.	Mean Fixation Area for Number 3 (mm ²)
24.	(Log-) Standard Deviation of Fixation Area for Number 3 (mm ²)
Saccades:	
25.	Median Diagonal Saccadic Velocity (deg/s)
26.	Median Horizontal Saccadic Velocity (deg/s)
27.	Median Vertical Saccadic Velocity (deg/s)
Blinks:	
28.	Blink Rate (number of blinks per minute)
29.	Median Blink Duration (ms)
Pupillary Dynamics:	
30.	Standard Deviation of Pupil Size (mm)
31.	Coefficient of Variation of Pupil Size

Models were developed and evaluated using both the original imbalanced dataset and a class-balanced dataset generated through SMOTE. The training data were standardized using the *StandardScaler* method

to ensure that features had zero mean and unit variance. The fitted scaler parameters were saved and subsequently applied to the testing dataset to maintain consistency in feature scaling during model evaluation.

Table 2: Class distribution of training and testing dataset from the original, imbalanced dataset.

Classification	CN Class	PMCI Class
Training dataset	135	29
Testing dataset	31	11

Table 3: Class distribution of training and testing dataset after applying SMOTE to get an augmented, class-balanced dataset.

Classification	CN Class	PMCI Class
Training dataset	135	135
Testing dataset	31	11

2.4 Feature Selection

Feature selection was conducted in a two-step process to reduce redundancy and retain features with high predictive value. First, highly correlated feature groups were identified using Pearson's correlation coefficient, with a threshold of 0.8, consistent with established practices for multicollinearity reduction (Dormann et al., 2013). Each group consisted of two or more features that exhibited mutual correlation above this threshold. Within each group, a Random Forest classifier was employed to assess the relative importance of features, and only the feature with the highest predictive importance was retained while the others were discarded. In the second step, a univariate evaluation of the remaining, uncorrelated features was performed using a Decision Tree classifier. Each feature was individually assessed based on its Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) score. Features with ROC-AUC scores less than or equal to 0.5 were excluded, as they contributed no better than random performance in classification.

Both models were trained using the pre-processed and feature-selected dataset. Key performance metrics including recall, precision, specificity, F1-score, accuracy, and the area under the precision-recall curve (AUPRC) were computed for comprehensive assessment of predictive performance. Figure 2 illustrates the complete workflow of the model comprising feature extraction, data pre-processing, feature selection, and predictive modelling steps.

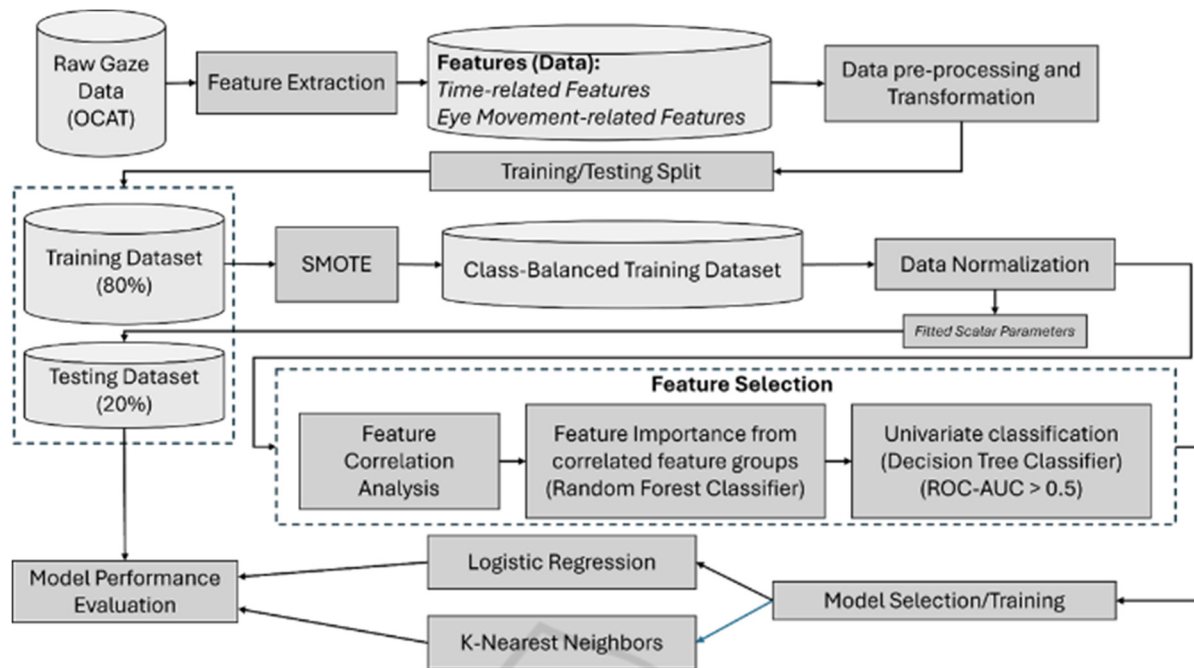


Figure 2: Workflow of the predictive modelling process.

3 RESULTS

By using OCAT testing, this study aimed to predict whether a participant would score below 140 on the DRS, reflecting a higher risk for the possibility of MCI. The classification performance of Logistic Regression (LR) and K-Nearest Neighbours (KNN) was evaluated under both imbalanced (original) and class-balanced (SMOTE- augmented) datasets with different feature combinations described in Table 1.

Table 4 shows that the LR model trained on SMOTE-balanced data containing both time-related and eye movement-related features demonstrated superior and consistent performance across all metrics, achieving perfect precision (1.00), specificity (1.00), and F1-score (0.95), with high recall (0.91) and accuracy (0.97), indicating strong discriminatory ability without overfitting. In contrast, the LR model trained on the original imbalanced data showed reduced recall (0.73 at DT = 0.45 and 0.64 at DT = 0.5), while maintaining high specificity (0.97) and precision (≥ 0.88), suggesting a bias toward the majority cognitive normal class.

KNN also benefited from SMOTE, with the balanced model ($k = 6$) yielding improved recall (0.82) and F1-score (0.82), along with high specificity (0.94) and AUPRC (0.95). Interestingly, the KNN model ($k = 5$) with original, imbalanced dataset achieved perfect precision (1.00) and

specificity (1.00), but at the cost of lower recall (0.73), indicating under-identification of the minority possibly MCI class despite overall high accuracy (0.93). Both models show optimal performance under the SMOTE-balanced condition, as also seen in the precision-recall curve (Figure 3).

4 DISCUSSIONS

Multiple predictive models were developed using time- and eye movement-based OCAT features. The LR models trained on SMOTE-balanced datasets consistently demonstrated the most balanced and robust performance across all metrics. These results highlight the utility of SMOTE in improving recall while maintaining favorable balance between precision and specificity. The model developed yielded high recall, precision, specificity, F1-score, accuracy, and AUPRC, indicating reliable predictive power for diagnosing PMCI. This means that the model developed is robust to false positives and negatives. In the context of MCI screening, false positives may lead to unnecessary patient expense and stress, as well as provider time, but the screener result does not definitively make the diagnosis. Rather, it rather prompts further evaluation via DRS or comprehensive neuropsychological assessment. False negatives, on the other hand, pose a more

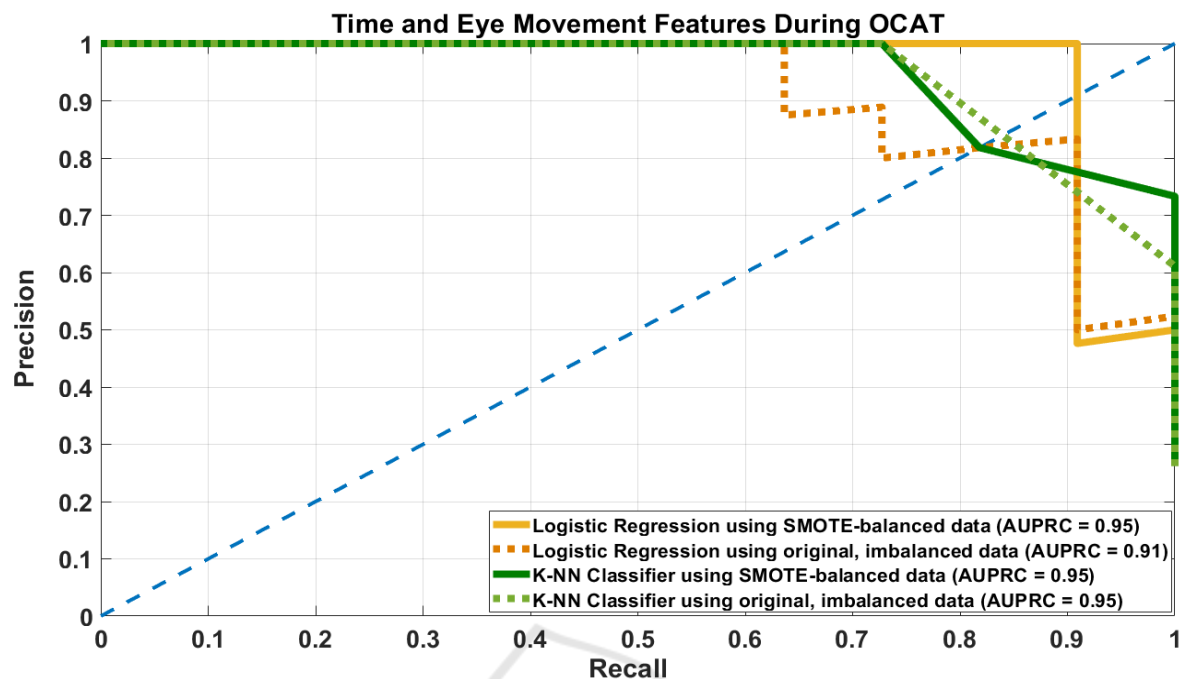


Figure 3: Precision-Recall Curve of Logistic Regression (LR) and K-Nearest Neighbors (KNN) models using both SMOTE-augmented balanced and original, imbalanced datasets with time and eye-movement features during OCAT.

Table 4: LR and KNN model performance with SMOTE-balanced and imbalanced datasets.

Model	Hyper-parameter	Recall	Precision	Specificity	F1-score	Accuracy	AUPRC
LR – SMOTE	DT = 0.45	0.91	1	1	0.95	0.97	0.95
	DT = 0.5	0.91	1	1	0.95	0.97	
LR - original	DT = 0.45	0.73	0.89	0.97	0.8	0.9	0.91
	DT = 0.5	0.64	0.88	0.97	0.74	0.88	
KNN- SMOTE	Best k = 6	0.82	0.82	0.94	0.82	0.9	0.95
KNN - original	Best k = 5	0.73	1	1	0.84	0.93	0.95

serious concern in cognitive screening, since missing the indicators of MCI when it is present could delay timely intervention. This is particularly critical now that there are disease modifying treatments for Alzheimer’s disease as well as for individuals with other causes of cognitive impairment, such as concussions, hypoxia, vascular or metabolic conditions (Biessels & Whitmer, 2020; Pradhan et al., 2019)

In such cases, early identification and intervention may facilitate cognitive recovery, or prompt additional diagnostic measures, including neuroimaging and further cognitive evaluation (Biessels & Whitmer, 2020). These findings support the continued use of OCAT with integrated eye-tracking in clinical settings, as garnering the broader

range of cognitively relevant features improves diagnostic accuracy and enhances the tool’s potential for early detection of cognitive impairment. There is broad consensus that the total health care cost could be greatly reduced by more efficient resource utilization as well as earlier diagnosis and intervention for cognitive and neurological disorders, especially when traditional clinical diagnostic tools lack sufficient sensitivity (Laguna et al., 2011; Mosimann et al., 2005). As a screening tool, OCAT can help to narrow the focus of resource deployment to those at greater risk for disease and may be applicable to other conditions that also affect eye movement. For example, sports-related concussion has also been associated with oculomotor dysfunction such as saccadic eye movements, accommodation,

smooth pursuit (tracking), fixation, and sensitivity to light in 90% of athletes (Ciuffreda et al., 2007). Further refinement of LR and KNN models that use both eye-movement and time-based features could lead to a highly sensitive screening tool in clinical and sideline settings where subclinical markers of cognitive impairment can inform diagnoses.

5 CONCLUSIONS

OCAT leverages the well-established relationship between eye movement dynamics and cognitive function to facilitate early detection of cognitive decline associated with MCI or other neurological disorders, like Alzheimer's Disease, dementias, traumatic brain injuries, substance use, and fatigue. By combining reflexive saccadic eye movements with time-based and attentional effects under varying cognitive loads, OCAT provides a multidimensional profile of cognitive performance. As a rapid, non-invasive assessment tool, OCAT can be seamlessly integrated into outpatient clinics, primary care settings, and neurology practices. Its use as an initial screening tool may assist clinicians in identifying patients who would benefit from more extensive evaluations, such as full-extent DRS testing, ultimately conserving time, reducing medical and insurance burdens. With further refinement and dissemination, OCAT could serve as a standardized intake instrument for both preliminary assessment and longitudinal tracking of cognitive state. By featuring OCAT into routine assessments, healthcare providers can enhance early detection, streamline cognitive evaluations, and improve patient outcomes to reduce healthcare costs.

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