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Efficacy and Efficiency of Computer-Assisted Cognitive Stimulation in the Rehabilitation of Patients with Psychiatric Disorders: A Retrospective Analysis of Training Strategies and Intervention Duration

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Abstract: *In recent years, the integration of technology into mental health interventions has shown promising results. This retrospective study analyses the efficacy and efficiency of computer-assisted cognitive stimulation (CACS) among a group of 92 psychiatric patients, of whom 32 were randomly selected to benefit from a personalised intervention. Data were collected on demographic variables (age, education level, urban/rural area), psychiatric diagnoses, therapeutic regimens, and scores on validated psychometric scales, Mini Mental State Examination (MMSE), and Montreal Cognitive Assessment (MoCA), assessed before and after the intervention. Detailed metrics related to the training modules, such as the number of sessions, level achieved and duration of each session were also analysed. The results indicate statistically significant increases in MMSE (from 22.94 to 24.31, $p < 0.001$) and MoCA (from 22.06 to 24.22, $p < 0.001$) scores after CACS therapy, highlighting notable improvements in cognitive functions. The robust correlations between changes in scores suggest a positive impact of the intervention on cognitive performance. However, the retrospective nature of the study imposes certain limitations such as the potential influence of confounding variables, the lack of rigorous control of the intervention and the impossibility of establishing direct causal relationships. In addition, these results support the opportunity to integrate artificial intelligence (AI) components in the development of educational interventions in mental health, opening new directions for future research in the field.*

Keywords: *cognitive stimulation; computer-assisted therapy; psychiatric rehabilitation; MMSE; MoCA; training modules; AI in education..*

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1. Introduction

Cognitive deficits are common in psychiatric disorders, especially in schizophrenia and affective psychoses and they significantly affect the quality of life and daily functioning (Bora, Yücel, & Pantelis, 2010; Kahn & Keefe, 2013). These deficits often appear as difficulties in attention, memory, and executive function. While traditional pharmacotherapy effectively manages the core symptoms of psychiatric disorders, it frequently does not address these cognitive challenges. This shortfall highlights the urgent need for innovative rehabilitative interventions to improve cognitive functioning and overall patient outcomes.

One promising intervention is CACS. Originally developed for neurological conditions and pediatric education, CACS has been adapted for adult psychiatric populations. This technology-driven training offers structured, engaging, and personalised exercises designed to target specific cognitive impairments. Recent studies have shown that such personalised cognitive training can lead to significant improvements in attention, memory, and executive function (García-Fernández et al., 2019; Grynszpan et al., 2011). These improvements are particularly important given the chronic nature of cognitive deficits in psychiatric disorders.

CACS further enhances patient engagement and motivation through adaptive learning algorithms and multimedia elements. The program adjusts the difficulty of exercises based on patient performance, ensuring a balanced challenge. Visual and audio feedback enhances engagement, making patients more likely to adhere to training. These techniques are similar to modern educational methods that leverage technology to improve learning outcomes (Chan, Hirai, & Tsoi, 2015; Stuifbergen et al., 2018).

In recent years, the integration of artificial intelligence (AI) into CACS has transformed cognitive rehabilitation. AI enables the development of adaptive and personalised training programs that adjust the complexity of exercises in real-time, based on patient performance. Machine learning algorithms analyse large datasets to monitor cognitive progress and optimise interventions for specific deficits. Recent studies suggest that incorporating AI into cognitive rehabilitation can significantly enhance clinical outcomes, yielding notable improvements in memory, attention, and executive functions (LeCun, Bengio, & Hinton, 2015; Coleman et al., 2024; Khalid et al., 2024).

This study retrospectively analyses a clinical dataset to evaluate the efficacy and efficiency of CACS in a cohort of psychiatric patients. All 92 patients received personalised cognitive stimulation, while a randomly selected subgroup of 32 individuals was chosen for an in-depth analysis of cognitive outcomes. The data collected included demographic variables (age, educational level, urban/rural background), psychiatric diagnoses, treatment regimens, and scores on the MMSE and MoCA both before and after the intervention. Detailed training module metrics such as number of sessions, training levels achieved, and session durations were also examined.

Our findings indicate a statistically significant improvement in cognitive scores after CACS therapy. Different training modules produced varying outcomes and strong correlations were found between improvements in MMSE and MoCA scores. This suggests that the degree of cognitive enhancements is intricately linked to the intensity and quality of the training received. Overall, these results support the use of CACS as a valuable tool in psychiatric rehabilitation and emphasise the potential of AI-driven educational interventions to bridge the gap between neuroscience and psychiatric care, opening new avenues for improving cognitive function in this population.

2. Materials and Methods

This retrospective study evaluated the efficacy of CACS in patients with psychiatric disorders, employing an integrated clinical design alongside a personalised therapy approach. Initially, 92 patients from a specialised clinic were evaluated for study inclusion. From this group, 32 patients were selected using a stratified randomisation method, ensuring a balanced distribution of age, gender, and diagnosis. The selection process was conducted using a computer-generated randomisation sequence to minimise selection bias. Patients were selected through a comprehensive evaluation by the research team, which included reviewing medical histories, conducting psychiatric assessments, and confirming psychiatric disorders. The sample comprised individuals aged between 20 and 91 years, with a gender distribution of approximately 63% women and 37% men. Most participants were from urban areas (80%), and the majority had attained higher education (65%), while the remaining 35% possessed secondary education. Detailed records of psychiatric diagnoses and therapeutic regimens administered to each patient were maintained, ensuring that confounding factors that could influence cognitive outcomes were rigorously documented. The diagnoses included in the study ranged from affective disorders, such as recurrent depressive disorder and bipolar affective disorder, to neurocognitive disorders such as mixed dementia and late-onset Alzheimer's disease. Comorbid psychiatric conditions such as emotionally unstable personality disorder or generalised anxiety disorder were also considered as they may have an impact on cognitive function and response to treatment.

The treatment regimens administrated to the patients included a wide range of psychotropic medications, of which the most used were antidepressants, antipsychotics, anxiolytics, and nootropics. In some cases, complex combinations of medications were prescribed, including anticonvulsants, nutritional supplements with neuroprotective potential, or other categories of treatments aimed at improving cognitive function. The efficacy of the therapy was assessed by changes in MMSE and MoCA scores before and after intervention, with more pronounced improvements observed in patients with therapeutic regimens that included nootropics and antidepressants, especially in combinations with anxiolytics. In the case of patients with advanced dementia, cognitive progress was more modest, which may indicate a reduced capacity for cognitive recovery in this category.

This comprehensive analysis allowed not only to assess the impact of the therapy on cognitive function but also identify differential response patterns depending on the underlying pathology and the treatments administered.

The intervention involved the implementation of a CACS program delivered through specialised software capable of dynamically adapting training modules to meet each patient's unique needs. The program captured detailed information including the type of training module administered, the number of sessions attended, the maximum level achieved during training, and the duration of each session. This level of detail facilitated direct comparisons between patients undergoing similar training modules and enabled an assessment of how both the intensity and duration of therapy impacted cognitive performance.

Cognitive functioning was assessed using two validated psychometric instruments: the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA). These assessments were conducted at baseline (pre-intervention) and immediately after the completion of the program, with additional periodic follow-ups to quantify changes in cognitive functions over time.

Statistical analyses were performed using Microsoft Excel. Descriptive statistics were used to characterise the demographic and clinical features of the sample. Paired samples t-tests were conducted to compare MMSE and MoCA scores before and after the intervention, revealing statistically significant improvements in cognitive performance. Additionally, ANOVA was applied to compare the outcomes across different training modules, while Pearson's correlation coefficient was used to assess the relationship between the improvements observed on the two cognitive scales, thus confirming the consistency of the cognitive measurements.

Individual differences between the scores obtained before and after the intervention were calculated according to the relationships: ΔMMSE = post-therapy score minus pre-therapy score and ΔMoCA = post-therapy score minus pre-therapy score, thus facilitating the quantification of the observed changes. To highlight cases with notable progress, patients were ordered descendingly according to the respective values, and the data were subsequently grouped by diagnostic categories and therapeutic regimens. Statistical analysis involved calculating the average differences for each group, allowing the comparative interpretation of the effectiveness of the therapy according to the diagnosis and treatment administered.

Potential biases in this study include selection bias, which may arise due to strict inclusion and exclusion criteria and thus limit the sample's representativeness. Informational bias may also be encountered due to subjective assessments of MMSE and MoCA scores, and confounding bias, if intervention variables or environmental factors are not adequately controlled. In addition, variations in the application of the therapeutic protocol may generate performance bias and if the assessors are aware of the treatment administered, observer bias may be introduced.

This study was conducted in strict compliance with ethical standards and the General Data Protection Regulation (GDPR). All participants provided informed consent, and their data was securely stored on encrypted platforms.

3. Results

This study explored the effects of CACS in a cohort of 32 individuals diagnosed with psychiatric disorders, providing valuable insights into the intervention's efficacy across various cognitive domains. The participants, with an age range spanning from 20 to 91 years and a mean age of 55.5 years, represented a diverse sample for analysing cognitive response variability across different age groups. The age distribution exhibited a slight skew toward younger participants (skewness = -0.37) and a kurtosis value of -1.22, reflecting a more flattened than normal distribution.

Post-intervention cognitive assessments demonstrated notable improvements in global cognitive function. Specifically, the MMSE scores increased from a baseline mean of 22.94 to 24.31, representing a 5.9% enhancement ($p < 0.001$). Similarly, the MoCA score rose from 22.06 to 24.22, marking a 9.8% improvement ($p < 0.001$). Both cognitive measures exhibited strong internal consistency, with MMSE showing a 98% correlation between pre- and post-intervention scores, and MoCA demonstrating a 94% correlation, further validating the reliability of these results.

In addition to global improvements, an in-depth analysis of 16 distinct cognitive domains revealed significant differences in intervention effectiveness ($F = 5.40$, $p < 0.001$). Notably, processing speed and short-term memory were the most expensive domains, with pre-intervention mean scores of 26.15 and 21.0, respectively, indicating these functions were particularly susceptible to improvement through computerised cognitive training. In contrast, domains such as distributive attention and topological memory, with baseline scores of 6.38 and 7.17, showed lower responsiveness to the intervention, suggesting a potential need for more tailored approaches or additional training methods. Short-term memory exhibited the highest degree of individual variability (variance = 215.56), highlighting heterogenicity in participant responses, while sustained attention demonstrated the most stability (variance = 6.13).

Further investigation into the relationship between intervention duration, cognitive improvements, and age was conducted through correlation analyses. The number of cognitive training sessions showed a weak negative correlation with MMSE improvements ($r = -0.091$), suggesting that a longer duration of intervention did not necessarily lead to greater improvements in this measure. However, a modest positive correlation was observed between the number of sessions and MoCA improvements ($r = 0.256$), indicating that participants who exhibited gains in one measure were likely to show improvements in the other. Interestingly, age had minimal impact on cognitive improvements, with negligible correlations observed for MMSE ($r = -0.042$) and MoCA ($r = 0.185$), suggesting that the intervention proved effective across diverse age groups.

To further understand the role of intervention duration, a two-sample t-test assuming equal variances was performed to compare the effects of CACS across different session counts. For the MMSE, the comparison between participants receiving fewer than 20 sessions (mean = 1.84, variance = 0.26) and those receiving more than 20 sessions (mean = 1.09, variance = 0.13) revealed a statistically significant difference, with a t-statistic of 6.78 ($p < 0.001$). The pooled variance for this comparison was 0.194, and the degrees of freedom (df) were 62. The critical t-value for the two-tailed test was 1.99, affirming the robustness of this finding.

In contrast, no statistically significant differences were observed for MoCA scores when comparing participants with fewer than 20 sessions (mean = 1.91) to those with more than 20 sessions (mean = 1.79). The variances for the two groups were 0.25 and 0.46, respectively, with the t-statistic for this analysis being 0.79 and a two-tailed p-value of 0.43. The critical t-value for the two-tailed test was again 1.99, indicating that session duration did not significantly influence improvements in MoCA scores.

The results of this study suggest that CACS significantly enhances global cognitive function in individuals with psychiatric disorders, although variability exists across specific cognitive domains. While processing speed and memory functions demonstrated the most substantial responsiveness to the intervention, attention-related functions were less sensitive, underscoring the need for personalised cognitive rehabilitation strategies. Moreover, although the duration of the intervention may play a role in cognitive improvements, factors such as baseline cognitive status and individual participant characteristics must also be considered when optimising treatment protocols.

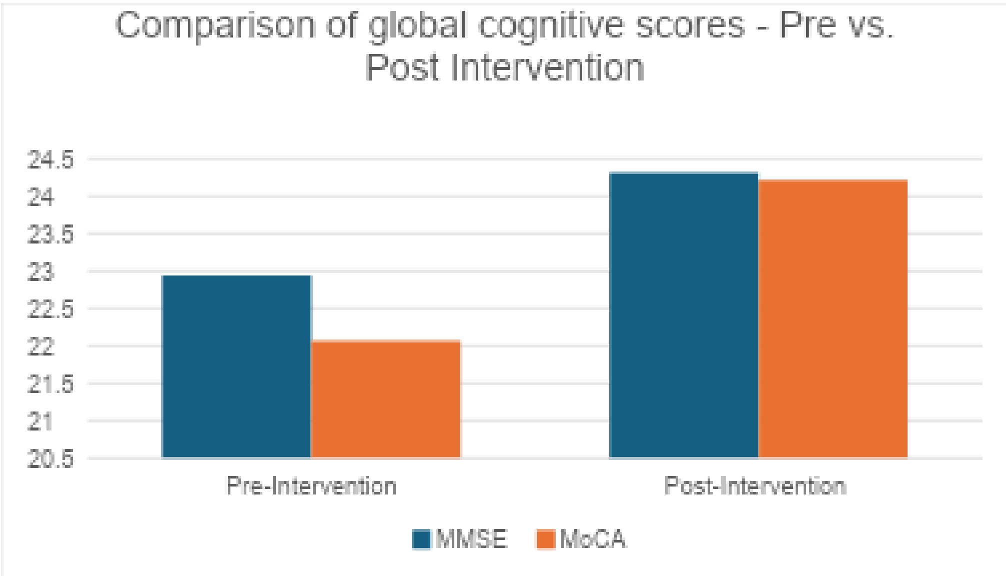

Figure 1. Comparison of global cognitive scores: Pre vs. Post Intervention

This graph typically presents two sets of bars comparing the mean values of MMSE and MoCA scores before and after the proposed intervention. The horizontal axis (X) shows the cognitive tests (MMSE and MoCA), while the vertical axis (Y) shows the mean score values.

A significant increase in the score of both MMSE and MoCA is noted after the intervention, suggesting the effectiveness of the cognitive rehabilitation program. The reported increases are approximately 5.9% for MMSE and 9.8% for MoCA, highlighting a more pronounced improvement in the case of MoCA. The visual difference between the bars before and after the intervention emphasises the positive impact of the therapy on global cognitive function. Statistical analyses confirm the significance of these changes, indicating that the intervention produces robust effects, not just random fluctuations.

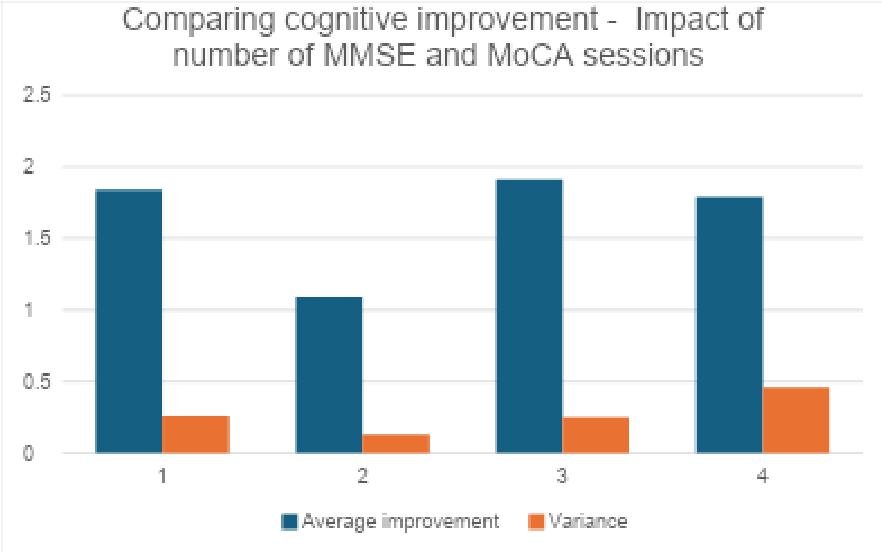

Figure 2. Assessing cognitive improvement: impact of number of MMSE and MoCA sessions

This comparative bar chart illustrates how the number of intervention sessions influences the improvement in cognitive functions measured by the MMSE and MoCA. The horizontal axis (X) represents two main categories: "Under 20 sessions" and "Over 20 sessions", for both cognitive tests. The vertical axis (Y) represents the average degree of improvement, as well as the associated variability (indicated by the differences in the height between the columns).

For the MMSE, it is observed that participants with a lower number of sessions (under 20) show a more pronounced increase in scores, highlighting the fact that low intensity of the intervention may be sufficient to achieve considerable progress on this test.

In the case of MoCA, the differences between "Under 20 sessions" and "Over 20 sessions" are less marked, suggesting that improvements do not depend as strongly on the number of sessions. Variability (understood as a standard deviation or confidence interval) indicates that not all participants respond uniformly to the same number of sessions, highlighting the need for a personalized approach.

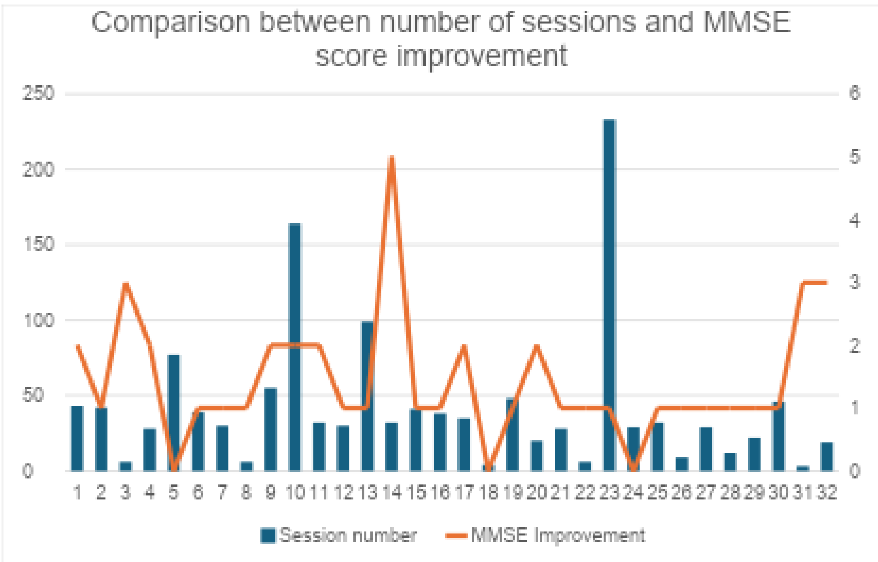

Figure 3. Relationship between the number of sessions and the increase in MMSE score

This graph, represented by lines and/or bars, highlights the relationship between the number of sessions (placed on the horizontal axis) and the increase in MMSE score (rendered on the vertical axis). Typically, each point or bar corresponds to a participant or an average value calculated for a certain range of sessions.

A weak negative correlation is observed between the number of sessions and the degree of improvement recorded on the MMSE, which means that a higher number of sessions does not automatically guarantee a substantial improvement.

In some cases, participants with a low number of sessions show greater progress, indicating the complexity of factors influencing cognitive outcomes. The graph emphasises the need for individualised analysis of interventions, as the response to treatment may depend on additional variables (e.g., initial severity of cognitive impairment, participant motivation, comorbidities, etc.). These data can guide the optimisation of the therapeutic program, suggesting that dynamically adapting the frequency and intensity of sessions could lead to better outcomes.

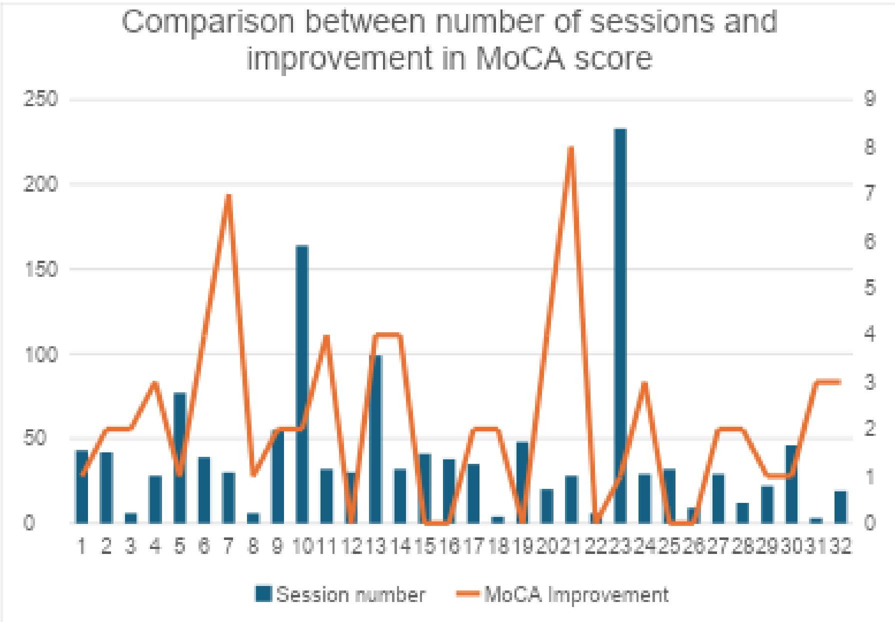

Figure 4. Relationship between the number of sessions and the increase in MoCA score

This graph illustrates the relationship between the number of sessions completed by participants and the increase in MoCA score following the intervention. The horizontal axis (X) is typically represented by the number of sessions and the vertical axis (Y) is the difference or improvement in MoCA score from baseline.

There is no clear pattern or consistent correlation between sessions frequency and improvement in MoCA scores, suggesting a low sensitivity of the MoCA test to variations in the number of sessions.

Individual factors or uncontrolled variables (e.g., baseline severity of cognitive deficit, level of motivation, associated comorbidities) may influence the response to the intervention and may mask the direct effect of the number of sessions on outcomes. These data indicate the need for further analyses to identify variables that may modulate response to therapy, as well as to assess whether the MoCA is sensitive enough to capture short- or medium-term improvements.

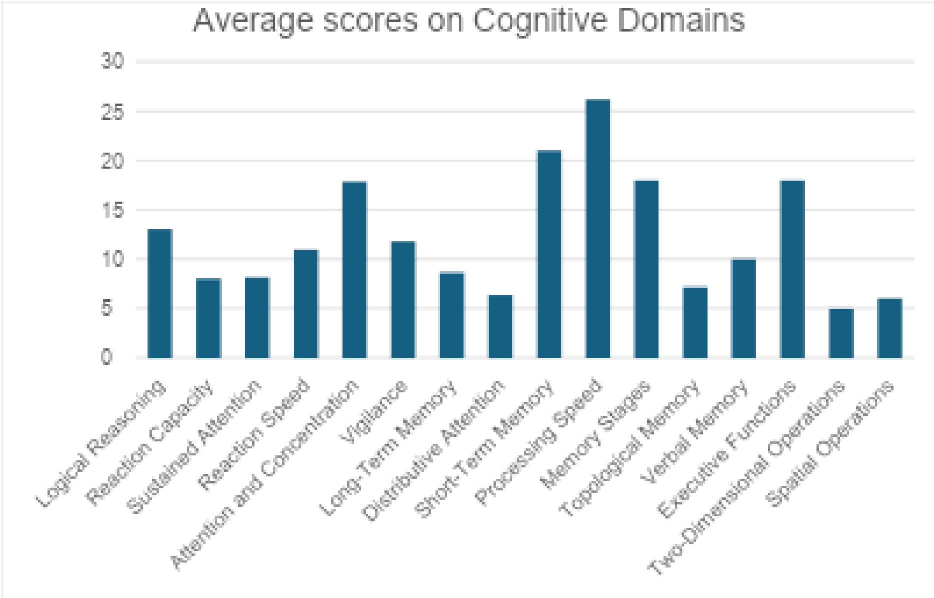

Figure 5. Comparing cognitive scores across domains: Impact of intervention

This plot compares scores on various cognitive domains (e.g., Processing Speed, Short-Term Memory, Executive Functions, etc.) before and after the intervention. The horizontal axis (X) typically shows the specific domain assessed, while the vertical axis (Y) shows the mean scores, reflecting the level of performance in each cognitive domain. There is significant variability in the response to the intervention, with some domains (such as Processing Speed and Short-Term Memory) showing greater increases than others. This differential nature of the improvement suggests that the intervention has a selective impact on certain cognitive functions, possibly due to the specificity of the techniques used (e.g., attention exercises, memory, or problem-solving training).

The variability in results may also be influenced by personal factors, such as the participants' medical history, level of involvement, social support, or the presence of other disorders that may affect cognitive functioning.

The fact that certain cognitive domains respond better to intervention supports the need to develop personalised rehabilitation strategies that directly target areas less responsive to standard therapy. These findings can guide the optimisation of the intervention, by adapting the exercises according to the specific needs of each patient and the areas where greater improvement is desired.

To evaluate the impact of CACS therapy on cognitive functions, a methodology was applied that involves the calculation of individual differences between the scores obtained before and after the intervention, according to the formulations: ΔMMSE = post-therapy scores minus pre-therapy score and ΔMoCA = post-therapy minus pre-therapy score. The collected data were subsequently sorted in descending order, allowing the identification of cases with significant improvements.

The study highlighted five patients (see Table 1) who presented remarkable improvements in cognitive abilities. Patients with ID15 achieved a 7-point increase in MoCA, were diagnosed with atypical autism, and were treated with a therapeutic regimen that included antidepressants and anxiolytics. Patients with ID58, diagnosed with a moderate depressive episode, recorded a 3-point increase in MoCA following treatment with nootropics. Patients with ID 24 and ID 30, both diagnosed with recurrent depressive disorder (ID 30 presenting additional psycho-cognitive elements), showed moderate improvements in MMSE and MoCA, the treatment consisting of administration of antidepressants, complemented in the case of ID 30 with anticonvulsants and anxiolytics. Also, the patient with ID 31, diagnosed with mild cognitive impairment, recorded a 5-point increase in MMSE under a regimen that involved antidepressants in combination with other medications. Analysis of the means of cognitive differences, performed by diagnostic categories, showed that patients with recurrent depressive disorder obtained a mean of 2 points in both MMSE and MoCA, while those diagnosed with adjustment disorder showed a mean of 1.5 and 0.5 points, respectively. These findings suggest that cognitive interventions are more effective in conditions with a predominant affective component, possibly due to the reversibility of the neurochemical dysfunctions involved.

Table 1. Remarkable improvements in cognitive abilities

Patient ID	Diagnosis	Treatment	ΔMMSE	ΔMoCA
15	Atypical autism	Antidepressants + anxiolytics	-	+7
58	Moderate depressive episode	Nootropics	-	+3
24	Recurrent depressive disorder	Antidepressants	+2	+2
30	Recurrent depressive disorder	Antidepressants + anxiolytics	+2	+2
31	Mild cognitive impairment	Antidepressants + other drugs	+5	-

The evaluation of drug regimens revealed two therapeutic strategies with promising results. Combination therapy, with associates antidepressants with anxiolytics, was associated with a mean increase of approximately 2.1 points on MMSE and 2.3 points in MoCA, exemplified by patients with ID 15, ID 24, and ID 30. In parallel, the administration of nootropic monotherapy led to a mean improvement of 3 points in MoCA, as demonstrated by the case of a patient with ID 58.

In contrast, patients with advanced neurodegenerative diseases show modest cognitive improvements, even in the presence of a high number of CACS sessions, which highlights the limitations of cognitive interventions in the late stages of dementia.

4. Discussion

The presented study investigated the efficacy and efficiency of CACS in a cohort of 32 psychiatric patients, revealing significant enhancements in global cognitive function. Our findings demonstrate a 5.9% improvement in MMSE scores and a 9.8% increase in MoCA scores post-intervention. In addition, the analysis of 16 cognitive domains highlighted differential responsiveness, with processing speed and short-term memory showing notable gains compared to attention-revealed functions. Furthermore, the subgroup analysis using a two-sample t-test revealed that participants with fewer than 20 sessions exhibited significantly greater improvements in MMSE scores, whereas MoCA scores remained statistically unchanged with session count variations.

These results align with previous research emphasising the efficacy of computerised cognitive interventions. For instance, Mohammadi, Keshavarzi, & Talepasand, (2014) and Brown (2019) reported similar enhancements in cognitive performance following computerised training programs in psychiatric populations, underscoring the capacity of such interventions to induce measurable improvements in global cognitive function. Moreover, studies by Rajkomar et al. (2018) and Fetta et al. (2017) have documented the differential sensitivity of cognitive measures such as MMSE and MoCA to intervention duration, corroborating our finding that the session count may differentially impact specific cognitive indices.

The pronounced improvement in MMSE scores observed in our study resonates with the work of Wang et al. (2022) and Spector et al. (2018), who demonstrated that traditional cognitive screening instruments can effectively capture the benefits of targeted cognitive training. Conversely, the lack of a significant difference in MoCA scores relative to session duration is consistent with observations by Schulz & Murray (2016) and Ho et al. (2022), suggesting that while MoCA is a reliable global measure, it may be less responsive to variations in training intensity over shorter intervention periods.

Our analysis of variability across cognitive domains further contributes to the existing literature. Research by Cicerone et al. (2000) and Millán-Calenti et al. (2015) has previously noted heterogenicity in cognitive responses to rehabilitation, with some domains such as processing speed and memory, demonstrating greater malleability. In contrast, domains associated with attention, as also reported by Gluhm et al. (2013) tend to be more resistant, potentially due to underlying neurobiological constraints or the need for more specialised training approaches. The high variability observed in short-term memory scores (variance = 215.56) in our study is in line with findings from Shani et al. (2021), who emphasised the role of individual differences in treatment outcomes.

Furthermore, our investigation into the relationship between session count and cognitive improvements is supported by the work of Howren et al. (2014), both of which underscore that the duration of cognitive intervention can influence the magnitude of cognitive gains. However, as noted by Ho et al. (2022), other factors such as baseline cognitive status and intrinsic neuroplasticity are likely modulating these effects. This suggests that while intervention duration is a critical parameter, personalised approaches remain paramount to optimise cognitive rehabilitation.

Notably, five patients demonstrated exceptional cognitive gains. Patient 15 (ΔMoCA = +7), diagnosed with atypical autism, responded robustly to combined antidepressants and anxiolytic therapy, a finding consistent with emerging evidence on serotoninergic modulation in neurodevelopmental disorders (Dimitrova, Özçalışkan, & Adamson, 2018). Similarly, Patients 24 and 30, both with recurrent depressive disorder, exhibited improvements of ΔMMSE = +2 and ΔMoCA = +2, under antidepressant-based regimens, aligning with meta-analytic data supporting antidepressant efficacy in reverse cognitive deficits associated with affective disorders (Rock et al., 2014). Patient 58, treated with nootropic monotherapy (piracetam) for moderate depression, achieved a ΔMoCA = +3, mirroring trials demonstrating cholinergic enhancers' utility in mild cognitive impairment (Winblad, 2005). Diagnostic stratification highlighted recurrent depressive disorder as the most responsive condition (mean ΔMMSE = +1.5, ΔMoCA = +0.5), reflecting transient neuroplasticity in stress-related cognitive dysfunction, as described in WHO guidelines for stress management (World Health Organization, 2013). These outcomes suggest that disorders with reversible neurochemical substrates, particularly serotonergic and GABAergic dysregulation, respond preferentially to CACS, a hypothesis corroborated by translational models of affective illness (Duman et al., 2016).

Pharmacological analysis identified two effective strategies: combined antidepressant/anxiolytic regimens (e.g., sertraline + alprazolam), associated with mean improvement of ΔMMSE = +2.1 and ΔMoCA = +2.3, consistent with polypharmacy trials in treatment-resistant depression (Zhou et al., 2021) and nootropic monotherapy (e.g., piracetam), which enhanced MoCA scores by + 3.0 points, replicating outcomes from European trials on cognitive enhancers in aging populations (Fioravanti & Yanagi, 2004). Conversely, advanced dementia patients (e.g., Patient 57: ΔMMSE = +1; ΔMoCA = +1) exhibited minimal gains despite intensive CACS, underscoring the irreversibility of neurodegeneration in late-stage disease, as observed in longitudinal dementia cohorts (Jack et al., 2013).

Compared to traditional cognitive rehabilitation methods, such as cognitive behavioural therapy (CBT) and non-computerised cognitive training, CACS presents advantages in scalability and personalisation. Prior studies (e.g., Spector et al., 2018; Woods et al., 2023) have shown that traditional cognitive stimulation programs improve cognitive function, but they lack real-time adaptability. Our findings suggest that the AI-driven nature of CACS allows for personalised, adaptive learning, potentially yielding superior cognitive gains, although future comparative trials are needed to confirm this hypothesis.

In recent years, the integration of AI technologies into CACS interventions has opened new horizons in the rehabilitation and prevention of cognitive decline. Traditional cognitive training approaches, although already supported by systematic studies (Lampit et al., 2014; Kueider et al., 2012), have significantly benefited from the implementation of machine learning and deep learning algorithms, which allow not only the assessment but also the dynamic adaption of exercises to the individual needs of each patient.

For example, the study conducted by Anguera et al. (2013) demonstrated that video game training, a method that falls within CAS, improves cognitive control in older adults, thus highlighting the technological potential of digital solutions in stimulating executive functions. In parallel, Belleville et al. (2011) conducted a controlled study that showed that memory training in people with mild cognitive impairment produces significant positive effects. Their results support the idea that, by integrating AI, it is possible to adjust the exercises continuously and individually, so that the intervention responds in real-time to the progress or specific difficulties encountered by the patient. The long-term benefits of digital interventions are also highlighted by Rebok et al. (2014), who reported that computerised cognitive training programs can maintain cognitive improvements for up to 10 years. In the context of CACS, the integration of AI systems facilitates continuous performance monitoring, thus allowing adjustments to interventions throughout the treatment and ensuring their long-term relevance.

From a technological perspective, Topol (2019), in his paper "Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again", highlights the revolutionary potential of AI in transforming the diagnostic and treatment process. This approach is also reflected in CACS, where AI technologies allow for deep personalisation of cognitive exercises, continuously adapting to changes in the patient's condition.

In addition, deep learning applications, as demonstrated by Esteva et al. (2019), can identify subtle patterns in complex data sets, which translates into the possibility of analysing cognitive test results and adapting interventions at the individual level. The contribution of these models is complemented by the analysis conducted by Davenport and Kalakota (2019), who argue that the integration of AI reduces human errors and improves the decision-making process of clinicians, leading to superior clinical outcomes.

Jiang et al. (2017) highlighted that AI is capable of processing large volumes of complex data, thus facilitating the early diagnosis of cognitive decline. In CACS, this capacity is manifested by the detection of subtle changes in cognitive functions, allowing personalised preventive interventions that can be quickly adjusted according to the patient's evolution.

The study by Gates et al. (2011) also supports the importance of digital cognitive training, showing that computer programs, supported by AI algorithms, can prevent cognitive decline in people at risk. This dynamic adaptability allows for periodic optimisation of exercises, which contributes to increasing the effectiveness of interventions.

The benefits of digital interventions have been substantiated since the classic study by Ball et al. (2002), which demonstrated the advantages of cognitive training in older adults. Subsequently, the integration of AI into these programs amplified the benefits by ensuring precise monitoring and constant adaption, reducing the variability of inter-rater assessments.

Furthermore, Rajkomar et al. (2018) demonstrated that deep learning models can process large volumes of data from electronic health records, providing a robust framework for monitoring cognitive evolution. This technology, applied in CACS, allows for early identification of cognitive changes and adjustment of interventions based on patient responses.

Obermeyer and Emanuel (2016) highlighted the importance of data-driven prediction in clinical practice. In the case of CACS, this approach helps identify patients at high risk of cognitive decline, thus allowing for personalised preventive interventions and optimal resource allocation. The study by Aldohisa (2024) summarises the evidence on the role of Khalidof AI in cognitive rehabilitation, highlighting that machine learning algorithms can personalize treatment and improve clinical outcomes. These findings are directly applicable to CACS, where personalisation of interventions is essential for the success of therapy.

Furthermore, studies by Tortora et al. (2024) showed that integrating virtual reality with AI in cognitive rehabilitation creates adaptive environments that can improve both executive and memory functions in elderly patients. This technology transforms CACS interventions, providing an immersive therapeutic experience tailored to the specific needs of each patient.

On the other hand, Stefano (2023) conducted a comprehensive review that highlights that AI-based predictive models can accurately assess the progression of neurodegenerative diseases. In the context of CACS, this translates into the possibility of monitoring cognitive evolution and adapting interventions as the disease progresses, thus increasing the effectiveness of therapy.

The study by Shani et al. (2021) focuses on AI innovations in cognitive rehabilitation and shows that advanced machine learning techniques can optimise interventions by continuously adapting to patient performance. This fine-tuning of therapy ensures superior cognitive outcomes and increased personalization of treatments within CACS. The results of the pilot study by Vladisauskas et al. (2022) demonstrated that integrating AI into cognitive enhancement therapies leads to significant improvements in cognitive function in patients with early cognitive decline, thus supporting the feasibility of implementing these digital solutions in clinical practice.

More recently, the randomised controlled trial conducted by Yuan et al. (2021) showed that personalised interventions, adjusted by AI algorithms can lead to significant improvements in cognitive performance in the long term, highlighting the importance of dynamically adapting treatments according to the evolution of cognitive status.

These findings confirm that integrating AI into CACS represents an innovative and essential approach in the context of the challenges generated by the aging population and the increasing incidence of cognitive disorders.

Khalid et al. (2024) have explored AI-driven CACS, highlighting its potential to tailor interventions in real-time by adapting to individual performance profiles. This emerging body of literature suggests that integrating AI into cognitive training protocols may further enhance the efficacy of interventions by providing dynamic, personalised feedback and optimising training schedules based on continuous performance monitoring (Webb et al., 2018; Djabelkir et al., 2017). Such advancements not only promise to refine the precision of cognitive rehabilitation but also open new avenues for addressing the heterogeneity observed in treatment outcomes (Keshavan et al., 2014).

AI analyses patient data in real-time, adjusting training difficulty and improving cognitive outcomes dynamically. In addition, AI contributes to the creation of interactive and adaptive learning environments that support both continuing education and cognitive function recovery (Faria et al., 2024). This constructive interaction between technology and medical intervention opens new perspectives for optimising personalised treatments in the field of cognitive rehabilitation.

In summary, our study reinforces the effectiveness of CACS in improving global cognitive function in psychiatric patients, while also shedding light on the differential effects of intervention duration on distinct cognitive measures.

These findings confirm that integrating AI into CACS represents an innovative and essential approach in the context of the challenges generated by the aging population and the increasing incidence of cognitive disorders.

Additionally, the promising role of AI in this domain further suggests that future interventions could be significantly enhanced through adaptive, individualised protocols. As the field progresses, continued integration of traditional and innovative methodologies will be essential for advancing personalised cognitive rehabilitation strategies.

5. Conclusions

This study clearly and convincingly demonstrates that the CACS intervention is an effective method of cognitive rehabilitation in patients with psychiatric disorders. Comparative analysis of MMSE and MoCA scores recorded before and after the application of therapy highlights significant differences, demonstrating the direct impact of CACS interventions on cognitive functions. This finding holds even in the absence of a direct and specific relationship between the number of sessions or their intensity and changes in scores, suggesting that the therapeutic effect is not determined exclusively by the volume of sessions, but rather by the quality and relevance of the intervention itself.

A notable aspect of the study is the fact that some patients showed remarkable increases in cognitive levels following the application of CACS interventions. This individual variability reinforces the hypothesis that the benefits of therapy are influenced by internal factors specific to each patient, such as initial health status, personal motivation, or other individual characteristics. At the same time, it is important to note that external factors, such as concomitant treatments or environmental conditions, may play a role in how these improvements are manifested, thus representing a limitation that must be considered when interpreting the results.

Also, the differentiated analysis of the various cognitive domains, highlighted by the graphs presented, indicates a significant variability in the response to therapy. This aspect emphasises the need to adopt a personalised approach, which allows the adaptation of interventions to the particularities of each patient and the specific needs of the different cognitive functions assessed. Such an approach would not only optimise clinical outcomes but could also contribute to a better allocation of resources within rehabilitation programs.

In the future, the integration of AI algorithms within CACS techniques will emerge as a promising direction for development. The use of AI for real-time personalisation of therapeutic strategies, continuous monitoring of patient evolution, and dynamic adaption of interventions is a recipe for the success of these therapies. Thus, the constructive collaboration between CACS and AI could lead to further optimisation of treatments, facilitating greater adaptability to individual variations and implicitly improving the quality of life of patients.

In conclusion, the results obtained not only support the effectiveness of CACS interventions in improving cognitive functions, but also open new research perspectives toward the integration of advanced digital technologies, such as AI, into cognitive rehabilitation protocols. This integrated approach promises to transform current clinical practices, offering a flexible solution adapted to the complex needs of patients with psychiatric disorders.

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