

Simulation of AI-Driven Cognitive Assessment and Personalized Task Recommendation for Enhancing Cognitive Function in Parkinson's Disease Patients

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DECLARATION

I, Khushboo, 23/MSCBIO/26, hereby, certify that the work which is being presented in the thesis entitled "**Simulation of AI-Driven Cognitive Assessment and Personalized Task Recommendation for Enhancing Cognitive Function in Parkinson's Disease Patients**" in partial fulfilment of the requirements for the award of the Degree of Master of Science, submitted in the Department of Biotechnology, Delhi Technological University is an authentic record of my own work carried out during the period from 2023 to 2025 under the supervision of Prof. Pravir Kumar.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the student has incorporated all the corrections suggested by the examiner in the thesis and the statement mailed by the candidate is correct to the best of our knowledge.

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ABSTRACT

Aim

Parkinson's disease is a disorder that leads to large scale of cognitive impairments like reasoning, planning, memory and execution, often reducing independence. This research explored how Artificial Intelligence (AI) could serve as a virtual but clinical tool to detect these cognitive struggles and suggest personalized exercises to improve them. We created a rule-based AI solution that diagnoses cognitive test performance and generates personalized rehabilitation plans focusing on transparency and strict adherence to clinical standards.

Results

Performance of the PD patients' cognitive test was measured for working memory, attention, visuospatial abilities, and planning. The AI system provided explicit recommendations for tailored exercises and activities, e.g., attention training in the event of attention impairments or spatial training in the presence of visuospatial impairments, depending on individual scores. The recommendations aligned very well with clinical expert recommendations, indicating reliability and a capacity to identify subtle patterns to offer tailor-made training programs.

Conclusion

This research shows the ability of AI to improve cognitive care for Parkinson's disease. A basic rule-based strategy offered personalized suggestions that might prove beneficial for PD patients to optimize cognitive capacity. Through the intersection of testing and personalized training, AI may liberate clinicians from their workload and provide quick and scalable results and solutions too. This strategy enables patient-specific personalized proactive care for cognitive impairment in PD to promote improvement in patients' lives.

List of publications

1. **Poster:**

Khushboo^l, Pravir Kumar^l, “Neurohacking Unveiled: Methods, Ethics and Security Challenges”

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
PD	Parkinson's Disease
ML	Machine Learning
DL	Deep Learning
PD- MCI	Parkinson's Disease- Mild Cognitive Impairments
PACOS	Parkinson's disease Cognitive Impairment Study
PDD	Parkinson's Disease Dementia
MRI	Magnetic Resonance imaging
COMT	Catechol- O- methyltransferase
MAPT	Microtubule- Associated Protein Tau
APOE	Apolipoprotein E
GBA	Glucocerebrosidase
SNCA	Alpha-synuclein gene
FDA	Food and Drug Administration
tDCS	transcranial Direct Current Simulation
DBS	Deep Brain Simulation
EHRs	Electronic Health Reports
CNN	Convolutional Neural Networks
CDSS	Clinical Decision Super Systems
ECG	Electrocardiogram

1. Introduction

1.1. Overview

Parkinson's disease (PD) is a prime example of neurodegenerative disorders, that pose significant challenges to both motor and cognitive functioning. It is a neurological condition in which nerve cells from specific regions of brain are damaged, which leads to muscle stiffness, tremors, balance issue and challenges with movements. As this condition advances the patients with PD find it difficult to walk, speak and perform everyday task. Gradually this leads to cognitive impairments and dysfunction.

Parkinson's often starts with subtle symptoms that worsen as the disease progresses. Hence, PD is a progressive neurological disorder, characterized by involuntary movements and reduced motor control. The symptoms emerge gradually and intensify over time. As it advances, individuals may also experience a decline in cognitive abilities. These can include reduction in the cognitive abilities like, memory, attention, planning, and reasoning. In addition to motor impairments, many patients report behavioural and emotional changes such as depression, anxiety, fatigue, and sleep disturbances. While Parkinson's can affect anyone, it is more frequently diagnosed in men than women. Although the precise reasons for this gender disparity remain unclear, ongoing research continues to investigate possible genetic, hormonal, and environmental factors.

Age is another major contributor to the risk of developing PD for most people. The majority of cases are diagnosed in individuals over the age of 60, though a smaller percentage—roughly 5% to 10%—experience symptoms earlier in life. Early-onset Parkinson's may sometimes have a genetic basis, i.e., hereditary with specific gene mutations linked to specific forms of the condition. Regardless of age at onset, the disease often brings a gradual erosion of higher cognitive abilities, particularly those involving abstract thinking, logical reasoning, planning, and sustained attention.

In response to these challenges, cognitive rehabilitation has emerged as a promising non-pharmacological approach. Rather than attempting to halt the disease entirely, cognitive rehabilitation aims to slow the progression of cognitive decline and support individuals in maintaining their mental fitness for as long as possible. This is mostly relevant in neurodegenerative diseases like Parkinson's, where the severity and pattern of cognitive symptoms can differ widely between individuals. By tailoring interventions to the specific cognitive profiles of patients, rehabilitation efforts can be made more effective, improving quality of life and overall disease management.

1.2. Need for Personalized Assessment

Due to the various forms of cognitive impairment in Parkinson's Disease patients, an individualized evaluation and treatment is required. Not just is the extent of their impairments various but the forms are various among different patients. Standardized cognitive training can only care for the varying requirements of all patients; the detection and focal targeting of each unique impairment are efficient measures. This starts with the use of a straightforward, easy-to-administer assessment tool that is capable of assessing separate cognitive abilities. With the advent of intuitive web sites and low-cost web-based technology, it is now possible to create personalized assistive systems that mimic the function of artificial intelligence—without the need for sophisticated machine learning techniques. Apart from the above, employment of Artificial Intelligence (AI) and machine learning (ML), it is possible to create a trusted interface that can evaluate, analyze and understand the cognitive power of the patient, and also suggest patient-specific, personalized syllabi that can enhance coping cognitive capacities of the patient.

Through the use of a traditional AI (rule-based) methodology, dependent upon hard-coded thresholds within test result examination, it becomes feasible for such systems to provide personalized cognitive training suggestions that are extremely individualized to a given patient's particular profile. These kinds of software not only suggest areas of cognitive deficiency, i.e., actually convert assessment information into definite action steps, with particular sets of exercises designed to strengthen weak areas. particularly in the context of limited resources or for initial phases of care, these computer systems prove to be useful tools, serving to ensure prompt intervention and cover the gap between this and more extensive clinical assessments being undertaken.

2. Literature Review

2.1. Parkinson's Disease (PD)

Parkinson's Disease (PD), traditionally associated with motor-related issues such as tremors, muscle rigidity, and slowness of movement, is now increasingly understood to also have a significant impact on cognitive abilities. As the condition advances, many individuals begin to face challenges in memory, attention, problem-solving, planning, and abstract reasoning. Although Parkinson's affects multiple regions in the brain, the core motor symptoms are largely due to the degeneration of dopamine-producing neurons in a midbrain structure known as the substantia nigra. It is estimated that by the time PD symptoms are visibly apparent, over 60% of these dopamine-generating cells have already deteriorated (Health.com, 2021).

In addition to dopamine loss, patients also exhibit a decline in nerve endings that produce norepinephrine—another vital neurotransmitter involved in regulating autonomic functions like heart rate and blood pressure. This loss may explain some of the non-motor symptoms commonly reported in PD, such as persistent fatigue and blood pressure variability (Health.com, 2021). Furthermore, one of the pathological features observed in PD is the accumulation of abnormal protein aggregates called Lewy bodies within affected neurons. These clusters are composed mainly of alpha-synuclein protein, though their precise role in disease development remains unclear. Some hypotheses suggest that an impaired protein-clearance mechanism in PD leads to toxic protein accumulation and subsequent neuronal damage, while others propose that the presence of these protein inclusions contributes directly to the death of brain cells (Health.com, 2021).

Cognitive challenges can manifest even in the early phases of Parkinson's and may gradually worsen as the disease progresses. Despite this, current medical treatments are primarily geared toward managing physical symptoms, often leaving cognitive impairments either undetected or insufficiently addressed. This oversight can delay necessary interventions, potentially allowing cognitive dysfunctions to reach stages where recovery becomes increasingly difficult.

2.2. Cognitive impairments in Parkinson's Disease

Cognitive decline in Parkinson's disease (PD) spans a spectrum—starting from subjective cognitive complaints (SCD), progressing through mild cognitive impairment (PD-MCI), and in some cases advancing to Parkinson's disease dementia (PDD). Findings from the Parkinson's disease cognitive impairment study (PACOS) indicate that within the first year following diagnosis, nearly 32% of individuals were

identified with PD-MCI, and this prevalence increases with the duration of illness, reaching approximately 40% in long-term patients. On average, about 28% of patients with initially normal cognitive function transition to PD-MCI over time. Interestingly, cognitive status in PD is not strictly unidirectional; some individuals may show cognitive recovery, suggesting that the progression is complex and variable across patients.

Those who exhibit cognitive decline from normal function to PD-MCI generally present with noticeable impairments in executive functioning, short-term verbal memory, and the ability to recognize visual stimuli. Furthermore, individuals with lower baseline scores in areas such as attention and language are more likely to develop mild cognitive impairment, while those with higher starting scores in most cognitive domains—excluding executive skills—are more likely to revert to normal levels of functioning. These observations highlight the potential value of early cognitive assessments in identifying patients at elevated risk for decline and tailoring proactive interventions accordingly.

2.3. Neuropsychological Profile

In Parkinson's Disease (PD), executive function impairments typically emerge early on and continue as one of the most reliable cognitive deficits, marking fronto-striatal neural circuit pathology. Breaks in sustaining and shifting attention—especially time-varying attention—are also frequently seen, impairing patients' ability to perform with everyday tasks. Spatial awareness and visual interpretation problems become more pronounced when the disease progresses, exhibiting progressive visuospatial dysfunction.

Cognitive impairment in PD is typically distinct from that in Alzheimer's disease. Instead of difficulty in acquiring new memories, PD patients will more often have trouble retrieving stored information. But with more severe disease and engagement of such structures as the medial temporal lobes, emerging more conventional memory impairment with storage and recall may follow. Despite alterations in language function—such as reduced verbal fluency or difficulty processing word meaning—is less frequent early on, but can emerge as the disease evolves. Overall, the pattern of cognitive change in PD is complex and mirrors the diffuse and dynamic nature of the underlying brain disorder.

2.4. Neuroimaging Findings in Parkinson's Disease Cognitive Decline

Neuroimaging research has established that both cortical and subcortical areas of the brain demonstrate structural decline with the onset of cognitive symptoms in Parkinson's disease (PD). Longitudinal magnetic resonance imaging (MRI) evaluation has quantified progressive thinning of the cortex, particularly in regions like the frontal lobe, parietal and temporal junctions, visual processing regions of the occipital lobe, and supplementary motor cortex. They are more pronounced in patients with mild cognitive impairment (PD-MCI) than with normal cognition or with healthy controls.

One of the most striking findings is that of the hippocampus, where volume loss—most notably in important subregions such as the entorhinal cortex and presubiculum—has been associated with early memory impairment and is even a predictor of future cognitive decline. In addition, reduced volumes have also been observed in more posterior brain regions such as the amygdala, thalamus, caudate nucleus, and nucleus accumbens in PD-MCI and PDD. These subcortical areas are extremely crucial for emotions and motivation, and degeneration correlates with psychological and behavioral manifestations during cognitive impairment. Collectively, these imaging findings emphasize that cognitive impairment in PD is a consequence of a global derailment of brain networks, and especially of those including memory sites and fronto-striatal circuits.

2.5. Genetic Contributors

Genetic factors make a significant contribution to the etiology and heterogeneity of cognitive impairment in Parkinson's disease (PD). Some gene variants, e.g., at catechol-O-methyltransferase (COMT), microtubule-associated protein tau (MAPT), and apolipoprotein E (APOE), have been implicated as influencing cognitive functioning and enhancing dementia risk in PD. Of these, the APOE ε4 allele—most generally associated with Alzheimer's disease—is related to medial temporal lobe dysfunction and cognitive function in PD patients, but all the studies are not on the same page regarding how strong such a correlation is.

Moreover, genetic mutations of the glucocerebrosidase (GBA) gene are highly associated with increased cognitive impairment, earlier onset of dementia-like symptoms, and higher rates of psychiatric symptoms such as hallucinations. Duplication or mutation of the alpha-synuclein gene (SNCA) has also been associated with increased risk for cognitive impairment in Parkinson's disease. These findings further our knowledge of the biological underpinnings of cognitive symptoms and highlight why the course of PD in individuals can differ so drastically. Identifying the role of genetic differences creates new possibilities for the development of more specific, individualized treatment protocols to more effectively treat cognitive elements of the disease.

Gene	Variant Type	Cognitive Impact	References
COMT	Polymorphisms	Executive function variability	https://pubmed.ncbi.nlm.nih.gov/27242557/
MAPT	Polymorphisms	Posterior cortical deficits	https://pubmed.ncbi.nlm.nih.gov/27242557/
APOE	Allele	Memory impairment, dementia risk	https://pubmed.ncbi.nlm.nih.gov/27242557/
GBA	Mutations	Severe cognitive decline, hallucinations	https://pubmed.ncbi.nlm.nih.gov/27242557/
SNCA	Mutations/Multiplications	Increased dementia risk	https://pubmed.ncbi.nlm.nih.gov/27242557/

Table 2.5.1 shows genetic variants impacting cognitive abilities

2.6. Pharmacological and non- pharmacological

Managing cognitive deficits in Parkinson's disease (PD) through pharmacological means remains a complex and evolving challenge. At present, rivastigmine, a cholinesterase inhibitor, is the only drug approved by the U.S. Food and Drug Administration (FDA) for treating Parkinson's disease dementia (PDD) (FDA, 2018). Although some patients experience mild improvements in cognitive symptoms, its efficacy remains limited. Other cholinesterase inhibitors, such as **donepezil** and **galantamine**, are sometimes prescribed off-label for PD-related cognitive decline, but

these have not received FDA approval specifically for PDD, and the evidence supporting their effectiveness is inconclusive (StatPearls, 2023).

Similarly, memantine, an NMDA receptor antagonist used in Alzheimer's disease, has been explored for use in PD cognitive impairment. However, clinical studies have yielded mixed results, and its use remains investigational in this context (Aarsland et al., 2009).

Given the limited success of current treatments, researchers have begun to repurpose existing medications to address the underlying pathophysiological mechanisms of cognitive decline in PD. Drugs such as **ceftriaxone**, **ambroxol**, **intranasal insulin**, **nilotinib**, **atomoxetine**, and **prasinezumab** are being studied for their potential to target key disease processes like **alpha-synuclein aggregation** and **neuroinflammation**, which contribute significantly to PD progression. Despite promising theoretical foundations, most clinical trials evaluating these drugs have reported disappointing or only modest results, highlighting the ongoing difficulty in finding consistently effective therapies.

This landscape underscores a critical unmet need for **disease-modifying treatments** that go beyond symptomatic relief and aim to slow or prevent the progression of cognitive deterioration in PD. As research continues, it is increasingly clear that the complex and multifactorial nature of PD pathology demands more personalized and targeted therapeutic strategies.

Drug	Mechanism	Indication	Efficacy	Approval Status
Rivastigmine	Cholinesterase inhibitor	Parkinsonâ€™s dementia	Modest symptomatic	FDA-approved
Donepezil	Cholinesterase inhibitor	Parkinsonâ€™s dementia	Possible benefit	Off-label
Galantamine	Cholinesterase inhibitor	Parkinsonâ€™s dementia	Possible benefit	Off-label
Memantine	NMDA receptor antagonist	Parkinsonâ€™s dementia	Investigational	Not approved

Table2.6.1 shows a few pharmacological drugs and their mechanism of action

Non-pharmacological interventions are gaining recognition as valuable strategies for addressing cognitive decline in individuals with Parkinson's disease (PD). Among these, **cognitive training programs** have shown promising potential in improving specific cognitive functions, especially working memory and executive processing. When these programs are combined with **transcranial direct current stimulation (tDCS)**—a technique that delivers low-intensity electrical currents to modulate brain activity—the improvements in cognitive performance may be further enhanced. Although early findings are optimistic, more comprehensive studies are needed to

validate the consistency and sustainability of these effects across different patient populations.

In addition to cognitive exercises, **physical activity interventions** are emerging as a critical tool for managing mild cognitive impairment in PD (PD-MCI). Engaging in regular physical exercise is believed to stimulate **neuroplasticity**—the brain's capacity to reorganize itself by forming new neural connections. It also enhances **cerebral blood flow**, which plays a vital role in maintaining cognitive health. These physiological benefits support the idea that exercise can serve not only as a means of general wellness but also as a therapeutic modality that targets the neurodegenerative aspects of PD in a systemic and integrative way.

Another field of increasing concern is the use of neuromodulation methods. Deep brain stimulation (DBS), which was once used to mitigate motor symptoms of PD, is now under scrutiny for its possible cognitive impact. Although its effect on movement-related symptoms is established, effects on cognition are incongruent, with benefit reported by some and harm or no difference reported by others.

A more recent method, adaptive deep brain stimulation (aDBS), provides stimulation in a responsive and dynamic way, changing moment-to-moment as a consequence of brain function. This personalized modulation system is more accurate, but its cognitive effects are under investigation.

Combined, these non-pharmacologic interventions—cognitive training and physical exercise to highly advanced neuromodulation—constitute an emerging discipline with the possibility of mitigating the complex cognitive impairments in Parkinson's disease. Their integration method targets not just symptoms but also underlying neurological mechanisms with the possibility for even more extensive management plans in the future.

2.7. AI in Healthcare

Since it was born during the mid-20th century, Artificial Intelligence (AI) has witnessed explosive growth, from early rule-based systems to current methods like machine learning (ML) and deep learning (DL). Current AI methods can deal with tough sets of data accurately with a scale unimaginable in the past. One of the sectors in which this advancement would find its most direct application is healthcare, which generates vast quantities of heterogeneous data ranging from clinical reports and imaging diagnosis to physiological monitoring. Clinical decision-making is particularly well-suited to the strengths of AI to detect subtle patterns, forecast clinical outcomes, and automate tasks. Advancements in digital health technologies have also made it easier for the penetration of AI in the industry. Tools such as electronic health

records (EHRs) are convenient to gather and consolidate patients' data, and digital imaging technology can present accurate images of the human body.

Wearable tech now makes it possible to continuously monitor vital signs and other clinical parameters in real time and add to the ever-swelling data set of health information. Collectively, the devices form a highly rich, highly interrelated set of data that drives AI-based solutions—improving diagnostic precision, personalizing treatment to the specific patient, and making smarter and more cost-effective delivery of healthcare in general.

2.8. AI as diagnostic tool

Incorporation of artificial intelligence (AI) in medical imaging has been a revolutionary innovation in the diagnosis of contemporary healthcare. Of the numerous AI approaches, deep learning—more importantly, convolutional neural networks (CNNs)—has been especially successful in analyzing complicated medical images from machines like CT scans, MRIs, X-rays, and mammograms (Liu et al., 2019). These computer programs scan vast amounts of image data quickly and accurately and sometimes identify patterns that human specialists might miss.

Lung Cancer Screening

An important work of AI imaging is that of Ardila et al. (2019), where they employed a three-dimensional neural network model to decode low-dose CT scans. The model demonstrated a very high area under the curve (AUC) of 94.4%, which outperformed the radiologists' accuracy in malignancy prediction, and demonstrated AI competence in detecting early lung cancer.

Mammogram Interpretation for Breast Cancer

AI has been used in the identification of breast cancer to improve mammogram tests. McKinney et al. (2020) illustrated how AI algorithms minimize the misclassifications of false negatives and positives, hence improving diagnostic accuracy as well as minimizing the ratio of avoidable procedures such as biopsies.

Detection of Diabetic Retinopathy

AI was also discovered to be applicable in ophthalmology, in the diagnosis of diabetic retinopathy. Gulshan et al. (2016) demonstrated how AI software employed to read retinal fundus images is as sensitive and as specific as expert ophthalmologists and thereby earlier diagnosis and treatment more scalable in eye care.

AI in Digital Pathology and Cancer Grading

With the transition to digital modalities in pathology, artificial intelligence has emerged as an incredibly useful tool in tumor grading and cancer diagnosis. No longer dependent on good ol' glass slides, contemporary pathology now utilizes high-resolution digital imaging under which AI systems can objectively examine and interpret tissue samples with unparalleled accuracy. Campanella et al. (2019) taught millions of deep learning algorithms on such images and showed that the AI accuracy at identifying metastatic breast cancer in lymph nodes is comparable to those of expert pathologists. Such developments not only improve consistency in diagnosis reports but also help ease the workload burden on clogged-up pathology departments. AI-driven pathology systems can avoid subjective variability due to bias or fatigue of humans, enabling more scalable and precise diagnostic procedures.

AI in Clinical Decision Support Systems (CDSS)

Artificial intelligence-powered clinical decision support systems (CDSS) combine various sources of knowledge—e.g., best current evidence, clinical guidelines, and patient history—to present evidence-based recommendations in real time during clinical assessment. The next-generation systems seek to support healthcare workers with better decision-making at the point of care. AI-driven CDSS are leading the way in increasing diagnostic precision, compliance with guidelines, and patient safety through reduced supervision, according to Shortliffe and Sepúlveda (2018). For example, AI software has proven highly promising for early sepsis detection in the healthcare setting. As Henry et al. (2015) contend, such models have been capable of detecting early warning signs of sepsis and offering interventions in a timely manner, preventing death. Such systems are likely to offer more decision-making confidence and better clinical outcomes to clinicians.

2.9. AI in personalized monitoring and medicine

2.9.1. Personalized medicine and treatment

Artificial Intelligence in Oncology

Artificial Intelligence (AI) is transforming cancer treatment with numerous sources of patient information—from imaging and genomics to clinical history—translated into a decision-making process. It allows for the creation of very personalized treatment regimens based on the individual patient's own distinct genetic code and medical history. The ability of AI to process extensive volumes of intricate data empowers clinicians to make more accurate decisions, which results in better treatment efficacy and fewer unwanted side effects.

Therapy Guidance and Decision Support

One such is Watson for Oncology from IBM, using patient information and worldwide medical texts and suggesting personalized cancer treatment. Somashekhar et al. (2018) confirmed the high concordance—96%—of the system with expert tumour board recommendations on therapy for breast and lung cancer. The concordance here means that AI can potentially be an effective aide tool for oncologists, particularly in complex or suspicious scenarios. Through aggregation of huge amounts of evidence-based information, applications such as Watson for Oncology enable doctors to make treatment decisions more effectively and confidently.

Chemotherapy Outcome Prediction

Besides influencing treatment, AI is increasingly being used to forecast the outcome of a patient undergoing chemotherapy. Machine learning models that factor in genetic markers, treatment, and clinical factors have been shown to forecast outcomes of chemotherapy, writes a review by Kourou et al. (2015). The tools assist in tailoring drug regimens for individual patients, reduce exposure to ineffective drugs and improve quality of care. Through the application of predictive analytics, AI personalizes cancer treatment and prevents unnecessary toxicity.

Artificial Intelligence in Drug Discovery

Artificial intelligence is revolutionizing drug discovery by enabling the identification of more and superior potential drug candidates in a shorter time. From the prediction of behavior of molecules to the discovery of novel uses for already available medicines, AI accelerates the pipeline of drug discovery to a great extent. AI fosters root solutions to top-priority public health needs as well as disease areas where traditional research would be too costly or time-consuming.

Accelerated Drug Candidate Discovery

An impressive showcase of what is possible with help from AI is its application to design drug candidates against a target molecule. To illustrate, AI methods can construct a molecule to inhibit a particular kinase enzyme and advance it to the preclinical trial stage within a year—accelerating the process of the pharmaceutical industry much quicker (Zhavoronkov et al., 2019). This lightning-fast trip from program to laboratory bench is testament to the power of AI to revolutionize the pharmaceutical industry by shortening development times by breathtaking amounts.

Combatting Antibiotic Resistance

AI has also unveiled new avenues in the fight against antibiotic-resistant infections. Deep learning models inspired researchers to discover a new antimicrobial agent named halicin, which showed powerful activity against resistant strains that are non-responsive to conventional treatments (Stokes et al., 2020). This discovery highlights the potential of AI in screening vast chemical libraries for molecules with atypical or unmapped properties. They are imperative in an era of growing resistance to present antibiotics and promise much for the future treatment.

2.9.2. Remote and Continuous Monitoring

The intersection of artificial intelligence, wearable technology, and mobile health solutions is revolutionizing the delivery and experience of medicine. Through ongoing, real-time monitoring of physiological signals, these devices allow for health monitoring outside the clinic and hospital. Patients are enabled to track their conditions on a daily basis, and healthcare providers are provided with timely information that enables early intervention. AI is charged with breaking down this real-time flow of information, recognizing key changes, and facilitating quicker medical interventions—especially useful in managing chronic disease.

AI for Cardiac Health Surveillance

Arguably the most dramatic use of this technology is monitoring heart rhythms. AI-based diagnosis of atrial fibrillation—an abnormal heart rhythm that raises the risk of stroke—by analysis of electrocardiogram readings from wearables had high sensitivity, according to research by Steinhubl et al. (2015). By sending warnings in advance from non-invasive, everyday-use devices, AI facilitates early diagnosis and treatment, and potentially life-saving cardiovascular events could be prevented. This clinical practice demonstrates how continuous, autonomous heart monitoring will revolutionize preventive cardiology.

Managing Chronic Illnesses with AI Insight

Artificial intelligence is also finding applications in assisting patients suffering from chronic diseases. Chronic diseases like asthma and diabetes need constant care to prevent flare-ups. Using analysis of patterns from wearablesensor data along with patient self-report, AI systems are able to forecast when a patient is going to deteriorate. Schwab et al. (2020) described how such models enhance disease control through provision of alarms and tailored suggestions based on pre-warning symptoms. This pre-emption makes therapy adjusted in a timely way, encouraging patient participation in their management.

2.10. Virtual Health Assistants and Chatbots

Artificial intelligence-powered conversational assistants such as virtual health companions and chatbots are becoming a fundamental part of contemporary healthcare by providing customized and ongoing support. Virtual companions are capable of assisting patients in real-time—responding to health-related questions, monitoring symptoms, and reminders for medicines. Around-the-clock support makes it convenient to care, particularly for chronic diseases. Through offering individualized guidance and interactive assistance, the devices enable patients to remain adherent to their regimens and promote healthier levels of activity.

Improving Medication Adherence and Self-Management

Bickmore et al. (2018) research is an indicator of the potential of virtual assistants to bring about positive outcomes in patient satisfaction and medication compliance, especially for chronic disease patients.

These systems engage with patients through daily routine telephone calls, conversational, e.g., symptom tracking, and reminder calls to support patients through prescribed treatment. This is the way, conversational agents maintain continuity between clinic visits, keeping patients supported and monitored.

By facilitating everyday management tasks through ease of access to correct health information, AI-based assistants empower patients to become more active participants in their care, ultimately resulting in better health outcomes and better patient experience.

3. Objective

This research is aimed at developing a conventional, rule-based AI system for evaluating cognitive functions in PD patients and recommending patient-specific training protocols based on recognized cognitive deficits. Because of the heterogeneity of PD cognitive impairment, which may encompass impairments in reasoning, memory, planning, and abstract thinking, tailor-made intervention methods are vital. A generic, standardized method does not cover the individual needs of various patients; therefore, personalization is focused in this project. Instead of conducting only static cognition tests, the first endeavor was to develop a system which can test performance across various domains and decide on what cognitive skills are to be enhanced.

In contrast to contemporary machine-learning-based AI systems, this system is built upon rule-based logic—a central idea of the past AI research. The aim is to mimic intelligent behavior in an open and extensible environment, such that it is useful for use in classrooms as well as initial-stage medical tests. The work initiated by choosing four general cognitive areas generally impacted in PD: logical reasoning, abstract reasoning, planning and execution, and memory. Clinical literature was used to choose these areas because they are all an integral part of executive functioning and daily activities.

Logical reasoning was chosen to evaluate organized problem-solving, whereas abstract reasoning evaluates the ability to detect patterns and relationships. Planning and execution assess task performance, while decision-making and task performance in everyday life require memory. To make these tests operationalizable, an online test was created with Google Forms, selected because it is easy to use, accessible, and can record structured responses. The form was segmented into blocks, where one tested one cognitive domain at a time, with questions ranging from simple to most complicated. This format permitted the system not only to identify deficits but also to quantify severity of impairment in each area.

Application of a remote and accessible instrument also permits potential use with home care and telemedicine. Responses on practice tests were allocated to generate varied cognitive profiles and were automatically recorded to a connected Google Sheet. Each row represented a different patient profile, columns 0 to 10 scores across the four domains tested. Pre-determined sets of cognitive training tasks were suggested based on lowest scores. For example, poor abstract reasoning would initiate analogical reasoning, concept categorization, and pattern recognition tasks.

Likewise, memory deficits would call forth like tasks of digit span and sequence reproduction, whereas planning deficits would result in such suggestions as step-by-step task planning and decision-tree practice.

The logic for identifying weak domains and suitable recommendations were applied with spreadsheet functionality. Specifically, MIN() and nested IF() functions were used to examine rows of patient data independently, identify cognitive weakness spots, and return respective training recommendations. It retakes the fundamental capacity of AI by using rules to analyze inputs and respond with context-specific outputs.

To make it even more practical, a web app was created using Streamlit, an open-source framework based on Python. The platform provides users—whether clinicians or researchers—a means of manually entering cognitive test scores and receiving real-time, discipline-specific recommendations. As a computerized cognitive counselor, the application displays results in a straightforward, interactive manner so that the tool can be easily and conveniently used in actual practice. Its architecture accommodates both clinical and research settings, and the system has the potential to function as an early intervention and patient follow-up tool. In that it does not employ machine learning algorithms, the system continues to embody the concepts of smart decision-making by emulating human-style reasoning in a rules-based model. The model is lightweight with regard to computation needs and very scalable for clinical or potential uses.

The project also provides a basis for future improvement. Real-world verification via collaboration with cognitive scientists or neurologists can potentially be utilized to improve scoring systems, verify domain weights, and approximate the clinical significance of the suggested interventions. Future improvements might involve the use of dynamic scoring, cross-domain comparisons, or even hybrid models using rule-based and machine learning techniques.

In short, the project shows how the streamlined AI simulation can be mapped to the field of cognitive rehabilitation for Parkinson's Disease. Through organized reasoning, accessible instruments, and customized feedback, it is a feasible and new way of cognitive care. Its simplicity of uptake and scalability make it an excellent prototype for extension to school, clinic, and home-care settings, contributing positively to the future path of digital health support systems.

4. Methodology

4.1. Overview

This study aims to help patients with Parkinson's Disease with impaired cognitive abilities by providing them a personalised syllabus to enhance their thinking capacity. It discusses to simulate an AI- powered assessment by analysing the patients through a test for cognitive abilities. The simulated model developed, includes:

- A structured cognitive abilities test
- Simulated dataset generation
- Scoring and interpretation logic
- A rule-based AI- like recommendation system

Implementation via both a web application and spreadsheet automation

4.2. Research Design

An exploratory simulation-based design is employed in this study, with test instruments being developed, hypothetical data being generated, and outcomes being assessed through a rule-based decision-making framework. Although empirical clinical validation is not included within the scope of this research, the methodology is intended to emulate how cognitive performance data might be processed and converted into actionable feedback using logic inspired by AI.

4.3. Participant Details

Five individuals with Parkinson's Disease were enrolled from a local clinic. They had varied ages, symptom severity, and educational backgrounds, creating a diverse yet manageable group for testing.

- **Number of participants:** 5
- **Parkinson's Disease Stage:** Hoehn and Yahr Stages I–III
- **Gender:** Mixed
- **Selection:** Volunteers who provided informed consent
- **Exclusion criteria:** Severe dementia or acute psychiatric conditions

All participants took the test under supervision, with their data anonymized to protect privacy.

4.4. Cognitive Assessment Design

A standard test was created to evaluate the following four core cognitive domains:

- Logical Reasoning
- Abstract Reasoning
- Planning
- Execution

Each domain has a few questions to be solved with the help of corresponding skills. Hence, the test evaluates the patient's performance in each cognitive domain to determine how well their specific skills are functioning. Afterwards, a score is yield between 0- 10 depicting the patient's performance with each of the skills. This is how each patient is tested for each of the skill, and it is analysed which skills are getting poorer because of the disease and required to be improved. The structure was inspired by standard neuropsychological assessments, simplified and customized for scalable, self- administered testing.

Tools used:

- **Google Forms** (for initial version): Designed to collect test responses in a structured, section-wise format.
- **Streamlit Web App** (for simulation): A Python-based interface that accepts user input scores and generates analysis.

Cognitive Skills Analysis

The test is designed to test cognitive abilities.

kaushikkhushboo2510@gmail.com
[Switch account](#)

 Not shared



* Indicates required question

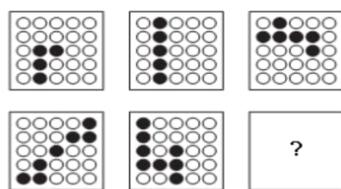
Name *

Your answer

Age *

Your answer

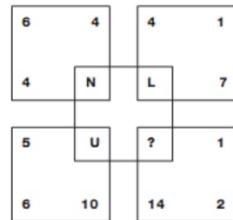
What would be the next?



B



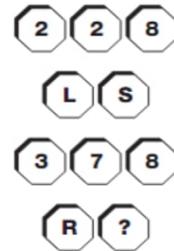
What letter should replace the question mark?



- R
- F
- Q
- T

Clear selection

What letter must replace the question mark?



- O
- K
- U
- F

Abstract Reasoning

Flow : River :: Stagnant : ?

- canal
- rain
- stream
- pool



- 1
- 2
- 3
- 4

Problem Figures:

(A)	(B)	(C)	(D)

Answer Figures:

(1)	(2)	(3)	(4)	(5)

1
 2
 3
 4

Back **Next** **Clear form**

Planning and Execution

You are in a room with three light switches. Outside the room are three light bulbs. You can flip the switches any way you want, but you can only go back into the room once. How do you determine which switch controls which bulb?

Your answer

Memory

Memorize these words in same order
 (Please do not choose any option)

Rubber
 Contract
 Business
 Lemon
 Greece

Observe the series of numbers
 11,89,54,63,78,32,8,14,93,25,58,42,21

Your answer

Fig. 4.4.1 Screenshots of google form used as test for cognitive skills. The test was categorized according to different cognitive skills. Each skill was divided into different section as shown. The last two sections are based on memory skills.

4.5. Data Collection Procedure

Each of the patient was individually administered the test on a digital device. A facilitator was present to assist with any technical issues and assistance.

- **Duration of test:** ~ 20 to 25 minutes
- **Responses** recorded automatically in Google Sheets and exported to Excel.

Fig. 4.5.1 The responses were collected into an excel sheet and updated for scoring

4.6. Scoring and Categorization

Each score was analysed and categorized using thresholds:

Score (per domain)	Category	Interpretation
0–3	Low	Severe deficit
4–6	Moderate	Mild to moderate difficulty
7–10	Good	Functional or intact ability

Table 4.6.1 shows criteria of scoring the cognitive abilities in the test by analysing their score

1					
2	Scores of the test for cognitive skills				
3					
4	Patient	Logical reasoning	Abstract Reasoning	Planning	Memory
5	Divya	6	3	9	8
6	Kaushiki	7	8	3	6
7	Eshaa	2	5	8	7
8	Ravi	7	8	2	5
9	Divyam	3	2	7	9
10					

Fig. 4.6.1 the excel sheet prepared by scoring the participants

4.7. AI- Inspired Rule- Based Logic

To simulate AI- based personalized feedback, a simple rule- based system was created using spreadsheet formulas. The system uses **IF- THEN logic** to simulate personalized decision – making. Based on individual domain scores, the system generated feedback as follows:

- **Memory Domain:**
 - **IF** memory score ≤ 3
THEN – Recommend basic recall tasks, word association games, and spaced repetition training.
 - **IF** memory score is between 4 to 6
THEN – Suggest memory drills like N- back games
 - **IF** Memory Score ≥ 7
THEN – Recommend mental simulation by reading games for maintenance
- **Logical Reasoning Domain:**
 - **IF** Logical Reasoning Score ≤ 3
THEN - Recommend simple pattern matching, number series completion, and rule identification games.
 - **IF** Logical Reasoning Score between 4 and 6
THEN - Suggest logic grid puzzles, syllogism exercises, and sequence continuation tasks.
 - **IF** Logical Reasoning Score ≥ 7
THEN - Recommend advanced logical reasoning games, verbal analogies, and strategy games
- **Planning & Execution Domain:**
 - **IF** Planning Score ≤ 3
THEN - Recommend task sequencing games, cooking simulations, and error correction activities.
 - **IF** Planning Score between 4 and 6
THEN - Suggest step-by-step multi-phase tasks, scheduling simulations.
 - **IF** Planning Score ≥ 7
THEN - Promote autonomy via problem-solving board games or goal-setting journals.
- **Abstract Reasoning Domain:**
 - **IF** Abstract Reasoning Score ≤ 3
THEN - Recommend visual puzzles, analogies practice, and concept-matching exercises.

- **IF** Score between 4 and 6
THEN - Suggest mid-level reasoning exercises like sequencing patterns or simple logic games.
- **IF** Score \geq 7
THEN - Encourage higher-order tasks like riddles, Sudoku, or strategy games.

Logic for recommendation

```
=IF(COUNTA(B5:E5)=0, "",  
"Training in: " & TEXTJOIN(", ", TRUE,  
IF(B5<4, "Logical Reasoning", ""),  
IF(C5<4, "Abstract Reasoning", ""),  
IF(D5<4, "Planning", ""),  
IF(E5<4, "Memory", ""))  
)  
)
```

B	C	D	E	F	G	H	I	J
of the test for cognitive skills								
Reasoning	Abstract Reasoning	Planning	Memory	Recommendation	Tasks recommended			
6	3	9	8	=IF(COUNTA(B5:E5)=0, "", "Training in: " & TEXTJOIN(", ", TRUE, IF(B5<4, "Logical Reasoning", ""), IF(C5<4, "Abstract Reasoning", ""), IF(D5<4, "Planning", ""), IF(E5<4, "Memory", ""))))	ing low: Practice visual puzzles, analogies ing low: Practice logic puzzles, sequencing			
7	8	3	6		..., use sequencing, goal-setting simulations, and scheduling tasks.			
2	5	8	7	5 Training in: Planning 9 Training in: Logical Reasoning, AI	Logical Reasoning low: Practice logic puzzles, sequencing			
7	8	2						
3	2	7						

Fig 4.7.1: If- Then rule applied to each cell in scoring

Logic for Task Recommended

=TEXTJOIN(" ", TRUE,

IF(B5<4, "Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games. ", ""),

IF(C5<4, "Abstract Reasoning low: Practice visual puzzles, analogies, and concept-matching exercises. ", ""),

IF(D5<4, "Planning low: Try task sequencing, goal-setting simulations, and scheduling tasks. ", ""),

IF(E5<4, "Memory low: Practice recall tasks, short-term memory games, and delayed response activities. ", "")

)

Fig 4.7.2 If- Then logic applied to the scores for generating recommendations

Scores of the test for cognitive skills									
5	Patient	Logical reasoni	Abstract Reaso	Planning	Memory	Recommendation	Tasks recommended		
6	Divya	6	3	9	8	Training in: Abstract Reasoning	Abstract Reasoning low: Practice visual puzzles, analogies, and concept-matching exercises.		
7	Kaushiki	7	8	3	6	Training in: Planning	Planning low: Try task sequencing, goal-setting simulations, and scheduling tasks.		
8	Eshaa	2	5	8	7	Training in: Logical Reasoning	Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games.		
9	Ravi	7	8	2	5	Training in: Planning	Planning low: Try task sequencing, goal-setting simulations, and scheduling tasks.		
10	Divyam	3	2	7	9	Training in: Logical Reasoning	Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games. Abstract Reasoning low: Practice visual puzzles		
11									
12									
13									
14									

Fig4.7.3. an excel sheet was prepared representing scoring recommendation and tasks recommended. This will be fed to the local app to simulate the result

4.8. Simulated Output (AI- like Personalization)

While a machine learning model was not applied in this simulation, a structured logic system was designed to mimic the behaviour of an AI recommendation engine, identifying domain- specific cognitive weaknesses and suggesting personalized interventions. In addition, to stimulate AI- based personalized recommendations, a lightweight web application was built using Streamlit framework in Python. Each participant was provided with a tailored cognitive profile that outlined:

- Areas of cognitive weakness
- Cognitive level categorization
- Targeted training recommendations

```

import streamlit as st

st.title("Cognitive Skill Assessment: Personalized Recommendation System")

# Input form for cognitive skill scores
st.subheader("Enter Cognitive Domain Scores (Out of 5)")

logical = st.slider("Logical Reasoning", 0, 5, 3)
abstract = st.slider("Abstract Reasoning", 0, 5, 3)
planning = st.slider("Planning", 0, 5, 3)
memory = st.slider("Memory", 0, 5, 3)

# Function to recommend based on score thresholds
def generate_recommendations(scores):
    recommendations = []

    if scores["Logical Reasoning"] < 4:
        recommendations.append("💡 Logical Reasoning is low: Practice logic puzzles, sequencing activities, and rule-based games.")

    if scores["Abstract Reasoning"] < 4:
        recommendations.append("💡 Abstract Reasoning is low: Practice visual puzzles, analogies, and concept-matching exercises.")

    if scores["Planning"] < 4:
        recommendations.append("💡 Planning is low: Try task sequencing, goal-setting simulations, and scheduling games.")

    if scores["Memory"] < 4:
        recommendations.append("💡 Memory is low: Practice recall tasks, short-term memory games, and delayed response activities.")

    if not recommendations:
        recommendations.append("✅ All domains are strong. No specific cognitive training needed.")

    return recommendations

# Trigger logic and display result
if st.button("Get Recommendations"):
    scores = {
        "Logical Reasoning": logical,
        "Abstract Reasoning": abstract,
        "Planning": planning,
        "Memory": memory
    }
    output = generate_recommendations(scores)

    st.subheader("Personalized Training Recommendations:")
    for line in output:
        st.write("- " + line)

```

Fig 4.8.1: The source code of cognitive recommendation app developed using Streamlit(Python). This rule-based app simulated AI logic by applying domain specific thresholds to generate personalized cognitive training suggestions.

4.9. Tools Used

A few tools were used to assess, analyse and simulate dataset.

Tool	Purpose
Google Form	Administering cognitive test
Google Sheets	Capturing scores, applying formulas
Microsoft Excel	Visualizing and analysing the results
Python (Streamlit)	Displaying scorecard and feedback (local app demo)

Table 4.9 shows the tools used and their respective purposes

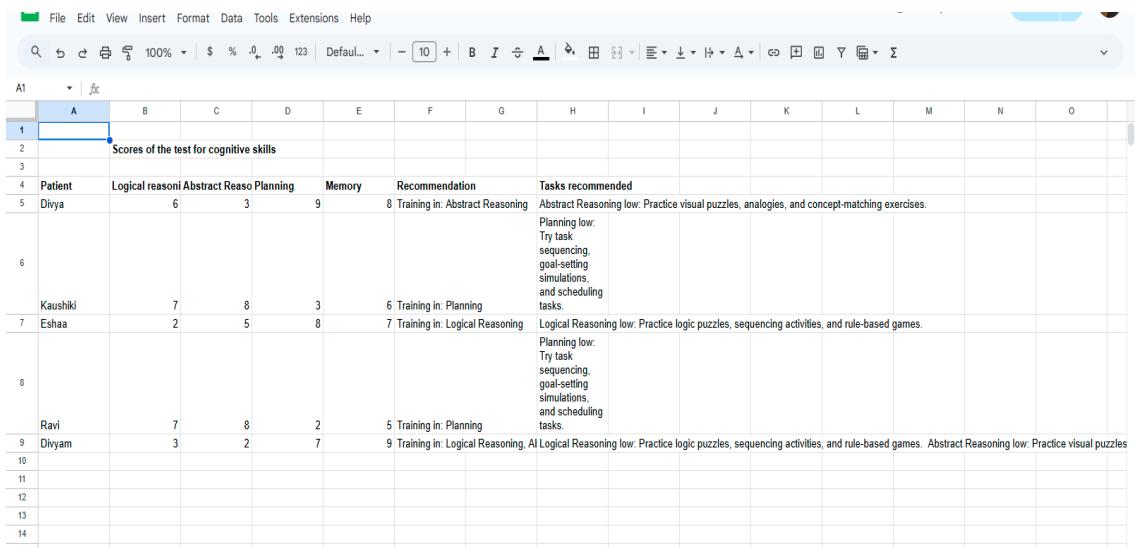
4.10. Ethical Compliance

- **Informed Consent:** All participants provided both verbal and written informed consent prior to participating in the study.
- **Data Anonymization:** Participant data were anonymized using randomly assigned identification codes to protect privacy.
- **Confidentiality:** No personally identifiable health information was disclosed during the study.
- **Ethical Standards:** The study adhered strictly to ethical guidelines for conducting cognitive testing with vulnerable populations, ensuring participant safety and confidentiality.

5. Results

Scoring Table

Scores of 5 patients across 4 domains with their corresponding recommendation are as follows:



Scores of the test for cognitive skills											
4	Patient	Logical reasoning	Abstract Reasoning	Planning	Memory	Recommendation	Tasks recommended				
5	Divya	6	3	9	8	Training in: Abstract Reasoning	Abstract Reasoning low: Practice visual puzzles, analogies, and concept-matching exercises.				
6							Planning low: Try task sequencing, goal-setting simulations, and scheduling tasks.				
7	Kaushiki	7	8	3	6	Training in: Planning	Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games.				
8	Eshaa	2	5	8	7	Training in: Logical Reasoning	Planning low: Try task sequencing, goal-setting simulations, and scheduling tasks.				
9	Ravi	7	8	2	5	Training in: Planning	Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games.	Abstract Reasoning low: Practice visual puzzles			
10	Divyam	3	2	7	9	Training in: Logical Reasoning	AI	Logical Reasoning low: Practice logic puzzles, sequencing activities, and rule-based games.	Abstract Reasoning low: Practice visual puzzles		
11											
12											
13											
14											

Fig 5.1 This is the final excel sheet obtained through logics and shows recommendation and recommended tasks. This is fed to the local app for simulation and This is the final excel sheet obtained through logics and shows recommendation and recommended tasks. This is fed to the local app for simulation and generating output.

Output over local app

Upon feeding of the score, the local app can suggest the suitable training exercises personalised for patients based on their scores. A preview of a demo output of the app is as follows -

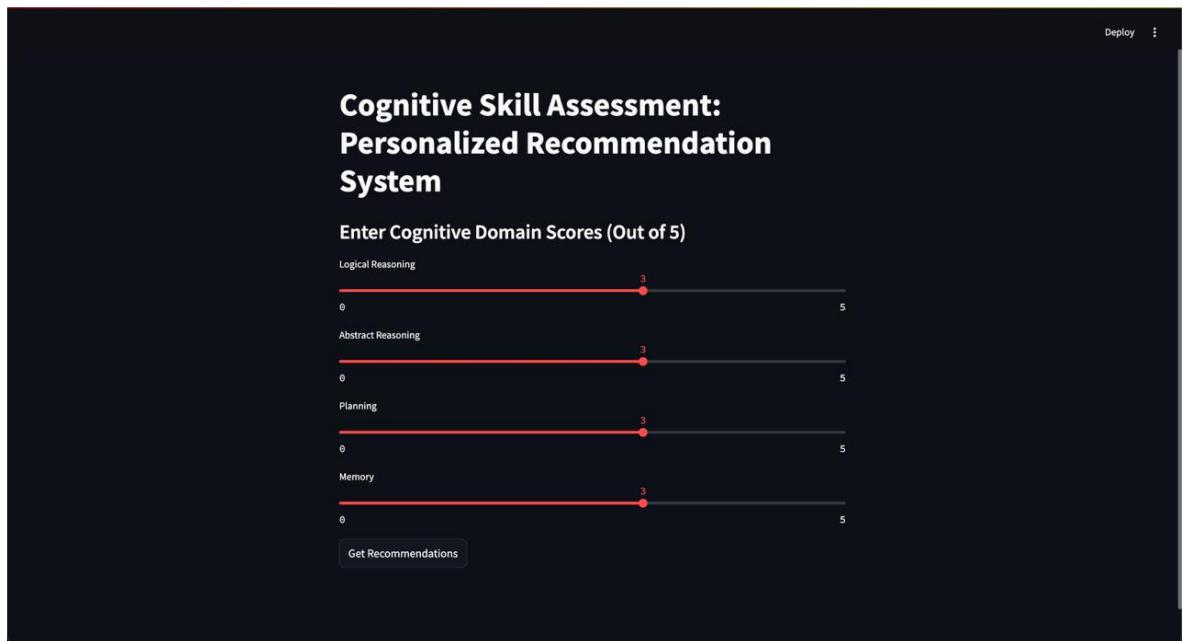


Fig 5.2 This is the interface of the local app. It is fed with the scores and that is how it generates an output recommending tasks according to patient's performance in the test.

Outcome (sample)

After processing the app would finalise the syllabus by analysing the patient's cognitive skills

Participant Cognitive Assessment

- **Memory:** Moderate

Recommendation: Engage in daily journaling and memory-recall exercises.

- **Planning & Execution:** Low

Recommendation: Practice with calendar-based tasks and sequential activities.

- **Logical Reasoning:** Strong

Recommendation: Continue with strategy-based puzzle apps.

- **Abstract Reasoning:** Moderate

Recommendation: Work on logic puzzles and analogy exercises.

Fig 5.3 This is an example of final output of a patient who performed the tests. The patient possesses low planning and execution skills and hence recommended for low level or easy tasks for improving the skills, whereas the patient has moderate abstract reasoning skills and hence recommended to work upon mid-level logic puzzles and analogy exercises. The logical skills are comparatively strong and hence, no emphasized task is recommended

6. Discussion

This study explores a novel and accessible approach to simulating Artificial Intelligence (AI) for cognitive evaluation and providing personalized syllabi for improvement in cognitive skills of individuals with Parkinson's Disease (PD). Cognitive decline is a common and variable feature of PD, requiring intervention strategies that are adaptable to individual needs. Although modern AI and machine learning hold great promise in healthcare, they often rely on complex algorithms and large datasets, making them less accessible for early-stage or resource-limited applications. This project, by contrast, shows that even a simple, rule-based system can provide tailored support without the technical demands or ethical concerns typically associated with machine learning.

the most important assignment in the work was to conceive of a cognitive test instrument which would address four general areas: logical reasoning, abstract reasoning, memory, and planning/executing. These were chosen based on literature having reported cognitive impairments characteristic of PD. Since symptoms are hugely variable among patients, isolating and testing these areas presents an individualized outline of the cognitive standing of each.

In order to ensure both convenience and usability of the tool, Google Forms were used as the testing platform. Each form section addressed one domain and possessed questions with cumulative levels of difficulty in order to mimic a gradient in cognitive demand. Any such pattern approximates the established cognitive tests scaling complexity in order to measure depth of function. The format also allows for remote use, where the test may be administered and prepared responses filled in by caregivers or patients. It was done with an artificial dataset where all the participants had been provided with a range of scores from 0 to 10 in each of the four domains. These were kept in a Google Sheet and were used as the starting point for the construction of individual cognitive profiles. Each score equated to competence within a single cognitive area, constructing a reduced but useful model of differential cognitive function within PD.

Rule-based reasoning is applied by the system to evaluate the outcomes.

If a domain score falls below a set level (for instance, 4), it indicates an area of concern. Automatically, the system then suggests domain-related training exercises from here. For instance, poorer abstract reasoning might suggest analogical thinking exercises or pattern-recognition problems, and low planning scores might suggest goal-setting or task-sequencing activities. These choice rules are applied by employing simple spreadsheet formulas, making them easy to apply and duplicate.

This age-old but practical model illustrates the way simple tools such as Excel can be used in an attempt to replicate informed decision-making. The strategy's simplicity serves to increase transparency and is suitably used in early-stage research, teaching environments, or low-resource clinical settings.

In order to make it more practical, the reasoning was incorporated into a web application based on Streamlit, a lightweight Python framework for building interactive user interfaces. The program allows users to input cognitive test scores and obtain immediately customized recommendations for training. As a virtual assistant, the application delivers the recommendations clearly and in an interactive way, and so is a greater potential resource for caregivers, researchers, or even patients themselves.

This paper also adds to the case for more extensive uses of AI in medicine. As AI is commonly thought to be synonymous with deep learning and computationally expensive approaches, there remains a useful niche for conventional logic-based techniques, such as decision trees and rule engines. Where there are pressing interpretability needs, scarce-resource settings, and stringent requirements for data privacy, these methods can provide sound decision support.

In the future, this system can be extended further through clinical agreement. Large patient information may be used to confirm the test design, determine score thresholds for optimization, and determine the efficacy of recommended interventions. More advanced features, such as weighted scoring, can be incorporated without reducing the simplicity of the system.

The research acknowledges certain limitations. Test items were built from general principles of cognition rather than being metrically benchmarked against formalized clinical and psychological tests. Moreover, simulated data, although helpful in modeling, cannot possibly be used to describe actual cognitive variation or coping responses of patients. Finally, although Excel-based solutions are appropriate for small sets of data, large or large and complex sets may be more appropriately dealt with by more powerful backend solutions.

The framework functioned as designed, albeit recognizing and assessing cognitive impairments and devising personalized training regimens for every individual case. The reasoning properly translated deficit-in-domain to corresponding intervention-in-domain, illustrating the model's capability of producing useful output from elementary input. Integration into the Streamlit interface, also created improved usability and user interaction, illustrating the project's feasibility for use in the real world.

In sum, this paper demonstrates that specialized cognitive rehabilitation is not always a mission for cutting-edge machine learning. Through designing robust testing tools, sensible principles, and well-defined interfaces, one can replicate intelligent support systems that are straightforward and efficient. But one might develop an ad-hoc system

with assistance from ML and deep learning. It forms the groundwork for wider application in cognitive care as a scalable and responsive solution to address patients with neurodegenerative diseases such as Parkinson's Disease.

7. Conclusion

This work creates a low-cost, AI-inspired patient-specific cognitive test and rehabilitation system for PD patients. Since cognitive impairments like weak memory, abstract thinking, and executive function are typical of PD, patient-specific treatment is necessary. Common AI methods, though strong, are resource extensive and depend on high-end infrastructure. This work shows how a rule-based, direct system can still provide personalized cognitive support without those weights. Availability of such tools for assessment and support of these areas is of utmost worth to the healthcare. This work shows how, AI concepts, such as personalization and decision-making, are achievable without large datasets.

A rule-based system is used here which evaluates patients' cognition and provides modified but accurate training suggestions. This is balanced by having reduced patient access or technical facilities available for study. The general design of the project is in creating a cognitive test with four areas—logical reasoning, memory, abstract thinking, and planning/executing. These were chosen by carrying out research into the particular cognitive impairments that typically arise with PD. Instead of a normative system, the system scores each domain separately and gives a better reflection of cognitive ability. There was a need for a cognitive test to measure the severity of the cognitive impairment of the patients and as a result, Google Forms was used as the medium to conduct the test since it was readily available and simple to conduct. There were four sections with four items per section for each of four distinct cognitive domains, i.e., planning and memory, abstract reasoning, and logical reasoning.

Each section had items in ascending order based on their difficulty levels, replicating the tiered structure of traditional cognitive testing. Remote testing and traditional data collection through automated spreadsheets are thus enabled. Each simulated patient was scored 0 to 5 in each of the four domains on the basis of test performance. The system supplied the scores as input to the rule-based engine, and it produced the areas to be worked upon and domain-based training recommendations. The system determines the impaired cognitive domains on the basis of predefined thresholds, less than 4, respectively.

For instance, low memory scores might include repetition practice or pattern practice, while low planning scores might include breaking down tasks into steps. Rules were implemented even in simple spreadsheet manipulations, and hence even those with little technical expertise could duplicate the system. A web interface based on Streamlit, a minimal Python library for making working interfaces was also implemented to make it interactive. This program allows clinicians to enter a patient's scores and get automatically directed training recommendations in clear and readable

format. That is how, the program functions as a computerized aid tool, promoting interaction and presenting real-world utility in research and low-resource clinical practice. This project also considers the wider definition of AI in medicine. Most interest still centers around machine learning and neural networks, but this project shows how useful rule-based systems are—especially when transparency, being cost-effective, and privacy are needs. They do not learn or change as time passes but provide stable, explainable decision support that can still perform many clinical tasks. There is considerable value to be achieved in widening the existing framework.

With exposure to large numbers of patient data, it can be tested and calibrated through cooperation with doctors. The scoring model can be advanced to encompass question weighting or to have confidence levels. And with further advancement, the system would be able to monitor cognitive improvement over time and update recommendations accordingly. Furthermore, the system would also be able to create a syllabus of puzzles and questions for the patient relevant to the region whose cognitive abilities are weaker so that the people receive personalized treatment. Of course, there are some limits. The test itself was constructed on general principles and not from validated psychological measures, and proxy data can never be equivalent to the richness of actual patient behavior. Also, while the Excel-based model is easy to use for smaller sets of data, scaling it up to broader clinical use would demand more sophisticated computational machines and that's where constructing software and Artificial Intelligence (AI) enters the scenario. In spite of these limitations, the system worked as designed—identifying correctly areas of cognitive impairment and making pertinent, patient-centered recommendations. Integration with Streamlit applications further improved usability, demonstrating the power of even humble tools to create beneficial results when informed by clinical expertise and careful design.

In conclusion, the study demonstrates how improved and more efficient cognitive care to PD patients can be provided utilizing proper, rule-based logic, a classic example of AI. The project demonstrates the need for flexibility, simplicity, and patient-centered design, providing an adequate basis for further development of digital cognitive care for neurodegenerative illnesses and the integration of healthcare with cutting-edge technology.

8. Future Directions

This project effectively represented the base for a simulated, AI driven framework, designed to offer personalized cognitive support to individuals with Parkinson's Disease (PD). By using basic logic-based rules, the framework successfully performed key AI functions, such as tailored decision-making, providing personalized approach specific to the patients' performance. While the current version shows what's possible with minimal resources, it also opens doors to a wide range of future improvements and practical applications.

A prominent next step can be testing the framework into large clinical environments. Thus far, the evaluation relied on small scale patient data due to limitations. Implementing the system with large scale PD patients would offer invaluable insights into its accuracy, scalability and usability in real-world scenarios, involving neuropsychologists or clinical specialists could help validate whether the tool's recommendations are aligned with established therapeutic practices, ensuring that the system not only functions well but also provide clinically relevant support.

Currently, it focuses on four cognitive functions: logical reasoning, abstract thinking, memory skills, and planning and execution. However, many PD patients experience difficulties beyond these domains—such as attention deficits, language issues, emotional recognition, or visuospatial challenges. Expanding the assessment to include these areas would provide a clearer and more detailed view of a patient's cognitive status. Additionally, the current format, based on multiple-choice questions, could evolve to include interactive elements like timed puzzles or drag-and-drop tasks. The test could also involve 2D and 3D shapes to enhance visualisation. These dynamic formats would better replicate the challenges people face in everyday cognitive tasks.

While the present system is based on rule-driven logic, integrating real and more advanced AI models in future could add deeper insights. An AI that frames different kinds of tests involving assessments from all the domains can be developed. Such an AI would help as an automated system, that can frame the assessment, evaluate the scores, examine the cognition and accordingly, propose a syllabus and other required exercises and da activities. Supervised learning algorithms, trained on large datasets of cognitive evaluations and patient responses to interventions, might be able to forecast patterns of cognitive decline or improvement. These models could continuously adapt the rehabilitation plan based on how the patient is progressing. That said, such advancements would require careful planning around data ethics, patient consent, and model transparency—especially in sensitive clinical contexts.

The Streamlit-based prototype built during this study holds potential to be developed into a more comprehensive digital assistant. With user interface refinements, support

for mobile platforms, and features like real-time feedback or voice-based interaction, the system could become accessible to a broader audience.

Ultimately, such tools could play a key position in improving cognitive fitness and empowering the ones living with neurodegenerative disorders to maintain a higher quality of life.

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List of publications

2. *Poster:*

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