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A Framework to Analyze Project Management Cognitive Process Using MNE-Python

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ABSTRACT

The objective of this paper is to present a comprehensive and simple framework utilizing MNE-Python to investigate the cognitive processes involved in project management tasks. MNE-Python was selected because it is a powerful Python library for analyzing brain activity data from magnetoencephalography (MEG) and electroencephalography (EEG) experiments. The methodology used was qualitative conceptual research to build conceptual frameworks for phenomena linked to multidisciplinary bodies of knowledge. The resulting framework is organized in several key stages: import data fNIRS Raw Data, preprocess data and visualization, analysis and statistical testing, and interpret findings. The implication of this work includes bridging the gap between neuroscience and project management research by providing a framework for studying the cognitive processes underlying project management tasks, the proposed framework holds promise for advancing our understanding of how project managers navigate complex environments, make strategic decisions, and optimize project outcomes.

Keywords: Analysis of MEG and EEG Data, MME-Python Framework implementation, Project Manager Cognitive Process,

INTRODUCTION

Significant research has been done in project management aiming to understand and improve processes, methodologies, and outcomes of managing projects across various industries and domains. However, project management research in the cognitive processes underlying decision-making, problem-solving, and information processing is limited. Thus, the problem that this research paper addresses is this limited research that could be due to several reasons such as interdisciplinary nature, practical constraints, lack of awareness of the opportunities, complexity, and lack of an analysis framework that can be used by researchers of project management. Therefore, the objective of this paper is to present a comprehensive and simple framework utilizing MNE-Python to investigate the cognitive processes involved in project management tasks. MNE-Python was selected because it is a powerful Python library for analyzing brain activity data from magnetoencephalography (MEG) and electroencephalography (EEG) experiments.

The methodology used was qualitative conceptual research to build conceptual frameworks for phenomena linked to multidisciplinary bodies of knowledge. This methodology was used because it serves as a cornerstone of scientific inquiry, providing the theoretical foundation upon which empirical studies build. The resulting framework is organized in several key stages: import data fNIRS Raw Data, preprocess data and visualization, analysis and statistical testing, and interpret findings. The intellectual merit of this work is bridging the gap between neuroscience and project management research by providing a framework for studying the cognitive processes underlying project management tasks. The proposed framework holds promise for advancing our understanding of how project managers navigate complex environments, make strategic decisions, and optimize project outcomes. The broad impact of this work is that the insights gained from this research can inform the development of cognitive interventions and training programs to enhance project management performance and decision-making efficacy with the potential to enhance project success rates and optimize resource allocation.

LITERATURE REVIEW

Cognitive processes refer to the mental activities involved in acquiring, processing, storing, and using information. It covers all modes of knowing, perceiving, remembering, imagining, conceiving, judging, and reasoning (Hunt, 1989). There are thirty-seven fundamental cognitive processes (CP) organized in seven layers according to the Layered Reference Model of the Brain (LRMB) (Wang et al., 2006) as shown in Table 1. Two of those CPs are decision-making (Wang & Ruhe, 2007) and problem-solving (Wang & Chiew, 2010). Decision-making and problem-solving play a vital role in how project managers perceive, interpret, and respond to various situations and challenges. Furthermore, these skills are recognized as pivotal in addressing the challenges of 21st-century careers, which are increasingly valued in the job market in the modern economy (Oku et al., 2023). Therefore, it is of particular importance for project management to understand these CPs.

Table 1. *Classification of Cognitive Process in LRMB*

Layer 1 – Sensational	**Layer 5- Meta Cognitive**
1 Vision (1.1)	*15. Attention (5.1)*
2. Audition (1.2)	16. Concept Establish (5.2)
3. Smell (1.3)	17. Search (5.3)
4. Tactile (1.4) Heat, Pressure, Weight, Pain, & Texture	18. Abstraction (5.4) 19. Categorization (5.5) 20. Memorization (5.6)
5. Taste (1.5) - Salt, Sweet, Bitter, Sour, & Pungency	21. Knowledge Repres (5.7) **Layer 5- Higher Cognitive** 22. Recognition (6.1)
Layer 2 – Memory	23. Imagery (6.2)
6. Memory (2.1)	24. Comprehension (6.3)
Layer 3 – Perception	25. Learning (6.4)
7. Self-Consciousness (3.1)	26. Reasoning (6.5)
8. Motivation (3.2)	27. Deduction (6.6)
9. Willingness (3.3)	28. Induction (6.7)
10. Goal Setting (3.4)	29. Decision Making (6.8)
11. Emotions (3.5)	30. Problem Solving (6.9)
12. Sense of Spatiality (3.6)	31. Explanation (6.10)
13. Sense of Motion (3.7)	32. Analysis (6.11)
Layer 4 – Actions	33. Synthesis (6.12)
14. Actions (3.1)	34. Creation (6.13)
	35 Analogy (6.14)
	36. Planning (6.15)
	37. Quantification (6.16)

Decision-making is a higher CP located at the higher cognitive layer by which a preferred option or course of action is chosen from among a set of alternatives based on given criteria. Decision-making can follow one of two distinct processes: an implicit, unconscious process based on "gut feelings," referred to as the intuitive-experiential process; or an explicit, controlled, and conscious process, known as the analytical-rational process. (Nowińska & Pedersen, 2024). The Analytical-rational decision process can be accomplished through three approaches: normative, descriptive, and prescriptive. The normative approach assumes a rational decision-maker who has well-defined preferences that obey certain axioms of rational behavior. The descriptive approach is based on empirical observation and experimental studies of choice behavior. The prescriptive approach focuses on methods of improving decision-making, bringing it more in line with normative desiderata (Wang et al., 2006).

Problem-solving is also a higher CP located at the higher cognitive layer that searches for a solution for a given problem or finds a path to reach a given goal. Problem-solving consists of using methods and tools, systematically, with the aim of finding solutions to specific problems (Fernandes et al., 2023). In the context of project management, problem-solving is mandatory, and regardless of whether traditional or agile methods are considered, there will always be a standard process, a method with tools, sufficient to improve the chances of success if applied correctly (Fernandes et al., 2023). In problem-solving, the representation of the problem is crucial and includes a description of the given situation, predefined operators for changing the situation, and assessing criteria to determine whether the goal has been achieved. In most problems of interest, the problem space can be too large to be searched exhaustively. Typical approaches to reduce search complexity in problem-solving are using heuristic rules to select a few promising states for consideration and recognition of cues in the situation that access relevant knowledge and suggest heuristics for the next transition (Wang et al., 2006).

Both decision-making and problem-solving involve the coordinated activity of various brain regions, but the key region is the prefrontal cortex (PFC). The PFC extends approximately two-thirds of the human frontal cortex (Nejati et al., 2021). Anatomically, the PFC is divided into three main areas, including:

1- Dorsolateral Prefrontal Cortex (dlPFC),
2- Medial Prefrontal Cortex (mPFC), and
3- Ventral, Inferior Orbital Frontal Cortex (OFC).

In terms of function and structure, the latter two regions are closely linked and frequently regarded as a relatively consistent entity known as the Ventromedial Prefrontal Cortex (vmPFC) (Nejati et al., 2021). The location of these three areas is shown in Figure 1.

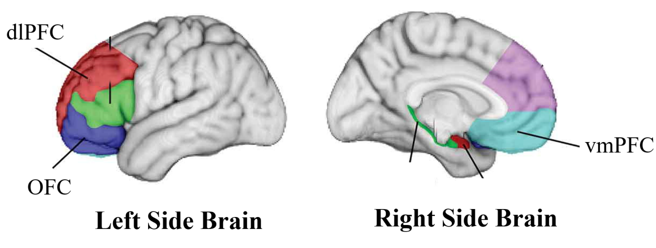

Figure 1. *Main Areas of the Brain Involved in Decision-Making and Problem-Solving (Moreno et al., 2017)*

The dlPFC primarily participates in executive functions and cognitive regulation. It plays a significant role in numerous psychological functions, including but not limited to working memory, creative thinking, executive focus, and the process of making decisions (Nejati et al., 2021). The vmPFC is sensitive to the reward or value of stimuli, value-based decision-making, anticipation of reward, and self-based evaluation (Nejati et al., 2021). The dlPFC is primarily engaged in overseeing cognitive regulation and executive functions, while the vmPFC is believed to play a pivotal part in emotional processing (Nejati et al., 2021).

Brain activity can be measured using brain imaging technologies that have revolutionized cognitive neuropsychology, providing a new way of mapping cognitive abilities and brain activity (Sulbaran, T. & Kisi, K., 2022). Brain activity can be measured using multiple imaging techniques including: 1-Electroencephalography (EEG), 2- Magnetoencephalography (MEG), 3- Functional Near-infrared Spectroscopy (fNIRS), 4- Positron Emission Tomography (PET), and 5 - Functional Magnetic Resonance Imaging (fMRI).

EEG records changes in the electrical potentials generated by large populations of synchronously active neurons(Lystad & Pollard, 2009). MEG is a technique that relies on the naturally occurring magnetic fields in living organisms. These fields are found in association with the electric currents that are part of normal brain function (Kimberley & Lewis, 2007). fNIRS is a non-invasive imaging technic that provides the relative change of blood oxygenation level in the superficial layer of the brain tissue (Rahman et al., 2020). PET typically measures regional cerebral blood flow (rCBF) or regional cerebral metabolic rate of glucose (rCMTG), using radioactively labeled molecules (tracer molecules), which are usually injected intravenously or continuously inhaled by the patient or research participant (Lystad & Pollard, 2009). fMRI depends on identifying slight alterations in the signals utilized for generating magnetic resonance images, which are linked with brain neuronal activity (John C. Gore, 2003). This method detects variations in the MRI signal's blood oxygen level, which emerge when changes in neuronal activity happen due to shifts in brain states, potentially induced by stimuli or tasks, for instance (John C. Gore, 2003).

Harrison et al., (2014) were able to predict whether a subject was experiencing no workload, low workload, or high workload using fNIRS (Harrison et al., 2014). Similarly, Billions et al., 2018, were able to measure an increase in brain activity upon stimulus activation (Billones et al., 2018). Another study shows that PFC oxygenation as measured by fNIRS increases with working memory load and task engagement (Herff et al., 2014).

Once the brain activity data is acquired (using one more of the imaging techniques), the next step is data analysis to extract meaningful information about brain function. Neuroimaging data analysis is complex due to the diverse nature of imaging modalities, imaging sequences, file formats, experimental protocols, and subject groups employed in neuroimaging experiments(Adamson & Wood, 2010). In general, this analysis involves time-domain or location-domain analysis techniques, depending on the research question and the type of data collected. Advanced analysis techniques need to be applied to investigate functional connectivity between brain regions, assess task-related changes in network dynamics, or localize the sources of neural activity. Visualizations, statistical tests, and computational models are used to elucidate the relationships between brain activity patterns and cognitive functions, providing insights into the underlying mechanisms of human cognition and behavior. Finally, the results of the advanced data analysis are interpreted in the context of the experimental design and research question, considering the neural correlates of specific cognitive processes or behavioral outcomes. Numerous computerized tools have been developed to assist in neuroimaging analysis. Some examples of neuroimaging analysis software include Analysis of Functional Neuroimaging (AFNI), Brain Connectivity Toolbox, BrainSuite, BrainVISA, Brain Voyager, FreeSurfer, FMRIB Software Library (FSL), Medical Image Analysis Lab (IALAB), RESting-state fMRI data analysis Toolkit (REST), Statistical Parametric Mapping (SPM) and Magnetoencephalography/ Electroencephalography – Python (MNE – Python) among others (Elster, 2024).

The MNE-Python serves as an open-source software package, offering advanced algorithms coded in Python. These algorithms cater to various tasks such as data preprocessing, source localization, data analysis, statistical analysis, and the estimation of functional connectivity among brain regions distributed across the brain (Gramfort et al., 2013). The MNE-Python package was used to implement the proposed framework because it is a versatile package that has a comprehensive set of tools. Furthermore, its flexibility and extensibility of the Python programming language, make it a valuable resource for researchers studying brain function and cognition. Whether investigating basic sensory processing, or project management cognitive functions. Because, the ability to recognize, evaluate, and counteract potential challenges holds the utmost significance in guaranteeing success in project management (Li et al., 2024).

Understanding the project managers' cognitive processes can lead to better strategies for problem-solving, decision-making, and communication within project teams. Therefore, this paper's objective is to provide a detailed and straightforward framework for implementing MNE-Python to study the cognitive process associated with the activities and skills in project management. The project management activities and skills are organized into four categories conceptual, human, negotiation, and technical skills (Tijani et al., 2024). This work will address the gap of limited research in cognitive processes underlying decision-making, problem-solving, and information processing in project management.

RESEARCH METHOD

This research was completed following a qualitative conceptual methodology. Qualitative research methodology is multimethod, involving an interpretative, naturalistic approach to a subject matter, studying things in their natural settings, and attempting to make sense of or interpret, phenomena in terms of the meanings (Aspers & Corte, 2019). Conceptual research was used because it serves as a cornerstone of scientific inquiry, providing the theoretical foundation upon which empirical studies build (Heinonen & Gruen, 2024). It also shapes the understanding of complex phenomena (as the one explore in this research), guides the development of new theoretical frameworks, and informs empirical work across contexts. (Heinonen & Gruen, 2024). In short, this methodology was selected for this research because it allowed the research team to explore the complex phenomenon of developing the proposed framework and understand its context with the flexibility and adaptability needed. Furthermore, the qualitative research methodology offered a rich and holistic approach to developing the proposed framework, emphasizing depth, context, and interpretation.

More specifically, within the qualitative methodology, the multidisciplinary framework-building methodology (Jabareen, 2009) was used to build the proposed "Framework to Analyze Project Management Cognitive Process Using MNE-Python" because it is complex and links multiple bodies of knowledge that belong to different disciplines (Jabareen, 2009). The framework created has ontological, epistemological, and methodological assumptions:

- *Ontological Assumptions* - relate to the structure of objects, properties, events, processes, and relations in events (Welty, 2003). They relate to knowledge of the "way things are," "the nature of reality," "real" existence, and "real" action (Guba & Lincoln, 1994)
- *Epistemology Assumptions* – correlate the way human beings comprehend knowledge about what is perceived to what exists (Becker & Niehaves, 2007) They relate to "how things really are" and "how things really work" in an assumed reality (Jabareen, 2009).
- *Methodological assumptions* - Refer to the process of constructing the conceptual framework and evaluating its capacity to provide insights into the tangible world (Jabareen, 2009).

The procedure used to develop the framework was composed of seven phases as shown in **Error! Reference source not found.** The following is a brief description of each phase:

Phase 1: Map Data Sources - recognizes the range of interdisciplinary literature concerning the phenomenon under consideration. This process includes identifying text types and other sources of data, such as existing empirical data and practices. It must begin with an extensive review of the multidisciplinary texts. Data collection should be comprehensive and complete (Jabareen, 2009).

Phase 2: Read and Categorize Data - read the selected data and classify it both by discipline and by a scale of importance and representative power within each discipline. The objective is to maximize the effectiveness of the inquiry and ensure effective representation of each discipline (Jabareen, 2009).

Phase 3: Identify and Name Concepts - read and reread the selected data and "discover" concepts (Corbin & Strauss, 2008). This method allows concepts to emerge from the literature (Jabareen, 2009).

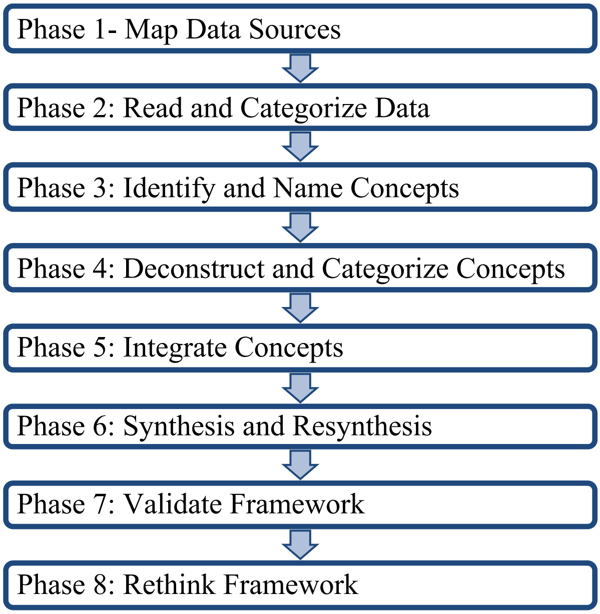

Figure 2. *Procedure to Develop Framework*

Phase 4: Deconstruct and Categorize Concepts - decomposes each concept; to identify its main attributes, characteristics, assumptions, and role; and, subsequently, to organize and categorize the concepts according to their features and ontological, epistemological, and methodological role (Jabareen, 2009).

Phase 5: Integrate Concepts - combines and group concepts that have similarities to one new concept. This reduces the number of concepts drastically and allows the manipulation to a reasonable number of concepts (Jabareen, 2009).

Phase 6: Synthesis and Resynthesis - incorporate the concepts into a theoretical framework. It is important to be open, tolerant, and flexible with the theorization process and the emerging new theory. It is iterative and includes repetitive synthesis and resynthesis until a general theoretical framework makes sense (Jabareen, 2009).

Phase 7: Validate Framework - Assess whether the suggested framework and its ideas are coherent not just to the researcher but also to other academics and professionals. Confirming the validity of a theoretical framework involves initial scrutiny by the researcher, followed by seeking validation from external sources. Introducing a developing theory at conferences, seminars, or other academic settings offers researchers a valuable chance to engage in discussions and receive input (Jabareen, 2009).

Phase 8: Rethink Framework – A framework depicting a multidisciplinary phenomenon is inherently fluid and subject to revision based on fresh perspectives, feedback, literature updates, and similar factors. As the framework is multidisciplinary, the theory should make sense for those disciplines and enlarge their theoretical perspective on the specific phenomenon in question (Jabareen, 2009).

RESULTS

The resulting Framework to Analyze Project Management Cognitive Process Using MNE-Python developed following the phases of the framework building methodology (Figure 2) is presented in this section. The framework is composed of the four stages shown in Figure 3.

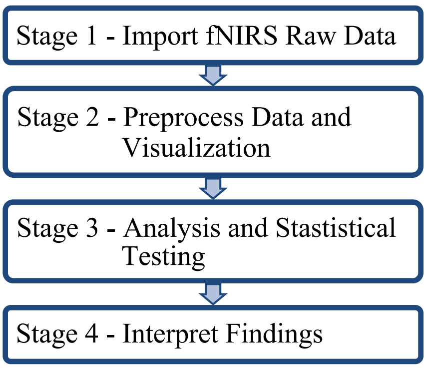

Figure 3. *Framework to Analyze PM Cognitive Process Using MNE-Python*

Stage 1 - Import fNIRS Raw Data: MNE-Python supports various file formats used by different MEG and EEG acquisition systems. MNE-Python allows to import data recorded in file formats such as hitachi, nirx, snirf, and boxy.
During this stage, the raw data in the file is loaded to a variable in the Jupyter Notebook (using mne.io.read_raw _snirf). The general information about the uploaded data is browsed for completeness particularly the number of channels and sampling size (using .shape) and finally, the channel names are checked (using .ch_names).

Stage 2 – Preprocess Data and Visualization: MNE-Python has extensive preprocessing capabilities, including data cleaning, filtering, noise/artifact (environmental and biological) suppression, signal normalization, and data cropping. It also has excellent visualization tools to visualize sensor data, topographical maps, time-frequency representations, and source estimates.
During this stage, the events and event dictionary are loaded to the respective variables (using mne.events_from_ annotations) containing the events/marker's

time and IDs. These event IDs are plotted against time (using mne.viz.plot_events) and are provided meaningful names (using annotations.rename or new dictionary). Repeated events/markers IDs are merged (using mne.merge_events). Channel locations (using .plot_sensors kind='topmap') and relative distance among them (using .plot_sensors kind='3d') are displayed. The fNIRS channels are picked (using mne.pick_types fnirs=True) and the distance between detectors are calculated (using mne.preprocessing.nirs.source_dectector_ distance) to pick only the ones that are more than 1 centimeter apart (using .picks dists >0.01). The raw fNIRS measurements of the channels are displayed (using .plot), converted to optical density (using mne.preprocessing. nirs.optical_density), and displayed (using .plot). The quality of each channel's optical density is evaluated using the Scalp Coupling Index (SCI). The channels with SCI below a certain threshold are added to a list of bad channels (using. append and .info). The locations of the bad channels on the scalp are displayed (using plot_sensors). The optical density measurements are converted to Oxyhemoglobin (HbO) and Deoxyhemoglobin (HbR) implementing Beer-Labert Law (using mne.preprocession.nirs. beer_lamber_law) and shown using (.plot). Heart rate is removed from hemodynamic responses (using. filter). Epochs are defined considering the maximum peak-to-peak signal amplitude (PTP) of HbO and/or HBR, start and end time window (using mne.epoch)

Stage 3 – Analysis and Statistical Testing: MNE-Python supports a wide range of analysis techniques, such as time-frequency analysis, event-related potential (ERP) analysis, connectivity analysis, and source localization. It can also perform statistical testing to assess the significance of experimental effects or differences between conditions. MNE-Python includes functions for permutation testing, cluster-based statistics, and other methods commonly used in neuroimaging research.

During this stage, specific channels and specific epochs can be viewed (using epochs.plot_image) to check for consistency of cognitive response across trials. Consistency across channels for specific epochs can also be viewed to see the HbO and HbR measurements of all channels. HbO and HbR of specific epochs are plotted on the same figure to illustrate the relation between the two signals on the epochs (using mne.viz.plot_compare_ evokeds). Topology representations of the epoch are shown (using epochs.plot_joint and epochs.plot_topomap) to show the cognitive activity in different regions of the brain over time. Statistical analysis of the HbO and HbR is done by converting the epochs data into a dataframe (using epochs.to.data_frame). The epochs data can also be converted into a dataframe by appending each epoch to a dataframe (using _append). After the data is in a dataframe, Data Analysis using Bootstrap-Coupled ESTimation (DABEST) is implemented (using dabest.load, .mean_diff, and mean_diff.plot) to determine the difference between the means and the 95% Confidence Interval (CI). On sample T-Test can also be done (using scipy stats.test_1samp)

Stage 4 - Interpretation: Evaluate the findings based on the results of the analysis and relate them to the research questions or hypotheses. Interpret the measured cognitive responses in the context of underlying neural mechanisms and brain function. Acknowledge any limitations or constraints in the study design, data quality, or analysis methods. Discuss the broader implications of the findings for the field of project management or neuroscience. Identify avenues for future research to build upon or further explore the findings of the study.

PRACTICAL IMPLICATIONS

The practical implications of this work lie in its potential to revolutionize project management practices by integrating insights from neuroscience into project management research. The implementation of this framework will contribute to a deeper understanding of the cognitive dimensions of project management. The following are a few of these practical implications:

Tailored Interventions: by developing customized interventions and training programs aimed at enhancing project management performance based on their particular cognitive process.

Improve Decision-Making: by gaining insights into how the project managers' brains process information, the project managers could make more informed and better decisions.

Strategic Planning: by analyzing the cognitive processes involved in strategic planning tasks, the framework can assist project managers in formulating more effective strategies and adapting to changing circumstances to improve project success.

Training and Development: by utilizing the insights from this research, neuroscience principles could be incorporated into training for organizations to enhance the cognitive skills of their project management teams, leading to improved performance and outcomes.

CONCLUSIONS

The framework presented in this paper to analyze brain activity using MNE-Python provides a comprehensive approach to studying cognitive processes related to project management. Through the stages outlined in this paper, researchers can import, preprocess, analyze, and interpret functional near-infrared spectroscopy (fNIRS) data efficiently and effectively. In essence, the framework presented in this paper offers a robust methodology for investigating the neural correlates of project management tasks using fNIRS data and MNE-Python analysis tools. Its systematic approach and integration of advanced analytical techniques contribute to advancing our understanding of cognitive processes in project management contexts and pave the way for future interdisciplinary research endeavors.

Although the framework presented in this paper is an important contribution to advancing the understanding of how project managers navigate complex environments, make strategic decisions, and optimize project outcomes, continuing work in this domain is important. Thus, some future work includes:

Validation and Rethinking of the Framework: Future research could focus on validating and extending the proposed framework presented in the paper. This could involve discussion and feedback from other research as well as testing the framework with different project management tasks, contexts, and populations to assess its robustness and generalizability. Additionally, researchers could explore modifications or additions to the framework based on feedback and empirical findings.

Application to Real-world Project Management Scenarios: Further research could apply the framework to real-world project management scenarios across diverse industries and domains. By investigating cognitive processes in actual project settings, researchers can gain insights into how project managers approach decision-making, problem-solving, and information processing in practice.

Exploration of Interdisciplinary Collaboration: Given the interdisciplinary nature of the proposed framework, future research could explore collaborations between project management and neuroscience researchers. This collaboration could lead to the development of innovative methodologies, tools, and interventions informed by both fields, enhancing the understanding of cognitive processes in project management.

Longitudinal Studies and Intervention Design: Longitudinal studies could be conducted to examine the effects of cognitive interventions and training programs informed by the framework on project management performance and outcomes over time. This could involve designing and implementing interventions aimed at improving decision-making efficacy, problem-solving skills, and cognitive flexibility among project managers.

Integration with Artificial Intelligence (AI): With the recent spike in the advancement of AI technology, future research could explore the integration of AI with the proposed framework. This integration could enhance data analysis capabilities, provide real-time feedback to project managers, and offer novel insights into cognitive processes in project management.

Diversity Studies: could be conducted to investigate diversity (such as ethnicity, gender, and socio-economic background) influences on cognitive processes in project management. By comparing cognitive strategies and decision-making approaches across different cultural contexts, researchers can identify cultural factors that shape project management practices and outcomes.

Overall, future research based on the presented framework has the potential to advance the understanding of cognitive processes in project management and inform the development of evidence-based project performance strategies.

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