Protocol Design for in-Class Projects: Comparative Analysis of EEG Signals Among Sexes

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Abstract: This paper focuses on the development of a structured protocol to support undergraduate students in conducting in-class projects. Project-Based Learning (PBL) has gained recognition as an effective educational approach, offering students practical, hands-on experience and fostering a deeper understanding of the application of theoretical concepts. Despite its advantages, undergraduate students often face challenges in successfully completing in-class projects due to the lack of well-defined protocols to guide their efforts. To address this gap, we, a team of graduate students serving as teaching assistants (TAs), designed this protocol based on their close interaction with undergraduates and an understanding of the challenges they face. This protocol aims to enhance the ability of undergraduate students to complete their project in a systematic and structured way. To demonstrate the implementation, we provide a step-by-step guide based on an in-class project conducted as part of the "Sensors and IoT" course (CS4432/5432) at the University of Minnesota Duluth.

1 INTRODUCTION

PBL is an educational approach where students engage in an extended learning process by investigating and solving real-world problems or challenges (Brundiers and Wiek, 2013; Krajcik, 2006). PBL is one of the modern technologies that universities in many parts of the world are adopting to develop engineering graduates capable of being the practical application oriented engineers needed in industry. This pedagogical approach is well established and has been reviewed extensively (Bell, 2010; Helle et al., 2006; Thomas, 2010).

In PBL, students collaborate in teams over an extended period, applying critical thinking, problem-solving, and research skills to produce tangible outcomes or products.

2 PROBLEM/ SOLUTION DESCRIPTION

Our research was motivated by the critical need to develop a comprehensive, adaptable methodology for undergraduate research that addresses the persistent challenges in experiential learning. Traditional educational approaches have increasingly struggled to prepare students for the complex, interdisciplinary de-mands of modern professional environments. By uti-lizing neurological assessment techniques, we aimed to create a robust protocol that not only facilitates effective project-based learning but also pro- vides insights into cognitive engagement across different tasks and potential sex-based cognitive variations.

Teaching assistants (TAs) work closely with undergraduates and maintain a deep understanding of the specific challenges they face while working on projects. This close involvement allows TAs to develop solutions that effectively address these needs.

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Therefore, the protocol we have developed is designed to be highly effective for undergraduate students.

2.1 Neurological Foundations

The human brain's remarkable plasticity allows for diverse cognitive responses across different neural regions. Our study specifically focused on four key brain wave channels that correspond to distinct cognitive states:

- Alpha Waves: Associated with relaxation and mental coordination, primarily observed in the oc-cipital and parietal regions
- Beta Waves: Linked to active thinking, problem-solving, and focused mental activity, predomi-nantly observed in the frontal and temporal lobes
- Theta Waves: Connected to creativity, emotional processing, and memory formation, primarily ac-tive in the limbic system
- Delta Waves: Characteristic of deep sleep and unconscious processing, typically associated with the default mode network

2.1.1 Sex-Based Neurological Variations

Emerging research has increasingly highlighted potential differences in neural signal activity between males and females. A seminal study by Ingalhalikar et al. (Ingalhalikar et al., 2013) demonstrated signifi-cant structural and functional connectivity differences in male and female brains. Specifically, their research revealed that male brains tend to show more intra-hemispheric connectivity, while female brains exhibit greater inter-hemispheric connectivity, suggesting nuanced differences in cognitive processing.

3 PROJECT HYPOTHESIS

We hypothesized that females might demonstrate heightened neural responses in certain cognitive tasks, particularly those involving:

- Complex social cognition
- Multi-tasking scenarios
- Emotional intelligence-related activities
- Fine motor skill coordination

This hypothesis builds upon previous research by Cahill (Cahill, 2006), which suggested that hormonal and structural differences can lead to varied cog-nitive processing strategies between males and fe-males. However, we approached this hypothesis with methodological rigor, acknowledging the potential for individual variability and the dangers of overgeneralization.

In the context of the current academic and professional landscape, traditional teaching methods often fall short in equipping students with the practi-cal skills and hands-on experience that are required in the current job market or graduate school. PBL has emerged as an effective pedagogical approach to bridge this gap, offering students valuable opportunities for experiential learning.

While graduate students commonly participate in projects, undergraduate students often face difficulties due to limited time, resource constraints, unclear ex-pectations, and inadequate support. Further, under-graduate students often lack the experience required to effectively collaborate in teams, leading to chal-lenges in communication, coordination, and delega-tion of tasks. To address these limitations, we de-signed a simplified yet effective protocol for under-graduate students that can help them in producing a successful project.

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4 RELATED WORKS

Philip et al. (Sanger and Ziyatdinova, 2014) outlined three common approaches for integrating projects into Project-Based Learning (PBL) curricula. These include:

- Demonstration-Type Competitive Projects: These projects are designed primarily for pedagogical purposes and are not typically industry-based. Their objective is to teach and practice project-related skills through competitive yet instructional activities.
- Focused Single-Discipline Projects: These are embedded within specific courses and concentrate on a particular academic discipline.
- Multidisciplinary Capstone Projects: These are typically senior-year projects that involve tackling complex, open-ended problems, often in collabo-ration with industry.

Zhang et al. (Zhang and Ma, 2023) conducted a meta-analysis of 66 studies spanning two decades, demonstrating that project-based learning significantly enhances students' academic performance, affective attitudes, and critical thinking skills when compared to traditional teaching methods.

Vogler et al. (Vogler et al., 2018) conducted a two-year qualitative study examining the learning pro-cesses and outcomes of an interdisciplinary project-based learning (PjBL) task involving undergraduate students from three courses. The findings highlighted the development of soft skills (e.g., communication, collaboration) and hard skills (e.g., programming, de-sign, market research) while emphasizing the impor-tance of course design improvements to fully achieve interdisciplinary objectives.

Cujba et al. (Cujba and Pifarre,´ 2024) per-formed a quasi-experimental study involving 174 sec-ondary students to examine the impact of innovative, technology-enhanced, collaborative, and data-driven project-based learning on attitudes toward statistics. The experimental group showed reduced anxiety, increased affect, and more positive attitudes toward using technology for learning statistics, while the control group exhibited no positive changes. The findings highlight the potential of this instructional approach to improve both statistical problem-solving skills and students' attitudes, emphasizing its educational significance.

Wurdinger et al. (Wurdinger and Rudolph, 2009) conducted a study at a student-centered charter school in Minnesota to explore definitions of success and the teaching of life skills by surveying 147 alumni, students, teachers, and parents. The results showed that life skills such as creativity (94%) and the ability to find information (92%) were highly valued, while academic skills like test taking (33%) and note taking (39%) ranked lower. Despite this, 50% of alumni graduated from college, above the national average. The study suggests that project-based learning schools should integrate academic skill development to better prepare students for college.

Rehman et al. (Rehman, 2023) highlight that PBL enhances critical thinking, engagement, and practical skills in computer science and engineering but faces barriers like faculty resistance, resource constraints, and assessment challenges. They propose addressing these issues with training, resources, and evaluation improvements.

5 METHODOLOGY

This study adopts a mixed-methods exploratory research design within the Project-Based Learning (PBL) paradigm, integrating both procedural innovation and empirical investigation. We propose a comprehensive protocol that goes beyond traditional project management approaches by emphasizing systematic rigor, methodological transparency, and scalable educational intervention strategies.

5.1 Protocol Architecture

1. Preparatory Phase: Conceptualization and Design

Problem Identification:

- Critical survey of research domain: Comprehensive examination of existing literature, identifying key theories, methodological approaches, and current research gaps in neurocognitive performance assessment.
- Identification of knowledge gaps: Systematically analyzing unexplored intersections between cog-nitive task performance, neural signal variations, and interdisciplinary research methodologies.
- Articulating precise research questions: Developing focused, measurable inquiries that address specific cognitive engagement and neural signal correlations across diverse experimental tasks.
- Comprehensive literature review: Conducting an exhaustive review of peer-reviewed sources, synthesizing theoretical frameworks, and establishing a robust conceptual foundation for the study.

Methodological Calibration:

- Systematic research design assessment: Critically evaluating potential research methodologies, en-suring alignment with research objectives and maximizing scientific rigor and reproducibility.
- Instrument selection and validation: Meticulously selecting measurement tools and validation pro-tocols to ensure precise, reliable data collection across multiple cognitive engagement scenarios.
- Preliminary feasibility analysis: Conducting a comprehensive assessment of resource requirements, technological capabilities, and potential methodological constraints.
- Epistemological alignment verification: Ensuring theoretical consistency and methodological coher-ence across experimental design, data collection, and analytical frameworks.

2. Operational Framework Sampling Methodology:

- Purposive, stratified sampling approach: Implementing a carefully designed sampling strategy that ensures representative participant selection based on predefined cognitive and demographic criteria.
- Demographic representativeness: Ensuring participant diversity and balanced representation across gender, age, and potential cognitive vari-ation parameters.

- Minimization of selection bias: Developing rigor-ous recruitment protocols that mitigate potential systemic biases in participant selection and data interpretation.

5.2 Sensor Setup Design

Our approach utilizes advanced sensor fusion techniques, strategically integrating multiple physiological measurement modalities to enhance data comprehensiveness and interpretative depth. The BIOPAC MP36 multi-modal sensor suite provided sophisticated capabilities for high-resolution Electroencephalographic (EEG) signal acquisition. Figure 2 represents the BIOPAC MP36 that we used for data acquisition.

Figure 1: BIOPAC MP36 Data Acquisition Unit.

Figure 2: Eilik Robot for Sensor Fusion.

Analytical Strategy

- Paired t-test statistical inference: Employing comparative statistical techniques to assess significant differences in neural signal characteristics across experimental conditions.
- 95% confidence interval framework: Establishing robust statistical confidence boundaries to validate research findings and minimize Type I error probability.
- Degrees of freedom: Implementing a three-parameter model specifically calibrated to the four-channel EEG signal acquisition system, en-suring precise statistical modeling.

Dimensional Analysis Approach

Our analysis diverge from traditional univariate approaches by:

- Examining multiple neuro-physiological dimensions: Simultaneously investigating intercon-nected neural signal characteristics to provide comprehensive cognitive performance insights.
- Investigating variations in signals from different individuals: Analyzing inter-individual neural response variability to understand cognitive processing heterogeneity.
- Mapping neural activity across specialized brain regions: Developing detailed neural activation maps to correlate specific cognitive tasks with lo-calized brain function.
- Correlating task-specific cognitive engagement: Establishing nuanced relationships between experimental tasks and corresponding neural signal patterns.

5.3 Experimental Parameters

Sample Characteristics:

The research cohort consisted of four carefully selected individuals, ensuring a controlled and focused study. The group maintained a balanced gender representation, with two male and two female participants, to mitigate potential biases arising from gender-based cognitive variations.

Experimental Tasks:

- Strategic cognitive engagement (chess): Assessing complex decision-making processes, strate-gic planning, and cognitive resource allocation through chess-based challenges.
- Interactive robotic interface interaction with Eilik: Exploring human-machine interaction dynamics and adaptive cognitive responses in technological engagement scenarios.
- Physical motor performance tasks, pushups, squats: Investigating neural signal variations dur-ing structured physical exertion and motor skill execution.
- Memory and cognitive processing challenges: Evaluating working memory capacity, informa-tion processing speed, and cognitive flexibility by making participants play a memory game.
- Fine motor skill coordination assessment: Ex-amining precise neuromuscular control, and cognitive-motor integration by balancing a pencil.

This methodology is a conceptual blueprint for optimizing educational research practices, by closing the gap between theoretical understanding and practical implementation.

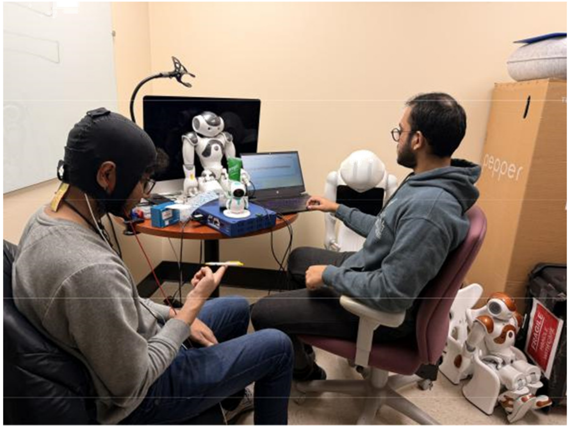

Figure 3: Sample image from our data collection sessions.

6 PRACTICAL CONSIDERATIONS AND METHODOLOGICAL CHALLENGES

Project Implementation Strategies.

6.1 Simplified Project Setup

The simplest way to establish an in-class project involves:

• Defining clear, measurable learning objectives: Articulating specific, quantifiable goals that align with course learning outcomes and provide a concrete framework for student research engagement.

• Selecting a focused, achievable research question: Identifying a narrow, manageable research inquiry that balances academic rigor with practical con-straints of in-class project limitations.

• Establishing minimal viable technological infras-tructure: Selecting cost-effective, accessible tech-nological tools that support research objectives without overwhelming student resources.

• Creating a flexible yet structured project timeline: Developing a comprehensive project sched-ule that allows for iterative progress while main-taining clear milestone achievements.

• Providing clear guidelines for collaborative work: Establishing transparent expectations, communi-cation protocols, and collaborative framework to maximize team productivity and individual ac-countability.

6.2 Dealing with Small Sample Sizes

Handling small sample sizes requires careful strategies to ensure reliable and meaningful results. One approach is to use statistical techniques like bootstrapping, which involves creating multiple simulated datasets from the original data to estimate patterns and variability. Another method is to focus on clear and transparent reporting, explicitly outlining the limitations of the study so that conclusions are interpreted with caution. Small studies can also be framed as exploratory, aiming to generate ideas or hypotheses for future research. Finally, researchers can minimize bias by carefully designing the study, controlling for key variables like age, gender, or other relevant fac-tors to reduce noise in the results.

6.3 Navigating Inconclusive Research Outcomes

Handling inconclusive results in academic projects re-quires:

• Recognizing negative results as scientifically valuable: Repositioning inconclusive findings as critical contributions to methodological understanding and future research design.

• Documenting methodological insights: Compre-hensively cataloging research challenges, limita-tions, and unexpected outcomes to enhance future investigative approaches.

• Articulating limitations transparently: Providing detailed, honest assessments of research constraints to maintain academic credibility and re-search integrity.

• Proposing future research directions: Developing constructive recommendations for subsequent in-vestigations based on current study's limitations and insights.

• Maintaining academic integrity in reporting: En-suring honest, comprehensive reporting of research outcomes regardless of initial hypothetical expectations.

6.4 Data Collection Without Formal IRB

Ethical strategies for preliminary human-subject data collection:

• Obtaining verbal or written informed consent: Developing comprehensive participant informa-tion protocols that prioritize individual autonomy and voluntary participation.

• Anonymizing participant data: Implementing ro-bust data anonymization techniques to protect individual privacy and research participant confidentiality.

• Minimizing potential participant risks: Conducting thorough risk assessments and implementing protective measures to prevent physical or psychological harm.

• Limiting data collection to non-invasive methods: Restricting research methodologies to minimally intrusive data collection techniques that prioritize participant well-being.

• Providing clear opt-out mechanisms: Establishing transparent participant withdrawal protocols that respect individual autonomy throughout the research process.

• Maintaining strict confidentiality protocols: Developing comprehensive data management strategies that protect participant privacy and adhere to ethical research standards.

6.5 Rapid Data Analysis Techniques

Efficient data processing involves utilizing preconfigured data analysis scripts, using automated cleaning protocols, and using machine learning preprocessing techniques to streamline workflows and improve accuracy. Modular frameworks enhance flexibility and scalability, while advanced visualization techniques enable rapid pattern recognition and intuitive analysis. Together, these strategies ensure re-liable, adaptable, and efficient data handling.

6.6 Neurological Task-Region Correlation Rationale

Our activity selection for specific brain regions was predicated on:

• Established neuroscientific literature: Grounding experimental design in comprehensive review of peer-reviewed neurological research and established cognitive mapping methodologies.

• Neuroplasticity and cognitive engagement principles: Incorporating contemporary understanding of brain adaptability and task-specific neural net-work activation.

• Maximizing signal-to-noise ratio in neural recordings: Strategically selecting experimental tasks to optimize neural signal clarity and minimize potential measurement artifacts.

• Targeting regions with known functional specialization: Focusing on brain regions with well-documented correlations to specific cognitive processes and performance metrics.

By integrating these practical considerations, we enhance the methodological robustness and pedagogical value of our research approach, transforming potential challenges into opportunities for methodological innovation.

7 RESULTS AND RECOMMENDATIONS

7.1 EEG Signal Analysis Methodology

Our protocol for analyzing EEG signals involved a comprehensive multi-channel approach using the Biopac MP36 sensor system. We focused on four distinct brain wave channels (Channels 40-43) corresponding to different neural activity states: Al-pha (relaxation), Beta (active thinking), Delta (deep sleep/unconscious), and Theta (creativity/emotional processing) waves.

7.2 Data Analysis Mechanism

To ensure robust statistical analysis, we employed a systematic data processing methodology:

• Recorded EEG signals across five distinct cognitive and physical tasks: chess, interaction with Eilik robot, physical exercise, memory games, and pencil balancing.

• Calculated average frequency values for each wave channel separately for male and female participants.

$$\bar{X}_i = \frac{1}{n}\sum_{j=1}^{n} X_{ij} \qquad (1)$$

Where:
–$\overline{X}_i$ represents the mean frequency for channel i
–n is the number of measurements
–X_{ij} represents the j-th measurement in channel i

• Utilized a paired t-test at a 95% confidence interval with three degrees of freedom to validate potential gender-based neurological differences.

$$t = \frac{\bar{D}}{\sqrt{\frac{s_D^2}{n}}} \qquad (2)$$

Where:
–$\overline{D}$ is the mean difference between paired observations
–s_D is the standard deviation of the differences
– n is the sample size

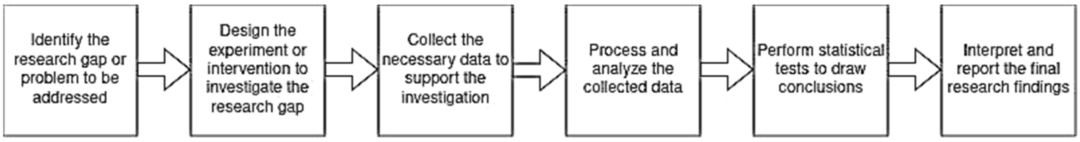

Figure 4: Our designed protocol for in-class projects of undergraduate students.

The paired t-test formula expanded:

$$s_D = \sqrt{\frac{\sum_{i=1}^{n}(D_i - \bar{D})^2}{n-1}} \quad (3)$$

7.3 Statistical Interpretation

Critically, our paired t-test results demonstrated that the observed variations did not constitute statistically significant differences. This finding is mathematically represented by:

$$|t_{calculated}| \le t_{critical} \quad (4)$$

Where:

- $t_{calculated}$ represents the computed t-statistic from our experimental data.
- $t_{critical}$ represents the threshold value at the 95% confidence interval.
- Degrees of freedom (n = four channels): $df = n - 1 = 3$

Significance criteria:

$$p \ge 0.05$$

This suggests that while individual task performances exhibited unique neurological signatures, aggregate brain wave patterns remained remarkably consistent across genders, with no statistically significant neurological differentiation detected.

7.4 Ethical Component

Throughout the research, we maintained stringent ethical standards. We obtained formal consent from the participants before conducting the experiments. We ensured inclusivity and equal treatment of all participants. We were attentive to minimizing participant discomfort and remained sensitive to gender-related considerations.

8 DISCUSSION

In this study, we have determined that the best way to start and finish an in-class project within a span of a short time is to implement a structured, yet flexible project-based learning (PBL) approach that balances systematic rigor with adaptive methodological strategies.

8.1 Key Findings and Insights

Our research yielded several critical insights into undergraduate project management and cognitive performance assessment:

The proposed protocol shows significant potential for standardizing undergraduate research method-ologies across disciplinary contexts.

Sensor fusion techniques provide a nuanced ap-proach to understanding cognitive performance, revealing subtle variations in neural signal pat-terns that traditional methods might overlook.

8.2 Limitations and Future Research Directions

While our study provides valuable insights, several limitations warrant acknowledgment. The number of small sample size (4 participants) really limits the generalizability of the experiment. Increasing the sample size and including participants from a diverse age group can improve the effectiveness of the results. But as our experiment was limited to the classroom and we did not have IRB training to experiment with human subjects we could not include more training samples. Expanding this experiment outside of the classroom can be a future-work for this experiment. Furthermore, our experiments focused on a specific set of cognitive tasks. Including a diverse set of cog-nitive tasks can capture the brain parts better.

9 CONCLUSION

Our research represents a significant step towards developing a more systematic, technologically inte-grated approach to undergraduate project-based learn-ing. By combining rigorous methodological frame-works with innovative technological tools, we demon-strate the potential to transform traditional educa-tional practices.

The proposed protocol is not just a procedural guideline but a conceptual blueprint for optimizing educational research practices. It bridges the critical gap between theoretical understanding and practical implementation, offering a scalable model for inter-disciplinary project management.

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