A MULTI-MODAL NEUROCOGNTIVE STUDY EXAMINING ENGINEER'S DESIGN PREFERENCES

by

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ABSTRACT

Design Neurocognition is an amalgamation of two distinctly different yet interdisciplinary fields, driven by the purpose of comprehending and predicting brain behavior during design activities. These domains include, but are not limited to, problem-solving, concept generation, process design, redesign, problem formulation, and problem preference. Identifying and defining the problem statements is the first step in the design process, which can influence downstream activities. Problem statements serve as stimuli to a designer, determining the designer's neurocognitive behavior, as an engineer can experience an immediate emotional reaction to a problem statement rooted in experience and interest. Word choice, stated goals, and relevant design information can impact an engineer's understanding of the problem statement. The structure and variation in problem statements may have different emotional and neurocognitive influences on a designer's behavior.

This research presents a novel approach to studying designer preference through the neurocognitive lens, to support understanding the source of preference. The author's prior research identifies two design dimensions that have been found to have an impact on engineering students' preference toward a problem statement: constraint and social value. Constraint here defines how open ended the problem is – allowing students the freedom to explore a wide solution space. Social value defines the social impact a problem has on society. To investigate the neural and cognitive underpinnings that shape these preferences, a multimodal neurocognitive study is performed, encompassing three distinct studies. The problem formulation study examines students' generated problem statements by identifying patterns, themes, and novelty. The problem evaluation study involves design experts rating the problem statements to identify the constraint and social value problems. The problem preference study involves presenting problem statements to students as stimuli, with neural responses recorded for each event.

This research has a far-reaching impact on numerous domains, as it informs educators, the industry, and the research community about the sources of design preference. It can be utilized to enhance student retention in engineering, the selection of engineering majors, success in engineering, and the development of industrial engineering programs.

INDEX WORDS: Design, Problem Formulation, Neurocognition, Machine Learning,

Engineering Education

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MS, Florida Institute of Technology, 2019

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2023

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December 2023

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To my husband, *Owen Whitehead.*

ACKNOWLEDGEMENTS

This journey wouldn't be possible without the love and sacrifice of my parents, Nutan Shah and Dhiren Shah. Thank you for inculcating the values of hard work and honesty, and being my guiding light in everything I do. My sister, Rashi Shah, thank you for being my biggest cheerleader. My husband, Owen Whitehead, you are truly my inspiration. Your patience and belief in me have helped me get this far. My late grandmother, Ruth Kantali for being the role model for generations of women to come. Thank you for everything! Sushi and Hemi, thank you bringing me all the luck and joy.

This research work wouldn't come to fruition without the guidance and support of my advisor, Dr. Beshoy Morkos. Thank you for making me a part of your research team, believing in me, and teaching me everything I know about research. I will forever be grateful. I am lucky to have Dr. John Gero in my committee, thank you for your mentorship and guidance. You have played an instrumental role in my journey of becoming a researcher. Dr. Lisa Benson, Dr. Ramana Pidaparti and Dr. Cheryl Gomillion, I cannot put into words how much I appreciate your mentorship, time and patience bestowed upon me during the program. And lastly to all the members of EETI, thank you for being a part of my story, I will miss you all dearly.

This story is incomplete without the family, friends, and colleagues who have influenced me and helped me become a better person. In no particular order: Sue, Barbara, Emily, Helen, Crystal, Rob, Alyssa, Andy, Marianne, Clay, Margaret, Gaurav, Andrew, Jason, Victor, Jasmine, Tolu, Bryce, Jesse, Amaninder, Ahmed, Jennifer, Logan, Mrugesh, Bela, Vensi, Shweta, Joanna, Daniel, Nidhi, Whitney, Katie, my lab mates, friends and teachers from all around the world.

TABLE OF CONTENTS

APPENDICES

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Design research is a quintessential part of engineering disciplines. In the seminal work by Pahl and Beitz, design is conceptualized as a systematic and structured process that goes beyond problem–solving; it is a creative, innovative an iterative process to conceive and develop products, systems, and address specific needs [1]. A design can begin with a need, followed by conceptualization, identifying requirements, analysis, and the iterative process of prototyping and testing, culminating into a finished product or solution that is functional and economically viable [1]. Design involves synthesis of knowledge and creativity, bridging the gap between theory and application [2]. The process of designing is classified as a high-cognitive load task; the engineer formulates a design problem statement by reflecting on the desired solution space and simultaneously considering the requirements, assumptions, and frequently changing constraints [3–6]. More often than not, the provided information is ill-defined [7,8]. A problem statement may lack crucial details pertaining to the needs of the end-user or incomplete look into the future of the product that stakeholder may desire [9]. Expert designers often utilize previous designing experiences and tacit knowledge to make assumption on the missing information to reach the solution space. Designers are expected to incorporate new requirements from various stakeholders at different stages of the product life cycle. Engineering design is an adaptive and an iterative process. The rigor and experience necessary for successful design and problem formulation is difficult to achieve within classroom setting. This also limits the understanding of the impact of design problems on novice engineers.

This is a three-phase research spanning across 5 years of data collection from university students enrolled in engineering programs. Insights derived from the research study will hold potential not only for enhancing design advancements but also for shaping the future of teaching and learning in engineering classrooms. The amalgamation of design research and neuroscience aims to underscore the profound relationship between design and the human brain, paving a way for an informed and neurologically-driven design strategies for the future of engineering education.

The field of has expanded to deepen our understanding into the cognitive and neurocognitive aspects of design. Design Neurocognition is one such branch of design research exploring how individual perceive, process and respond to various design stimuli. Neurocognitive studies in design primarily leverage advanced neuroimaging techniques such as Electroencephalography (EEG), functional near-infrared spectroscopy (fNRI) and functional Magnetic Resonance Imaging (fMRI) to examine and understand brain behavior. This research is a step in the direction of understanding two underexplored areas of design: design dimensions of problems and neurocognitive impacts of design problems.

Universities are tasked to equip students with the necessary learning and training required for entering workforce. The majority of engineering programs offer design courses such as cornerstone design course in first year, design methodology, and senior capstone course. ABET-accredited universities require engineering students to complete a year-long course prior to graduation and retain the formal design experience necessary to enter workforce and tackle real-world challenges. Senior capstone course provides an opportunity for students to test technical engineering skills and acquire necessary professional skills like teamwork, communication, presentation, time management, and budget management. Most engineering universities offer a diverse range of design projects in the senior capstone course. Students have the opportunity to collaborate with a team on their choice of projects. Researchers have significantly contributed to our understanding in the areas of student motivation [10–12], concept generation [13–15], design learning [16,17], problem exploration [9,18], and design thinking [2,19]. However, more research must be performed on how engineering students perceive design problems and its impact on their designing experience. Current design practices in engineering programs lacks understanding on the long-term impact of design choices on student success. Student interest and social factors may impact the individual design experience. This research is one major one step towards understanding the complex nature of design and its impact on engineers.

Problem statements serve as inputs and stimuli to a designer's mind, determining the designer's cognitive behavior [20]. Findings from previous study state that different types of design problems have different impact on student motivation. To fully understand designer's interpretation of problems and design process, the understanding and classification of the structure of design problems is crucial. Designers tend to "frame" problems in way a that reflect both the context of the problem and designer's own perspective and experience [21]. Cross describes structured problems to be found in mathematics or physical sciences, whereas design problems as inherently ill-structured resisting definitive formulation and capable of multiple interpretation [22]. Researchers have made efforts in defining the structure of problems and highlighted the importance of structure and it's critical role in methods and tool selection in design [23]. Structure of design problems can play a critical role in influencing designer's mind and the decision making, however its lacks investigation. The findings from this research will deepen our understanding of how designers create, perceive, and evaluate problems.

The author's prior research investigation into design projects and student motivation [24–26], it was discovered that students vaguely define problems on two distinct dimensions: constraint and social value of a problem. Constraints can be further classified into two categories: open-ended and close-ended problems. Students tend to gravitate towards a certain group of problems based on their interest or prior experiences, for example; open-ended problem are typically research based projects with limited requirements and provides room for a creative solution space, and close ended problems are often well defined with strict requirements and often similar to classroom problems, it provides student an opportunity to form a structured route for a desired solution. Students expressed an instant inclination experienced when reading a problem statement. The inclination is believed to be rooted in interest, cognition, past experience and future goals. The second design dimension is the social value of a problem: students determine for themselves if the design outcome may have a high or low social impact. If a design problem has the potential to create a positive and greater impact on human society by providing solutions that can solve some of the pressing humanitarian challenges, it can be classified as a high social value problem. Based on the described design dimensions, the interdisciplinary research investigates three activities to holistically understand the complex nature of design problems. Participants are tasked with creating, evaluating and rate design problems at various stages. Design problems are also referred to as design stimuli in the neurocognitive study. Design problems have never been studied from a student perspective and have never been evaluated neurologically for any correlation between participant preference and design stimuli. Thus, the findings from this interdisciplinary inquiry will play a critical role in our knowledge and understanding of design and neurocognition. The findings from this research hold the potential to contribute in various aspects of student learning. Educators can implement the findings in classroom setting to increase student motivation and provide an enriching experience and reduce student retention. The three research questions directing the study are:

RQ1: What themes emerge in design problems formulated by students?

RQ2: What is the relationship between the social and constraint design dimensions of said problems on design preference?

RQ3: What is the relationship between neurocognitive responses when design problems are presented as stimuli on design preference?

CHAPTER 2

PREVIOUS MOTIVATING STUDIES

Three motivating studies lay the foundation for the fruition of the multi-model research are discussed in this chapter. The three studies summarized in this chapter are:

1) Student motivation in capstone design course
2) Qualitative inquiry of capstone design course experience
3) A Neuroscientific Study of Incentivized Test/Retest on Student Performance

2.1 Examining the Differences in Student Motivation for Industry Projects and Non-Industry Projects in Senior Capstone Design

This study [10,27–31] investigates how different types of senior capstone design projects affect student motivation. Three cohort of mechanical engineering students were part of this study. A total of 188 students administered the Motivated Strategies for Learning Questionnaire (MSLQ) to measure student's motivation at two key timepoints: beginning of the fall semester and end of spring semester. The five factors of motivation measured are: intrinsic value, self-efficacy, self-regulation, presentation anxiety and cognitive value. The goal of the study was to determine if the project type (industry vs non-industry) influenced student's motivation levels and their changes over the course. The key findings of the study are shown in Table 1:

Table 1: Statistically Significant Results of ANOVA Analysis

Factor	Time of the survey	Notable observations on project groups
Cognition	Fall	**Industry** teams (4.96±0.73) had **lower cognition** than competition teams (5.24±0.67) in the beginning of the fall semester
Self-Regulation	Fall	**Industry (**4.80±0.85) had **lower self-regulation** in the beginning of the fall semester
Anxiety	Fall	**Industry** (3.76±1.64) showed **lower anxiety** in the beginning
Intrinsic	Spring	**Competition** (6.24±0.61) had **higher intrinsic value** among all teams
Efficacy	Spring	**Industry** (5.92±0.67) had **midway self-efficacy**
Cognition	Delta	**Industry** (0.19±0.89) **increased in cognition**
Intrinsic	Delta	**Industry** (0.32±0.69) **intrinsic value increased** about midway to other teams
Efficacy	Delta	**Industry** (0.51±0.80) **efficacy increased** about midway at the end

The results show that cognition was initially lower for students involved in industry projects, but there was a significant increase in cognition throughout the semester for these students. Non-industry teams such as the competition teams had higher intrinsic value by the end of the spring semester. And the industry teams showed an increased in self-efficacy by the end of the course. These results suggest that the type of capstone project significantly impacts various aspects of student motivation, with industry-sponsored projects showing notable improvements in certain motivational factors over the course duration. This study is crucial for educators and curriculum designers as it provide insights into how project selection can influence student motivation.

2.2 Development of a coding scheme for qualitative analysis of student motivation in senior capstone design

This research [25,32] delved into the qualitative analysis of examining student motivation in senior capstone course. The study methodology includes semi-structured focus group interviews with nine senior design teams. Each interview lasted approximately 30 minutes and focused on student experiences and reflection in the senior design course. The research led to a development of coding scheme using grounded theory approach. The coding scheme includes three main themes: project selection, project process, and project results. Each of these themes offer deep insights into various aspects of student engagement, motivation and decision-making making factors in the design projects.

1. Project Selection: This theme delved into the factors that influenced student's choices in selecting their capstone projects. It explored the criteria students used to select a project, such a personal interest, perceived relevance to future career goals, or the challenge it presented. The theme also considered how students assessed the constraints and opportunities of different projects, including factors like project's scope, resources provided, and potential social value of the outcome. Understanding of these motivating factors is crucial for educators in structuring projects that align with student interests and professional aspirations.
2. Project Process: This theme focused on the student's journey in the year-long course. It encompassed aspects like teamwork, problem-solving strategies, technical and administrative challenges encountered during the project's execution. The theme also shed light on how students navigated the iterative process of design from initial conception to

completion. This insight into the project process is vital for educators to facilitate effective learning environments and support systems that enhances student's problem-solving skills and collaborative abilities.

3. Project Results: The final theme addressed the outcomes and reflections of the students on their completed projects. It included student's self-assessment of their achievements, the acquired skills, and the impact of project on their understanding of design principles and practices. This theme also explored student's satisfaction with the end results and their perception of the project success, both technically and in personal growth.

These themes collectively provided a comprehensive framework for understanding student motivation and experiences in senior capstone design courses. The codes derived through understanding of student motivation and experiences, provides a rich context for exploring the various design dimensions and their pivotal role in shaping design preferences in engineering and design education. The interrater reliability of the coding scheme was found high, indicating a strong agreement between researchers in interpreting the qualitative data. The codebook offers valuable insights for educators to tailor design education to meet students learning needs and aspirations.

2.3 Design Evaluations in Educational Settings: A Neuroscientific Study of Incentivized Test Retest on Student Performance

This research [33,34] offers a pioneering exploration into the neurocognitive effects of incentives on student performance in design education, utilizing neuroimaging technique, electroencephalography (EEG), to monitor brain activity. The study involves 23 participants, divided into control and experimental group. Both the group administered a typing test, followed by an Emotional Stress Reaction Questionnaire (ERSQ). The choice of typing test as the evaluative task in the study was strategic, primarily because it represents a standardized, skill-based activity that allows for objective measurement of performance improvement. It draws parallels with the iterative and skill-focused nature of design tasks.

The key highlight of the study was the introduction of the monetary incentive for the experimental group, aimed to improve performance on the second typing test. The findings from this study are:

1. EEG Neural Activity: The experimental group demonstrated an increase in EEG sensor activity, particularly in the F6 and O2 sensors, which are associated with vision and emotion control. This suggests that the introduction of incentives heightened attention and emotional engagement.
2. Typing Performance and Emotional Response: The results showed a correlation between the performance of the experimental group and their emotional responses rather than the EEG data. The experimental group's performance did not significantly increase despite the heightened positive emotions.
3. Emotional Reaction to Incentives: There was a significant increase in the positive emotions in the experimental group during the incentivized test ($p = 0.017$). This highlights the impact of incentives on emotional states in a learning environment, where positive emotions were notably enhanced by the prospect of a monetary reward.
4. Typing Test Results: Contrary to initial expectation, the study did not find any significant improvement in the typing performance of the experimental group despite the introduction of monetary incentive. This indicated that while the incentives led to heightened positive emotional states, it did not directly translate into improved performance outcomes.

This study is significant for understanding the neurocognitive and emotional dynamics in design education. It provides empirical insights into how external stimuli, such as incentives, can modulate cognitive and emotional responses in design-related tasks. The findings are especially relevant in exploring how different types of stimuli can influence cognitive and emotional reactions in design settings, aligning with the broader aim of improving student engagement and performances in task selection, problem solving and creativity. And lastly the understanding of neurocognitive dynamics at play can significantly enhance the effectiveness o design education and practice by tailoring approaches that align with the natural cognitive and emotional inclinations of designers.

Summary of Motivating Studies:

The aforementioned studies lay a crucial foundation for design dimensions and design neurocognition, offering valuable insights into the relationship between student motivation, interest, and design choices. Further, the research provided insight that student motivation could be observed neurocognitively.

Investigating the cognitive processes involved in design can significantly aid educators in tailoring project offerings that enhance both performance and learning outcomes. A focus on senior design projects, both open-ended and close-ended, provides a practical context for examining how different types of design challenges affect student motivation. By analyzing student responses from both instructional and personal choice perspectives, we can gain a more comprehensive understanding of design thinking and its impact on educational experiences. This approach not only enriches the field of design education but also contributes to the development of teaching strategies that align with the cognitive and emotional needs of students in design settings.

CHAPTER 3

BACKGROUND

Engineering education research is traditionally governed by the use of quantitative, qualitative or mixed-method research approaches, however with recent changes in the engineering education research (EER) taxonomy, the addition of 'multi-modal approaches' have opened door for a new wave of scientific inquiry in education research [35]. Multimodal approach is different is from mixed-method or multi-method approaches. In a mixed-methods approach, the focus in on triangulating the findings from qualitative and quantitative approaching and drawing a meta-inference from the analysis. The mixing of data is also considered as inter-paradigm research, as a combination of qualitative and quantitative aspects within a study draws upon the different paradigms [40]. Over the years, mixed methods research has emerged as a new paradigm and an alternative to strictly quantitative or qualitative research. Multi-methods technique uses multiple data sources or approaches to confirm and validate one finding to another. Whereas the multi-modal approach focuses on the meta understanding of a phenomenon under investigation by collecting multiple layer of data in near-real time [35].The analysis in a multi-modal approach includes various set of tools/expertise, multiple frameworks, and potentially handling big data [35]. Through multi-modal approaches, researchers merge multiple means of communication, representation, and individuality in domains of literacy education [41], science education [42] design education [43], computing education [44,45], and many more [35].

3.1 DESIGN

Systems are more complex and interdisciplinary than they were in the 1960's, when the idea of design as a science originated [46,47]. Cross identifies the relationship of design methodology and science under three distinct categories: scientific design, design science and science of design [47,48]. Scientific design referring to the modern and post-industrial designs based on explicit scientific knowledge with a balanced blend of intuitive and non-intuitive design methods. Design science as described by Cross is a systematic, rational and clear organizing approach to design. Thus, suggesting design as a scientific activity. And lastly, he defines science of design as "body of work which attempts to improve our understanding of design through systematic & reliable scientific methods of investigation" [47]. Science of designing is interdisciplinary, fundamental, reliable and integrative process [49] As we stand at the forefront of Industry 4.0, the development and advancement of new systems and methods will require adaptability. Design problems are global and multifaceted. Engineering design process comprises of multiple stages such as concept generation, prototyping and manufacturing. This research will focus on how do we "define" design problems. Dorst highlighted having a blind spot for design problems in the grand picture of understanding design process [50]. The understanding of design problem is often oversimplified or ignored in the light of understanding how designers solve problems. Dixon and Penny characterize engineering design as an amalgamation of two fields, technical and cultural [51,52].

Design research serves as a cornerstone for conceptualization, development, and refining of complex mechanical systems and components. Designing is synonymous to problem-solving [1], a twofold activity comprising of identifying the problem and generating a solution for the said problem. Engineering curriculum at the university level typically culminates in a senior design capstone course, first major design experience for most students. The goal of the senior capstone design course is to challenge the students with an example of a real-world project, preparing them for industry. University curriculum focuses heavily on design and design challenges, typical of industry level engineering. Due to increasing system complexity, engineering curriculums were prompted to add more science and mathematics classes to help students understand needed tools and methods [53]. However, over time this led to a decreasing understanding of the practical applications of engineering and design [53]. The reintroduction of modern day senior capstone design in the 1980's and 1990's served to bring the practical application of technical topics back to university level engineering [54,55]. This course is carefully designed by educators to offer unique hands-on learning experiences by simulating real-world design challenges and ensuring student's preparedness to enter the workforce. The course offers a wide range of project choices for students to select based on their interests and future goals. Senior capstone design serves as a transition from compartmentalized learning experienced in introductory level engineering courses to the design and application desired by students entering industry. Further, it provides students the opportunity to work on a design challenges where they can address both, technical requirements and learn how to manage projects [56].

Author's prior research has shown that a project experience positively impacts student motivation in the course. Qualitative study on senior design students have shown various factors impacting their design experiences such has family background, high school projects and social influences. Some of the factors includes a vague perception of problem classification and a clear inclination to a particular type of problem. Identifying and defining the problem statement is the first step in the design process [57]. Senior design students are tasked with defining a problem statement as their first deliverable in the course. Most universities cannot accommodate any formal training in design methodology prior to capstone design course. However, there is little information on how students categorize design problems and its impact their motivation and performance. Merleau-Ponty in his phenomenology study of perception described “association of ideas” as an amalgamation of past experience and oneself to build an extrinsic connection. This connection creates perception and association [58]. The author hypothesize that engineers perceive design problems into different categories and have a natural inclination toward a certain type of problem.

Engineering education research has emphasized the importance of creativity, innovation, and practical application of theory in problem-solving [59]. Problem formulation is an iterative process [60]. Industries have periodically expressed concerns and demands for a greater understanding of problem solving, critical thinking, presentation and communication skills from the new graduates [61]. Design problems are classified as ill-defined, and hard to identify as completely open-ended or closed-ended problems. A design problem can have many solutions, thus providing room for open-ended problem statements and creativity to flourish. Some design problems can be categorized as constrained problems, allowing the engineers to follow strict design criteria, requirements, and resources to achieve the desired solution. Design projects offered in mechanical engineering programs can also be classified under humanitarian projects and non-humanitarian projects. Humanitarian projects are inferred to harness the altruistic trust of engineers. Studies have shown that students often possess a natural preference for humanitarian design projects [25]. However, the impact of altruistic projects on student performance is unknown. The knowledge of humanitarian impact during problem formulation is also unknown.

Humanitarian projects are considered to have a unique approach to amalgamate coursework application, innovation, empathy, and creativity. Universities implementing humanitarian design project has shown significant benefits in student learning and persistence in an engineering program [62]. Students have reported an increase in skills and interest in engineering for broader impact. Capstone Design course in Virginia Tech introduced international humanitarian projects including travel to under-developed nations for students to physically interact with stakeholders and analyze the environment of solution dissemination [63]. This initiative reported a higher involvement from students in the projects by a significant increase in working hours and demonstrated encouraging teamwork compared to non-altruistic projects. Interest and motivation playing a critical role in design choices. The interest can stem from various factors including their natural preference for a particular type, previous design experiences, and types of projects offered. Studies in design research have inferred that a project choice can impact student motivation throughout the year [26]. However, little is known about student's natural preference for different design stimuli.

3.2 DESIGN COGNITION

The cognitive aspects of design have been a topic of great interest, leading to the emergence of 'design cognition' as a distinct area of study. The intersection of cognitive psychology and design research, design cognition seeks to understand how designers think, reason, and create. Lawson and Dorst when exploring the design expertise highlight the iterative nature of design cognition, where designers oscillate between problem framing and solution generation, using both analytical and synthetic modes of thinking [64]. They discuss the role of schemas, mental models, and analogical reasoning in design thinking. The term "problem formulation" in design was first coined by Cross [22], describing design as an iterative problem solving activity with constant emergence of requirements and constraints. According to Cross [22], designers in practice must spend significant time reflecting on the problem and make initial assumptions about requirements and constraints. This process is defined as design problem formulation. Studies have suggested that there is a lack of opportunity in engineering program for students to construct real world problems [65]. Problem formulation occurs in the early stages of design and thus can have significant impact on the outcome on the successive stages and outcomes [66]. There is a severe lack of clarity in the goals identified by the stakeholders, more often characterized as incomplete and vague [67]. Researchers have independently identified various elements of a design problem, Jonassen hints toward a cultural value of this unknown entity [68]. Jonassen also suggests three elements associated with high level problems, structure, complexity, and domain-specificity [68]. The association between problem solving and memory was defined by Newell and Simon[69]. The natural inclination toward a certain type of problem calls for inquiry in design research. Donald Schön's classic text focuses on how professionals, including designers, engage in reflective practice [21]. Schön contends that when faced with unique challenges, designers often engage in a kind of "reflection-in-action," where they think about their actions while they are designing, especially when confronted with unexpected situations or problems. This reflexive process becomes particularly pronounced when designers work on projects with significant social or emotional value.

Problem statements are inputs and stimuli to a designer's mind, determining the designer's cognitive behavior [20]. Identifying and defining the problem statement is the first step in the design process [57]. Different types of problem statements may have different emotional and cognitive influences on a designer's behavior. A student can experience an immediate emotional reaction to a problem statement rooted in experience and interest. Word choice, stated goals, and relevant design information can impact student's understanding of the problem statement. Perceived value of a design challenge may have a profound impact on the designer's motivation, approach and eventual solution. Nigel Cross, in his book "Designerly Ways of Knowing", delves into the intrinsic nature of design thinking [70]. He elucidates the unique cognitive processes that designers employ, which are interestingly different from scientific or scholarly ways of understanding the world. Cross asserts that designers often grapple with problem statements that are inherently 'wicked' – problems that are complex, ambiguous, and laden with emotional or value-based dimensions. He argues that designers are uniquely equipped to navigate these challenges because of their ability to think in 'designerly' ways, blending emotion, empathy, and creativity. Design problems often have an emotional connotation. Kees Dorst dives deep into the heart of design thinking [71]. He posits that designers often engage with problems at a deep emotional and empathetic level, especially when the problems carry significant social implications. Dorst emphasizes the importance of understanding the 'core' of a problem and how its perceived value can shape a designer's engagement and innovation trajectory.

3.3 NEUROCOGNITION

Human brain is one of the most complex systems, performing multiple functions and remains to be one of the most explored but least understood part of human sciences. Human Nervous System controls body's response to internal and external stimuli. It consists of the brain, spinal cord, nerves and ganglia. It comprises of two main classes of cells: neurons and glia. Neurons are specialized cells in the human nervous system, it's unique structure and function allow them to transfer information across various locations in the human nervous system. Neurons have three main parts to their structure: a dendritic tree, a cell body, and an axon. The dendritic tree is the part that receives input from other cells, they act like antennae. The cell body also known as soma, is the part of the cell containing the nucleus and other cellular apparatus responsible for manufacturing the proteins and enzymes that sustain cell functioning. The axon is a long-tail like structure attached to the cell along which information is carried. It can be long or short.

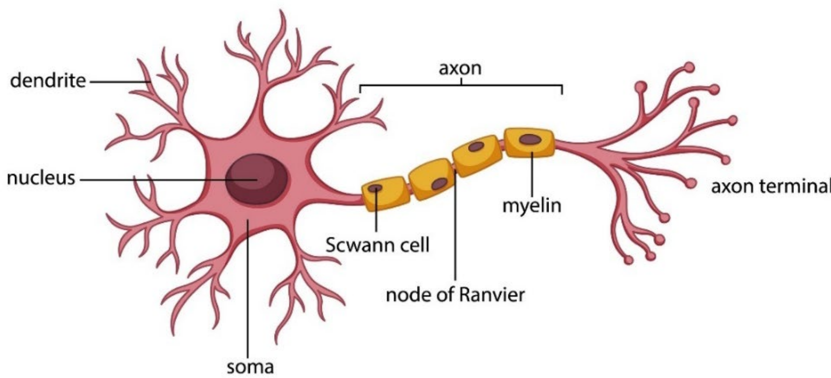

Figure 1: Neuron Anatomy

Neurons transfer this information by the means of electrical signals and chemical signals. Information is relayed within a neuron by electrical signal, and one neuron influences another neuron via a chemical signal. Neurons are often characterized as electrical device. There is an inherent difference in the electrical charge between the inside and outside of neurons. This is known as the resting potential or membrane potential, which is -70millivolts(mV). This voltage may vary by neuron type. The inside of the cell is more negative than the outside. The membrane potential isn't considered static, it is constantly changing upon receiving inputs from the axons of other neurons. The mechanism behind the resting potential is based on the electrically charged particles called ions. Ions are separated by the cell membrane from entering the neurons. Ions, such sodium and potassium, can traverse the cell membrane by special passage called ion channels. In some neuron configurations, the passageway is blocked and some not. The opening of ion channels can be impacted by the neighboring neurons' inputs. The resulting change in the ion concentrations of each side of the membrane is responsible for the neuron's change in electrical charge, positive or negative.

When the cell receives enough stimulus to reduce the voltage across the membrane to about -55mV, a threshold is passed and the cell fires. When the cell "fires", the electrical charge of the neurons reverses rapidly from -55mV to a peak of +40mV. Action potential is a rapid sequence of electrical changes that take place across the cell membrane of neurons. The neuron's action potential has three main stages: depolarization, repolarization and hyperpolarization. At its peak, it reaches a stage called depolarization. The electrical charge when returns back to its baseline resting potential, it is known as repolarization. Electroencephalography (EEG) is defined as the electrical activity generated as a result of neuron firing within the brain. The electrical activity is recorded at the human scalp, containing rhythmic movement, reflecting the neural oscillations

Event-related potentials (ERPs), formerly termed as evoked potentials, are event-related voltage changes in the ongoing EEG activity that are time-locked to sensory, motor, and multi-cognitive events [72]. ERPs are recorded in reference to particular events and characterized by distinct components: exogenous and endogenous. Exogenous components are linked to the physical characteristics of a stimuli and occur early in the waveform. Endogenous components appear to be driver by internal cognitive states, independent of stimulus characteristics. ERPs illuminates cognitive tasks and processes such as attentions, memory, spatial cognition, executive function and higher-order thinking [73]. Since, ERPs are brainwaves time-locked to certain events, it may be precede or follow a stimuli. In this study there are three-time locked events. Pre-stimulus, post-stimulus and pre-response. ERP components have smaller amplitudes than background EEG activity, hence techniques such as averaging and filtration are used to increase the signal/noise ratio.

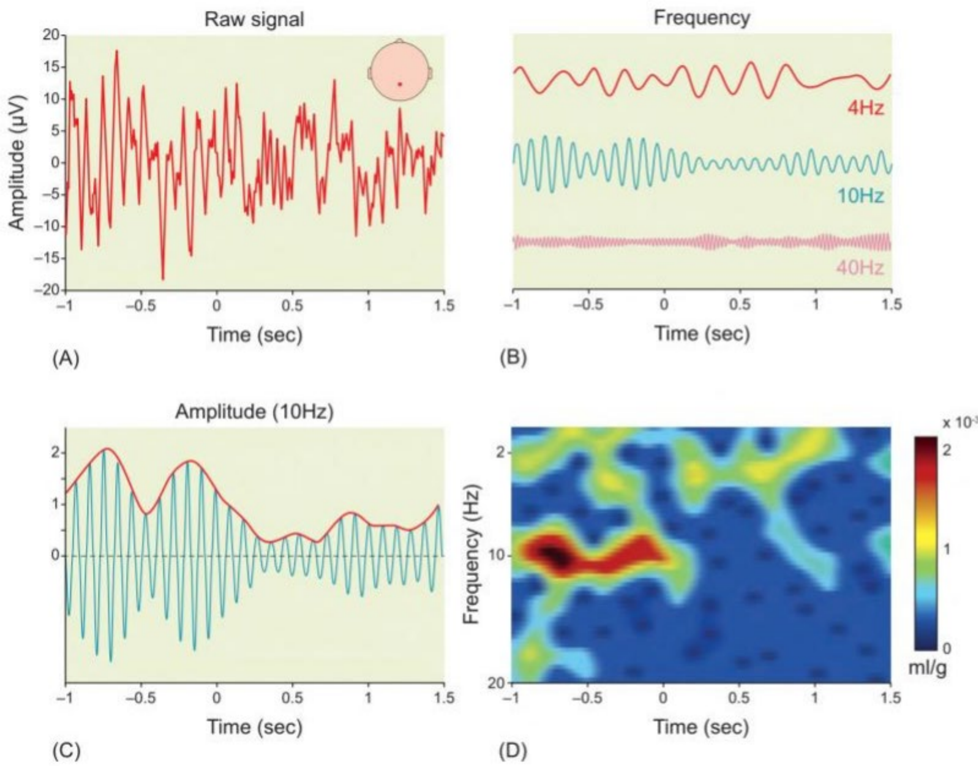

Figure 2: Time-frequency analysis of EEG data [74]

According to the Dr. Jasper's recommendation report for International EEG Congress in 1957, the 10-20 standardized EEG electrode placement was introduced [75]. The measurement technique is based on the standard landmarks of the skull; nasion, inion, right and left preauricular points. The numbers 10 and 20 refers to the distance between adjacent electrodes; meaning they are either 10% or 20% of the total front-back or right-left distance of the skull. Each electrode placement site has a letter to correctly identify the area or lobe of the brain; pre-frontal (F_p), frontal (F), temporal (T), parietal (P), occipital (O) and central (C). The Z nomenclature refers to the an electrode placed on the midline sagittal place i.e. Fp_Z , F_z, C_z, and Oz, mainly used for reference points [76]. Even number electrodes are placed on the right side of the brain and odd numbers refer to the left side of the brain.

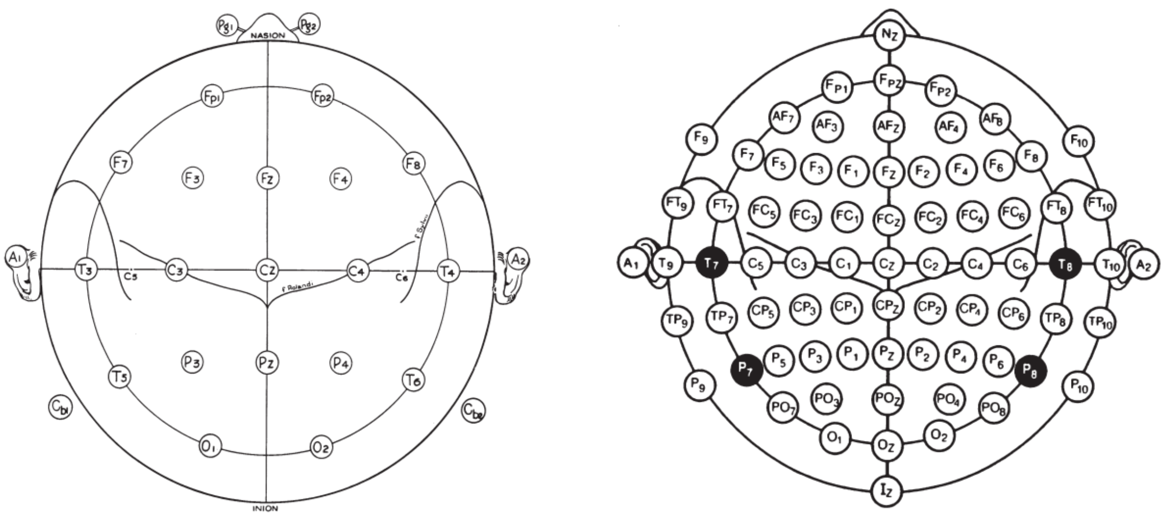

Figure 3: The 10-20 electrode system of the International Federation [77]

The four categorized lobes in the brain are occipital, temporal, parietal, and frontal. The occipital lobe is the smallest in the cerebrum cortex. It is responsible for visual processing in the brain. It determines the concept of color, depth, height, facial recognition, and formation of memory visuals [78]. The temporal lobe is associated with emotions, visual recognition, and audio processing. The temporal lobe lies in between the inferior of the parietal lobe and the posterior of the frontal lobe. The parietal lobe plays three important roles in the cortex. These are the integration of information from sensory modalities, integration of memory and information from the sensory world, and integration of the individual internal state with sensory information. The role of this integration is to provide feedback to the muscles, eyes, limbs, head, etc. The shape, size, and orientation are grasped from this lobe. The Frontal lobe is divided into three main regions: the primary motor region, the premotor region, and the prefrontal region. Frontal regions are associated with planning, guidance, and evaluation of behavior. Frontal lobes are also associated with emotional functioning, decision-making, and judgment. The frontal lobe is responsible for a varied range of activities including motivation, regulation of dopamine, and personality.

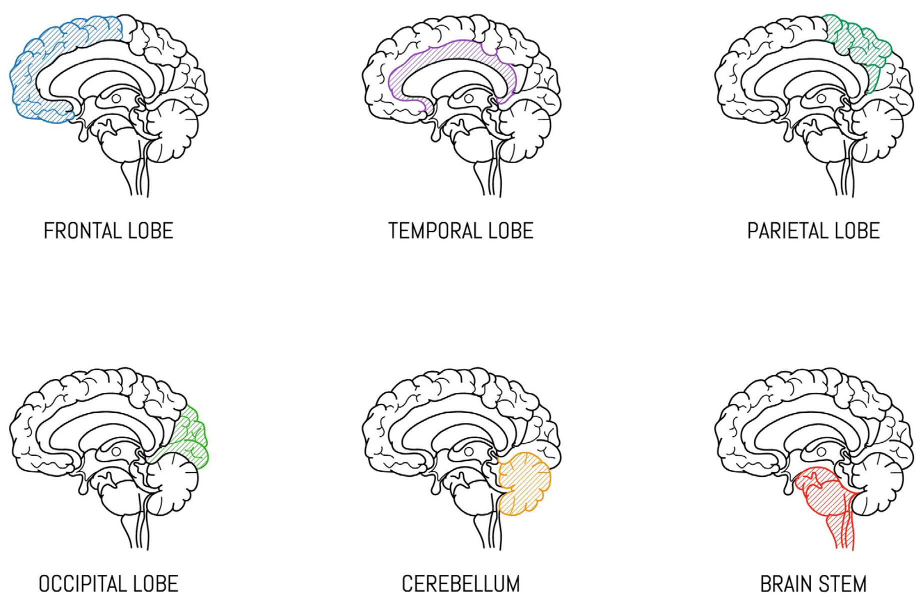

Figure 4: Brain Lobes

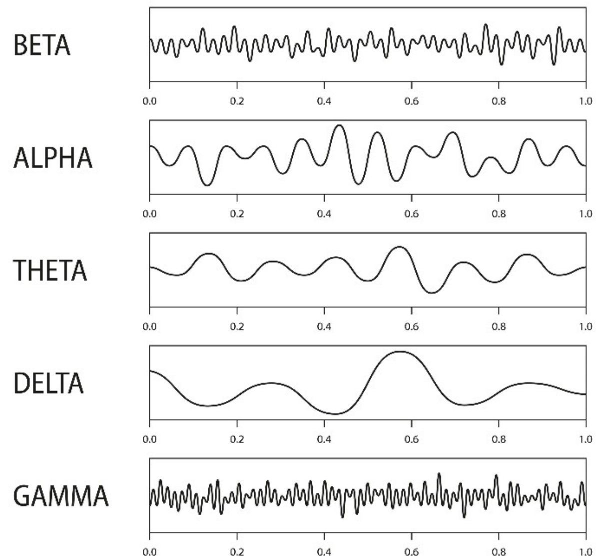

Figure 5: Brain Waves

Brain waves are categorized under four main groups depending on their frequencies: beta, alpha, delta, theta. Beta (>13 Hz) waves are the most commonly and frequently observed among adults and children [79]. Beta activities are relatively fast and predominate the wave frequencies in the brain [80]. Alpha (8-13 Hz) is commonly observed in the normal awake EEG recordings. It is associated with memory functions [81]. Theta (4-8 Hz) rhythms are often associated with a slow activity. It is observed in connection with creativity, intuition, and serves as a repository of memory, emotions, and sensations. Delta (0.5-4 Hz) is dominant in the deep sleep state [82].

New inventions in brain imaging technology have made research more accessible. Modern brain imagining techniques measuring neural responses include positron emission tomography (PET), near-infrared spectroscopy (NIRS), electroencephalography (EEG), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI). The neural response in experiments is measured in the form of frequencies and the region of the brain where the frequency is recorded.

An EEG detects neural activity by identifying the electric current representing brain activity. EEGs have a high temporal resolution. EEG signals reflect two types of brain activities, spontaneous and event-related activities. Spontaneous EEG responses are related to unproved activities, as in absence of stimuli. Spontaneous EEG has been used in clinical settings to measure seizure disorders. Event-related potentials (ERPs) are associated with specific stimuli or thoughts. Repeated stimulus and presentations, and signal processing techniques are required in ERP studies [83]. Repeated stimuli in this study are design problems statements. And students will identify their likelihood to solve each stimulus. There are two major techniques to detect event-related potential: the time-locked averaging technique and spectral analysis techniques. Time locked detect evoked activities, and can greatly reduce noise while preserving event-related signals from EEG. Time locked can further be divided into stimulus-locked or response-locked. In inducted activity is detected using the spectral analysis technique. Induced activity is an oscillatory activity that might have different phases in each measurement and can cancel out another in a time-locked average. Spectral analysis technique like Fourier transform is used because it is time-shift invariant in time and frequency domains.

Research findings in clinical settings have shown correlations between brain activity and working memory performance in infants, [84,85] and memory performance in toddlerhood [86]. In experimental settings, cognitive psychologists study the relationship between brain and mind and explain the different functions of the brain in event-related potentials. The two settings serve as the foundations of all neuroscience discoveries and applications. EEGs have multiple applications in discovering brain activity from impacts of trauma, addiction, brain damage, and stimuli response. However, it is unknown how neural activities and behavior change when processing stimuli of preferred tasks [87]. Reward and social cues are seen as fundamental motivators[88,89] but individuals differ in their motivation to pursue unique hobbies and different career choices suggesting that such choices are more motivating than others. Experiments measuring brain activity with the task of interest show great activation in the anterior insula [87], a part of the cerebral cortex. These findings were similar to other stimuli involving rewards. The second research question stems from the foundation of understanding neural activity in preferred tasks, design settings in this case. Motivation drives behavior and decision-making [87]. Decision-making, vision, and emotions are controlled and observed in the central-frontal cortex and occipital cortex. The design stimuli preference is aimed to measure short-term levels of motivation, which can be estimated for similar long-term design task motivations. Studies have shown a correlation between increased motivation levels and higher brain activity in the left pre-frontal hemisphere [90]. Motivation arousal is embedded in emotions. In neuroscience studies, human emotions are described as dispositions to action such as anger, fear, and desire. Suggesting that expressed emotions are grounded in motivational circuits that feedback to the sensory systems, increasing vigilance and information gathering, and reflexive autonomic and motor responses. In evolutionary history, these responses are to counter the threat, escape or achieve rewards.

In behavioral neuroscience of motivation, researchers define motivation as an energized behavior in pursuit of a goal [91]. Early theories of motivation, Hull's theory defined motivational drive to function as an energized response and not an initiation [92]. The motivation theory was later conceptualized as having a goal-directed and activational component [93,94] and is still in use. The authors of the modern motivation framework defined it as a vector, where length represents amplitude or pursuit, and angle represents its focus on a specific goal. This analogy can be applied to various motivation applications such as intrinsic motivation, rewards, achievement motivation, plasticity, risk-taking, and many more are studied in neuroscience. Today, motivation is studied through clinical, experimental, and comparative psychology approaches.

The neural basis of studying motivation in the brain is based on the neurotransmitter dopamine, which is transmitted through mesolimbic reward pathways to regulate motivation and reward responses [95]. There is not enough evidence available to explain the effects of dopamine on motivation [95,96]. A large of studies suggest the functional role of dopamine and its targets in stimulus-response learning[97–99], addiction[100,101], and movement[102,103], suggesting the promise of a unifying account linking systems neuroscience to motivated behavior [104]. However, neuroimaging has shown significant activity in the emotion response network related to dopamine levels and behavioral changes in motivation. The observable parts of the emotional response network are located in the cortex, observed through EEG. The emotional response includes the anterior cingulate cortex, the amygdala, and interactions between the midbrain regions and the lateral frontal cortex correlating to motivation [105,106]. Changes in EEG band power in the pre-frontal cortex are modulated by motivation, affect, and approach-withdrawal response to stimuli [107]. The relative difference in the EEG activity between the left and right hemisphere were reported in studies measuring changes in motivation. The "hemispheric valence hypothesis" states that the approach response to stimuli (like increased motivation) is processed in the left hemisphere and the withdrawal response in the right hemisphere [108].

It should be noted that motivation/ interest is not the same among different gender groups, and activities involving rewards can be used to increase motivation in a given task or class intervention study. The design stimuli preference is aimed to measure short-term levels of motivation, which can be estimated for similar long-term design task motivations. [109]. An EEG study measuring student motivation/ interest to solve MM (mathematical mindset) problems showed an increase in brain activity vs solving a standard math problem [96]. Students reported on 5 points Likert scale if they were likely to solve the problem or not. A significant correlation was established between student's reported motivation before the task and brain activity when choosing a mindset problem over a standard math problem.

Researchers have argued about the interdependency of motivation and cognitive control in influencing decision-making [110], and also if the cognitive systems are responsible for various decisions interaction [111,112]. Researchers have suggested that positive motivation for a task, enhances the cognitive control of the participant. However, upon testing cognitive control levels at the varying magnitude of motivation, including incentives, behavioral and neural data has shown that motivation and cognitive control are two independent systems operating parallelly to make decisions. With better accessibility of brain imaging equipment, researchers have found an interaction between cognitive control and motivation in the brain, with the beneficial effects of reward using MRI. But in absence of reward, the results do not show the same effects. The majority of neuroscience studies on motivation explore reward-driven, decision-driven, value-driven, and goal-driven motivations. Social value is one such motivator for decision-making. To understand motivation or interest and brain activity, experiments exploring motivation generating, motivation maintaining, and motivating regulating processes without an external reward should be performed [113].

Neurocognitive studies involving EEG to study design cognition include research experiments in problem-solving and open-ended design tasks [114], expertise in problem-solving [115], and drawing [116], design reasoning[117], sketching [117,118], and modeling tasks[119,120]. Goel and Pirolli identify design as a fundamentally mental, representational, and a signature of human intelligence, calling for a cognitive inquiry [121]. Studies examining brain activity during problem-solving have shown higher theta activity in the frontal and parietal region when participants were presented with open-ended and constrained tasks. It was observed that theta is higher in the constrained task than in open-ended tasks [57]. In contrast, the alpha activity was observed higher in the open-ended task. The results of the study suggested that constrained problem-solving tasks required more attention and cognitive response. Based on the foundation, exploring preference and neural activity in absence of external stimuli and social cues. Recall reflection plays a big role in understanding participant's perspectives in the experiments. This also highlights the step-by-step description of cognitive thinking, thereby understanding the factors of motivation and perspective in the experiment.

3.4 INTERVIEW PROTOCOL

Castillo-Montoya developed an interview protocol refinement technique (IPR). This is a protocol the researcher is comfortable using as it has been used in previous studies successfully [122]. The protocol consists of four phases [123]:

Stage 1: Aligning the interview questions to the research questions

Stage 2: Constructing an inquiry-based conversation within the interview

Stage 3: Peer-reviewing the interview protocol

Stage 4: Conducting a pilot study to test the protocol

Each stage of the interview protocol refinement technique aids in developing a research instrument required for the participant for the particular study. Stage 1 focuses on the alignment of interview questions to the research questions. The alignment is intended to increase the utility of the interview questions. It is important to conduct in-depth interviews with the participants, to fully understand the complex meaning behind the lived experiences. Thus, careful listening and intentional follow-up questions are an integral part of interviewing. Castillo-Montoya suggests constructing a matrix to develop interview questions, with interview questions in the row and research questions in the column. This technique can help in eliminating gaps. Rubin & Rubin suggests asking questions most related to the study's process in the middle of the interview, once the researcher and interviewee have established a conversation [124].

Interview protocol not only serves as an instrument for the topic of investigation but also an instrument to explore and converse the topic of interest with the interviewee [125]. Stage 2 requires the research to develop an inquiry-based conversation through a protocol comprising of

a) Writing interview questions different from the research questions

b) Administering common conversation courtesy in a social setting

c) Having a set of different interview questions

d) Carefully written script with follow-up questions and prompts

The difference between research questions and interview questions pointed out by Maxwell [126], explains that research questions are framed to understand the social reality under investigation, and interview questions are what helps one gain that understanding. The important terms of interviewing are asking one question at a time, and avoiding any jargon in the interview questions [127,128]. The main purpose of the interviewing is to gain more information on the topic of study.

The interview questions can be divided into four types to maintain the conversational and inquiry-based goals of the interview questions. The four types are [127,129–131]:

1. Introductory questions
2. Transition questions
3. Key questions, and
4. Closing questions

Introductory questions are used to establish a rapport with the participant and guide the conversation into a narrative description of the participant's life. Introductory questions also set the tone of the interview and serve as a signal to the researcher to adjust to the individual's conversational style. Transition Questions are a segue to the key questions of the interview [130].

Key questions are the main questions of the interview, intended to provide valuable information on the understanding of the topic of study. Key questions can be used by the researcher to remember the core questions in an interview. The closing questions typically involve clarifying questions, intended for the participant to add to any missing information. Closing questions also provide an opportunity for participants to reflect. Participants can slowly transition out of the interview through closing questions. Developing a script for the interviews is a technique that researchers must employ to provide a smooth transition. It also helps in addressing all the questions and prompts, that otherwise may be missed without a script. Follow-up questions and prompts are an important feature in interview protocol, as it helps researcher guide the conversation in the desired direction of the study. It is possible to stray away from the core questions; hence a script can aid in focusing on the intent of the interview.

Stage 3: Once the interview questions have been developed through stage 1 and stage 2, they can move to the peer review phase of the interview protocol. The goal of the first two stages is to form a conversational and inquiry-based interview. Peer feedback enhances the reliability and trustworthiness of the interview protocol as an instrument. The purpose of the feedback stage is to ensure if the questions translate the intent of the study [132]. A variety of questions, reading of the protocol, and think-aloud activity are important aspects of stage 3 [123]. The interview questions should be free of academic language, short, and easy to understand [133]. One can receive feedback from different colleagues, researchers' teammates, and fellow researchers.

Stage 4: After receiving peer feedback on the interview questions, stage 4 is conducting a pilot study. The researcher can now test the questions on participants and identify if the question framing, sequences, timing works or not [134]. It is the most important phase before conducting interviews for the actual study. With the completion of all four stages of the interview protocol refinement (IPR) method, one can increase the reliability of the interview protocol.

CHAPTER 4

THEORITICAL FRAMEWORK

The research examines the relationship between design preferences and neurocognition when presented with a design stimuli. Design stimuli refers to design problems in the study. To systematically and scientifically examine design stimuli, this chapter introduces design dimensions—a framework developed from the author's prior work on senior design projects in mechanical engineering and student motivation as discussed in chapter 2, motivating studies. [24]. The design dimension framework is the foundation for understanding the nature and structure of design problem statements, further guiding the examination of student interest and neurocognitive responses. The framework is the foundation for the three individual studies/phases conducted by the author as part of the dissertation.

Phase 1: Design Formulation

Phase 2: Design Evaluation

Phase 3: Design Preference

4.1 THEORETICAL FOUNDATION

The social reality under investigation is the relationship between a student's design preference and the neurological responses to various design stimuli. Design stimuli in this study mimic the real-world design challenges an engineer encounters during their career. These stimuli are short problem statements and are evaluated using the design dimension scale. The design dimension scale breaks down the structure and nature of the problems for a more in-depth understanding of the relationship. Figure 6 illustrates the three main components of the research design and research questions guiding the investigation. The goal of the study is to examine student's design preferences through the neurocognitive. The first research question examines the relationship between design dimensions and design preferences. The second research question under examination is student's neural responses upon making design choices. The third concluding research question examines the relationship between design stimuli and neural response through brain imaging techniques. The three research questions and hypotheses discussed below are derived from a thorough literature review and past research findings on designs and neurocognition. The research questions are examined through the design domain, where participant's preferences/inclination will be investigated using various design stimuli.

RQ1: What themes emerge in design problems formulated by students?

RQ2: What is the relationship between the social and constraint design dimensions of said problems on design preference?

RQ3: What is the relationship between neurocognitive responses when design problems are presented as stimuli on design preference?

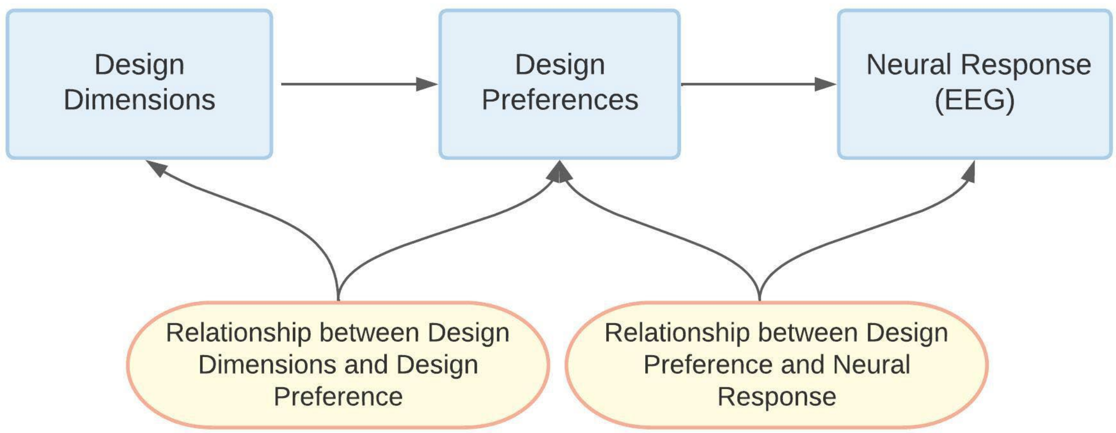

Figure 6: Proposed Research Questions

The variations in the design stimuli is presented through formation of two dimensions: (1) Constraints and (2) Social Value.

Design Dimension

A critical aspect of the study is to identify design dimensions. Design dimensions are the constructs of design stimuli. To systematically define a design stimulus for the experiment, a design problem statement is scored on a design dimension scale. The two design dimensions are the constraint and social value of the design. Constraint refers to the open-ended and close-ended problem statements.

Loosely defined project requirements can be considered open-ended compared to a problem with well-defined realistic constraints can be classified as a closed-ended problem. The second identified dimension is the social value aspect of the problem. Social value refers to the altruistic character of the problem statements. A humanitarian problem can be classified as highly altruistic versus an industry problem can be identifies as less altruistic. Students have indicated the influence of altruistic value in their decision to select humanitarian projects over the rest. To examine students' altruistic thrust and project preference, two design dimensions are investigated.

Dimension 1: Constraint

The constraints are the open-ended and close-ended characteristic of the problem. Problem statements have specified design and resource constraints in comparison to others that are not rule based and provide room for innovations and creativity. Focus group interviews has shown that students identify the characteristics of the constraints and understand the difference between the two [25].

The roots of capstone design date back to the late 18th century, with contemporary capstone experiences emerging in the 1970s. These experiences focused heavily on design challenges, akin to real-world industry problems, providing a platform for students to grapple with open-ended design issues [135]. In response to escalating system complexity, universities added more science and mathematics classes, attempting to equip students with technical tools and methods [53]. Capstone design bridges this gap by reintroducing practical applications of technical topics into university-level engineering. This principle persists in modern-day capstone design, emphasizing the importance of students engaging with open-ended design challenges. These experiences contribute to a more holistic understanding of the application of engineering principles, preparing students for the nuanced demands of industry [136]. Even professional bodies like the American Society of Mechanical Engineers (ASME) contribute to shaping current design curricula, advocating for richer practice-based engineering experiences. Institutions respond by implementing "design threads," providing students with year-long design experiences [137].

To that end, we utilize the concept of problem open-endedness to measure how much flexibility students have in solving the problem. We use the definition for open-endedness as defined in [138] which states "we define 'open-ended' as problems for which there is no singular correct answer nor singular solution path." We use the negative of this term however in our research as we define how constrained a problem is.

Dimension 2: Social Value

Social Value inclination is observed in engineers when they engage in problem-solving that has a greater impact on humanity. The designer that possesses altruistic thrust more than often disengage from traditional design practices to participate in broader impact design projects. An example of altruistic inclination in design is project preference that aims at solving humanitarian problems related to basic human needs like sanitation, water, energy, waste treatment and concerning global issues like climate crises.

The concept of addressing social problems in engineering design is not new as there has been a recent rise in the necessity to incorporate globalization and socio-economic elements in engineering design [139]. This has introduced new terms such as "complete engineer" to ensure they instill the necessary knowledge while developing project solutions [140]. Incorporating social elements into design is not just important, it is necessary as past examples have shown the damage that can occur when societal and human impact are not considered [141].

In this research, we consider the social value as problems that have the potential to have a positive impact on society or the human race. These are problems whereby the connection between the problem, solution, and societal impact are easily observed by the designer. This dimension is intentionally vague to capture the nuances of the variable. For instance, consider a military tank. One designer may note that this has high social value as it could save human lives while others may note its low social value because of the damage it can cause. The goal of this research is not to prescribe a social value, but rather to consider a participants perceived social value in the analysis.

4.2 TIMELINE

The research implements three pilot studies with multiple iterations for each phase prior to deployment. The phase 1 is titled as the Problem Formulation Study. Problem Formulation Study is designed to examine the engineering design problem creation by undergraduate engineering students. Phase 1 addresses the gap in our understanding of problem formulation by engineering students. The phase 2 is titled as the Problem Evaluation Study. Problem Evaluation Study is followed post analysis of Phase 1. The design problems collected from the Phase 1 study are an integral part of Phase 2. In phase 2, graduate students and instructors' rate and group the problem statements on the 2*2 design dimension scale. The 2*2 design dimension scale lays a foundation for the visualizing the problems 4 design quadrants generated as a part of the data analysis. On completion of the agreement analysis, the chosen design problems are transferred to Phase 3.

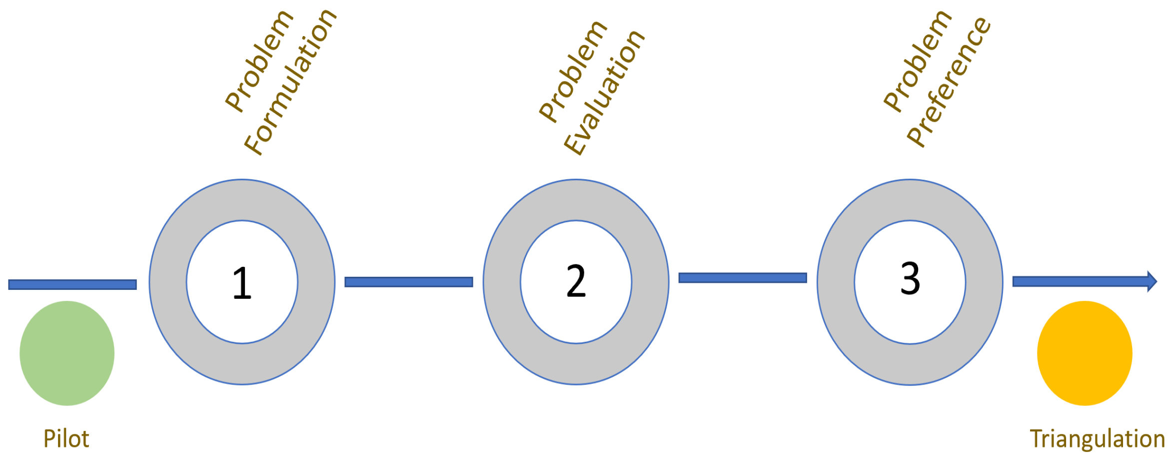

Figure 7 : Research Studies

As seen in Figure 7, Phase 2 is followed by the final study: Problem Preference Study. The Problem Preference Study was curated to examine participant's neurological response to various design scenarios along with a preference score, a self-reported score indicating participant's likelihood to work on a similar design problem. Participants were presented will multiple design stimuli ranging from highly altruistic to least altruistic, and highly open-ended to highly closed-ended problems. The average of all design preferences determined student's ultimate preference to project offerings. On completion of the all three studies, we are able to observe how design preferences can be observed neurocognitively – going to the source of student preference and motivation toward design problems. The following sections described the theoretical framework.

4.3 RESEARCH QUESTIONS AND OBJECTIVES

As seen in Table 2, the research objective of individual tasks and research dissemination plan is listed.

Table 2: Research Description, Objectives, and Deliverables

Phase	Task Description	Objective	Research Dissemination
1	"Design Problem Formulation"	Collect student-generated problem statements. Identify patterns, similarity/novelty in problem statements	• Conference • Journal
2	"Design Problem Evaluation"	Identify design dimensions: constraints and social construct based on expert evaluation of design problems	• Conference • Journal
3	"Design Problem Preference"	Identify relation between neural activity and design preferences. Engineers rate preference for problem statements presented as design stimuli	• Conference • Journal

Research Question 1: What themes emerge in design problems formulated by students?

Hypothesis: The researchers hypothesize emergence of design themes within the design dimensions (constraints and social value).

Research Question 2: What is the relationship between the social and constraint design dimensions of said problems on design preference?

Hypothesis: The researchers hypothesize the influence of design dimensions on student preference.

Research Question 3: What is the relationship between neurocognitive responses when design problems are presented as stimuli on design preference?

Hypothesis: The researchers hypothesize that there is a correlation between design problems and their neurocognitive response.

4.4 RESEARCH EXECUTION

Phase 1: "Design Problem Formulation" was a survey designed for the senior student participants. It gave students an opportunity to generate three unique engineering design problem statements stemming from interest and past experience. To add contrast to the design problems generated by the student participants, the two cohorts of participants selected were mechanical engineering students in the beginning of senior year, i.e. fall semester and end of year, i.e. spring semester. Students in their senior year work on a year-long senior design project which gives them a unique opportunity to collaborate in teams on a desired project and have hands on designing and manufacturing experience. In contrast, students in the beginning of their senior year have limited design experiences in the engineering program. Additional design experiences like internships, projects, etc., are also accounted in the analysis. Along with design problem statements, students were also asked to fill voluntary information on demographics, family background, designing experience, and career goals. The survey was designed in an online format using Qualtrics and takes place in a classroom. The estimated time for survey completion was 50-60 mins. Individual problem statements ranged between 142 to 250 words, i.e., a 1000 character in the online version. The data was analyzed using Natural Language Processing (NLP), an artificial intelligence tool. Topic modeling analysis within NLP helped in identify hidden themes, similarities and novelties in the problem statements. Post analysis, these design problems were used in Phase 2.

Phase 2: "Design Problem Evaluation" study required participants to rate multiple statements on two constructs: constraint and social value. Participants are experienced graduate students and rated each design problem on 5-point Likert scale based on their understanding of constraints and social value. Participants were briefed on the design dimensions before the study and required a training round before the actual evaluation study. A score of 1 on constraint indicated open-ended nature of the problems vs a score of 7 indicated a close-ended i.e. highly constrained. Similarly, a score of 1 indicated low social value vs 7 indicated high social nature of the problem.

As shown in Figure 8, a sample of the design dimension framework is generated. The 5-point scale indicates the Likert scale used to rate the problems and the dots indicate their respective rating from the raters. Similar to this example scatter plot, post phase 1, the design problems were plotted on the social value and constraint axes to be discussed in the result chapter.

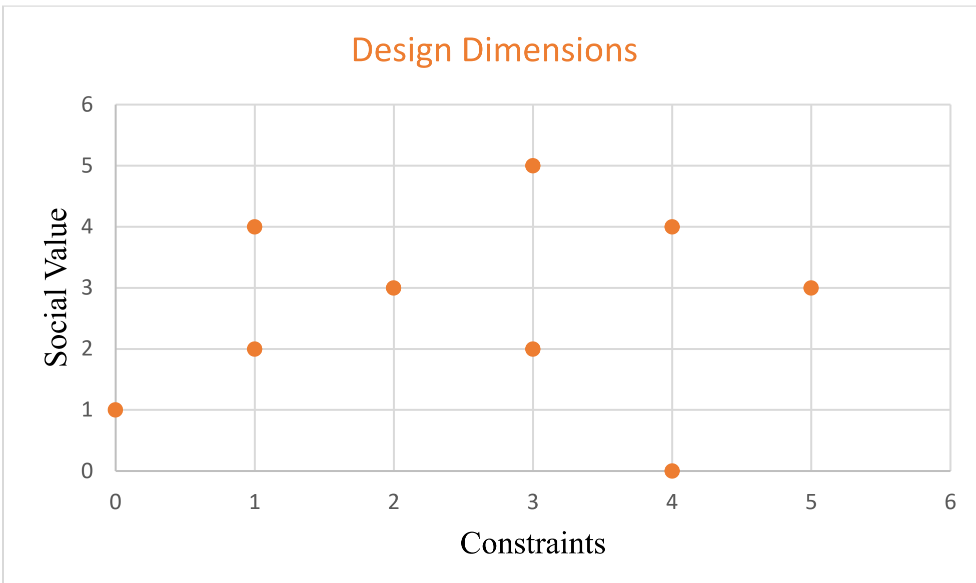

Figure 8 : Design Dimensions Framework Sample

A score of 5 depicted a highly altruistic problem and 1 to the least altruistic problem on the y-axis. Similarly, 5 on the x-axis depicts the open-ended problem and 1 as the closed-ended problem. To identify the scores of each problem statement as illustrated in the scatter plot, participants shall rate multiple problem statements in the "Design Problem Preference" study. For example, a problem statement with a score of 5 on a social value and 3 on the constraint of the problem can be identified under the first quadrant as high altruistic and open-ended. Examples of problem statements for each quadrant are as follows:

Quadrant 1: High Social Value and High Constrained Design

"*The goal of the project is to design a system that can provide the necessary optimal environmental conditions for a premature baby, control temperature and humidity at a low cost. The most challenging and important aspect of the design is maintaining an ambient temperature within the incubator which provides a stable body temperature for the premature baby in a safe manner.*"

Quadrant 2: High Social Value and Low Constrained Design

"More than two billion people use open fires as the only way to heat the water they use for cooking, cleaning dishes, and bathing. It is estimated that there are about 4.5 million premature deaths per year caused by indoor open fires. The cost of fuel is an added burden. Design and optimize a cost-effective solar water heater that provides running hot water and is safe to use."

Quadrant 3: Low Social Value and Low Constrained Design

"Design a decorative desk decorative piece for corporate executives. The piece should be aesthetically pleasing and provide a mild form of entertainment during breaks but doesn't need to serve any other specific function or adhere to strict dimensions or materials."

Quadrant 4: Low Social Value and High Constrained Design

"Design and manufacture a solution that is capable of individually maneuvering two, unique cylindrical masses. It must be capable of translational movement along a rail, 360° rotation about the vertical axis, and at least 75° of tilt below the horizontal. The solution must solely interface

with a 0.375" lip of an interface component that is attached to the top of the aforementioned unique cylindrical masses."

Phase 2 groups the design problem on the constraint vs social value plot. Phase 2 also includes a focus group interview with the experts on the topic of design problems and design dimensions. The interview follows a semi-structure format. Interview takes place post problem evaluation study on the timeline. The interview is analyzed using thematic analysis approach. Participants are instructed to score various design problems on the dimensions and those problems that exhibit consistency (as measured through the interrater reliability of the scores) are selected for the next study. Interrater reliability is measured through Inter Class Correlation. Problems with high interrater reliability were placed on the design stimuli dimension space for subsequent experiments. The above-stated problem statements are an example of design stimuli presented during the phase 3 experiment.

Phase 3: "Design Problem Preference" is a lab-controlled experiment. Design problems from phase 1 were presented as design stimuli in phase 3. Participants scored design stimuli on 5-point Likert scale. 1 referred to "least likely to work" on the problem and 5 refers to "most likely to work" on the problem. Students were equipped with an EEG instrument during this task. The stimuli and EEG recording were timed for accurately capturing brain activity. Participants spent two hours for EEG electrode placement preparation and study. Participants were incentivized with $100 Amazon gift card.

CHAPTER 5

METHODOLOGY

The research questions are addressed by the implication of multi-model data collection and analysis techniques. The research encompassed 3 unique studies spanning across five years of data collection and analysis. The three studies are referenced as Phase 1, Phase 2 and Phase 3 for discussion purposes. The methodology chapter introduces the design of experiments, data collection strategies, research population and analysis methods. The objective of this research is exploratory in nature to truly understand the complexity of design and its implications on engineers.

5.1 DATA COLLECTION AND ANALYSIS

The data collection method and population selection were uniquely designed to address the proposed research questions. The sample size and group of participants are different for all the phases. The multi-model study captures the data by utilizing various quantitative and qualitative approaches. The data collection and analysis process of individual study is discussed in the following subsections.

1. Problem Formulation

Phase 1 study was designed to examine and understand student generated problem statements. The study provided students with an opportunity to create three unique engineering problems using their interest, experience, and creativity. The participants for Phase-1were senior engineering students at the University of Georgia. This study took place in the Fall and Spring semester, 29 students participated in the Fall Semester and 33 students in the Spring semester. The study was strategically divided across two semesters of senior year to allow students with varied levels of design experience in the experiments. Students in the fall semester had just enrolled in the senior design class with little to no prior design experience, whereas the spring semester students were close to completion of the year-long senior design project and had more knowledge into the workings of a successful design project. A total of 62 senior year students voluntarily participated in this study; 6 females and 55 males. There was no incentive offered for Phase-1 study.

Upon completion of the demographic survey, the Qualtrics link displayed an instruction page for participants. The students were not required to provide solutions for the generated problem statements. As shown in Table 3 , students are refrained from using an external help for the completion of the study. The cue provided for generating three distinct problems were small, medium and large-scale problems. The small, medium and large-scale cues were used to allow students to think of three distinct problems and not iterate on the same problem. The cues were left for student interpretation.

Table 3: Design Study Instruction Phase 1

Your task is to generate three design problems of varying levels that stem from your experience or interest. Interpret the task to the best of your ability; below are some helpful pointers. • There is are no wrong answers, and no solution is required. • This is an individual task, please refrain from discussing anything about this project with others including your classmates. • Please refrain from using the internet or any other external source during the course of the study. • You shall not be scored for the given activity, it is for research purposes only. Please reach out to the researcher if you need clarification before you begin. Thank you. Enjoy!

As seen in Table 4, a minimum 1000 characters count was required to submit the design problem statement. Participants were also asked to interpret small-scale, medium scale, and large-scale terms to the best of their ability.

Table 4: Design Study Cue Phase-1

Create one small/medium/large-scale engineering design problem of your choice. It should be at least 1000 characters i.e. approximately 170 words. Character count will be indicated as you type.

To analyze the large set of data obtained from problem formulation study, a machine learning technique "topic modeling" is administered. Topic Modeling is a computational method to abstract topics from a collection of documents. Among the various topic modeling algorithm, Latent Dirichlet Allocation (LDA) is selected for analysis of problem formulation study for its solid statistical foundation and ability to generate interpretable topics [142]. Along with LDA, Hierarchical Dirichlet Process (HDP), and Gibbs Sampling Dirichlet Mixture Model (GSDMM) for topic modeling are also selected.

The Latent Dirichlet Allocation Algorithm is an unsupervised machine learning model to identify latent topics in a particular textual dataset. LDA is a generative and probabilistic model for collection of discrete data such as text corpora, it builds on the premise of finding the balance between topic distribution within documents and word distribution within topics. The LDA model is represented as a probabilistic graphical model as seen in Figure 9.

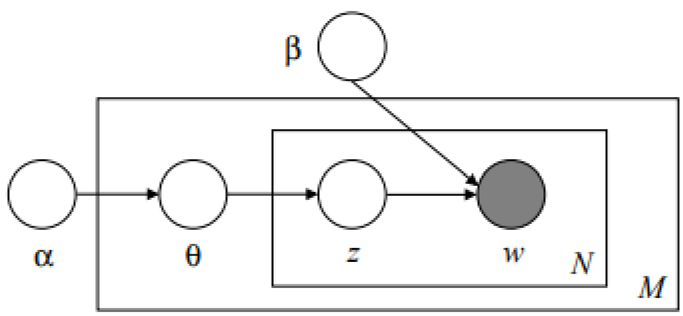

Figure 9 : Graphical Model Representation of LDA

The circles ("Nodes") represent random variables. Filled circles denote observed variables, those that constitute of actual words in the documents (w). Unfilled or empty circles represent latent (hidden) variables, which the model aims to infer, such as the topics (z) and topic distribution (θ). Arrows indicate the dependencies between the variables. The outer box/plate denotes replication over a set of elements. Nested within the 'M' plate is another plate labelled 'N', indicating the repetition of structure for each N words in the document. The α and β are hyperparameters of the Dirichlet distribution for the topic distribution θ , hyperparameters are depicted by the circles outside the plate since they are not repeated for each document or word, but they affect the entire model globally. z represents the topic assignment for each word in a document, and w represents the observed words which is dependent on topic assignment z.

The joint probability distribution of the topic mixture (θ), the topic assignment (z) and the observed words (w) can be expresses as:

$$p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha)\prod_{n=1}^{N} p(z_n|\theta)p(w_n|z_n, \beta)$$

Before analyzing the LDA model, a series of pre-processing step are essential to ensure optimal model performance. The standard pre-processing steps implemented are:

1. Text Cleaning: Removing irrelevant data
2. Tokenization: Splitting the textual data into individual words or tokens
3. Lowercasing: All words within the document is converted into lowercase for consistency
4. Stop word Removal: Eliminate common words and preposition such as "and", "the", "is" which do not add meaning to the context of the text.
5. Stemming/Lemmatization: Converting words from their base or root form
6. Document-Term Matric (DTM): Converting the document into matrix of rows as documents and columns as terms (or tokens). Each cell containing frequency of a term in the document.
7. Additional Stop words: Some additional stop words with respect to the prompt provided for the study.

Post cleaning, a dictionary of all unique words in the dataset was created and transformed into a document-term matrix. The LDA model was trained on the developed matrix with a set number of topics.

Hyperparameters like α and β are tuned to optimize the coherence score. A Grid search approach was employed to explore the range of hyperparameters and find the best combinations in the dataset.

α: document-topic density. With the higher α, documents are likely to consists of higher number of topics. Lower α denotes the sparsity or distinctness in topic structure.

β: topic-word density. A high *β* indicates topics are likely to contain mixture of most words, and lower values indicates set of distinct words.

Model Evaluation: Two metrics widely used in gauging the effectiveness of the LDA model are perplexity and coherence. The developed model was evaluated for its effectiveness. Perplexity measured the alignment between the probability distribution and the actual distribution of word in the corpus. Perplexity is mathematically expressed as:

$$\text{Perplexity}(D) = \exp\left\{\frac{\sum_{d=1}^{M} \log_p(w_d)}{\sum_{d=1}^{M} N_d}\right\}$$

Where:

D represents the dataset

M denotes the number of test documents

N_d is the number of words in the document d

$P(w_d)$is the likelihood of the document.

A lower perplexity score signifies a better fit of the model to the data. Coherence score is complimentary to the perplexity. Coherence measures the degree of semantic similarity between the higher scoring words of a topic. Topics with higher coherence score are considered better quality. The coherence measures the pairwise word similarity scores of the words in the topic, then taking an average. C_v falls within the range of 0 to 1. Perplexity and coherence scores provided a comprehensive insight on the LDA model performance.

Hierarchical Dirichlet Process (HDP) is an extension of the Dirichlet Process, a non-parametric approach in topic modelling[143]. It doesn't allow for absence of parameters, rather allows the number of parameters to grow with the data. One of the biggest challenges in topic modelling is the determination of right number of topics. Along with the number of topics. Mathematically, HDP is defined as the distribution over topics using the Dirichlet process D P (γ, *H*). where γ is a concentration parameter and *H* is a base distribution [143]. Like LDA model, HDP also includes hyperparameters and to govern the granularity of the topics. Using HDP in conjunction with LDA, HPD introduced flexibility for the model to remain adaptive.

Gibbs Sampling Dirichlet Mixture Model: Unlike traditional LDA, GSDMM is designed for short-text clustering. GSDMM is a non-parametric and the number of topics can be inferred from the add thus adding additional flexibility[144]. It works under the assumption of one topic per document, thus suitable for short texts like the problem statements. GSDMM with *z* is topic, *k* is a selected topic, and *d* is the document is represented by mathematically by:

$$P(z = k|d) \propto (n_k + \alpha) \times \frac{n_{d,k} + \beta}{n_k + V\beta}$$

n_k is the number of documents assigned to topic k

$n_{d,k}$ is the count of words in document d that are associated with topic k

V is the vocabulary size

α and β are hyperparameters

The three models chosen for topic modeling analysis in the study, *"Problem Formulation"* holistically analyzed the dataset for a layered and comprehensive view. Each model added a unique benefit. LDA served as a foundational technique, thus a good starting point for analyzing large dataset of short problem statements. It captured broad range of topics and overarching themes within the dataset. LDA required a predefined number of topics, thus incorporating HDP was beneficial. HDP operated non-parametrically by identifying an optimal number of topics based on the data structure. The study is exploratory in nature, making HDP a crucial choice for exploring unexpected and novel themes from the problem statements. And lastly GSDMM recognized the brevity of problem statements, hence perfectly suited for short-text clustering. Each problem statement encapsulated a unique idea or concern penned by students, GSDMM assumed each document as a topic, thus providing with a granular view into the results.

2. Problem Evaluation

Twelve graduate students, aged 22-40 years old, participated in the Phase 2 (Problem Rating) Study. The problem evaluation study is a mixed-method study where participants first rated various design statements on two scales: constraints and dimensions, and ended with a focus group interview.

- Constraint: This dimension identifies the extent to which a design problem is bounded by technical, financial, and other limitations.
- Social Value: This dimension helps in gauging the societal implications of a problem, thus assessing how beneficial the outcome might be to a larger community.

The participants were Masters and PhD students currently enrolled within The College of Engineering, and have held teaching experiences at various capacities within the engineering and STEM departments at UGA. There were 6 female and 6 males participating in the evaluation study.

Prior to recruitment, it was ensured that participants weren't a part of the Phase 1 (Problem Formulation) Study. The participants were then randomly divided in three groups, and assigned a three-hour time slot for the study. Each participant was provided with a unique Qualtrics link upon arrival. A total of 12 unique Qualtrics Link were generated using BIBD (Balanced Incomplete Block Design) for rating problems. The link included a demographic survey and problem statements from Phase 1. Each link contained 44-45 unique problem statements to be rated on the 2*2 design dimension scale: constraints and social value as shown in Figure 8. From the Phase 1 study, student-generated problem statements were further rated by experienced graduate students. Each problem statement was rated by three graduate students, with each student rating 44-45 problem statements. Graduate students rated individual problem on the mentioned design dimension using a 7-point semantic differential scale. A semantic differential scale captured the connotative meaning and emotional reaction a person can have toward an object, event, or concept [145]. The scale is constructed with a series of bipolar adjectives or adjectives phases [146], for this study the scale ranged from “open ended - close ended” and “high social value – low social value”.

The rater and problem matrix are generated using the Balanced Incomplete Block Design (BIBD). Balanced Incomplete Block Design is part of a Random Block Design method used to design treatment-based trails for a sample of large population [147,148]. A balanced incomplete block design (BIBD) is an incomplete block design in which five parameters denote design as $D\ (b, k, v, r; \lambda)$. The parameters b, k, v, r and λ are defined as:

- (v): number of treatments (or varieties)

- (b): number of blocks

- (r): number of times each treatment is replicated (i.e., the number of blocks containing a particular treatment)

- (k): number of treatments in each block

- (λ): number of pairs of treatments that appear together in a block

The BIBD satisfies the following relationships:

1. Each block contains (k) distinct treatments.

2. Each treatment appears in (r) different blocks.

3. Every pair of treatments appears together in (λ) blocks.

Mathematically, these can be represented by the following:

$$(b \times k = v \times r)$$

This states that the total number of "placements" of treatments across all blocks (i.e., ($b \times k$)) is equal to the total number of "placements" of each treatment across the entire design (i.e., (v × r)).

$$[\ r\ (k\ -1) = \lambda(v\ -1)]$$

This relationship ensures that every pair of treatments appears together (λ) times. Upon completion of the rating study, the experts were divided into three focus groups for a 30-minute interview. A $50 incentive was offered for participation.

The data analysis for this study includes descriptive statistical analysis, inter-rater reliability, cluster analysis and cluster validity. The initial examination involves computing z-scores for all the ratings. The z-score is a statistical measure describing relationship between data points and mean of a group of points [149]. The standardization provides a baseline, adjusting for any potential rater biases and ensuring the scores are comparable across raters and problems. To determine the consistency and agreement among raters, the Interclass Correlation Coefficient (ICC) is computed to each design dimension. ICC values close to 1 suggest strong agreement among rater, establishing reliability of the rating process. The ICC values are interpreted as follows [150]:

Table 5 : ICC Reliability Values

< 0.5	Poor Reliability
0.5 – 0.75	Moderate Reliability
0.75 – 0.90	Good Reliability
< 0.90	Excellent Reliability

Cluster Analysis is a fundamental technique in unsupervised machine learning where grouping of similar data points into clusters or groups takes place with the help of Elbow Method. The Elbow Method is a straightforward method of finding the optimal number of clusters (k) in a given dataset. In this study, cluster analysis is performed to partition the data points into clusters and ensure the validity of the predicted design dimensions. Elbow Method involves plotting the variance as a function of number of clusters. The Within-Cluster Sum of Squares (WCSS) is calculated for a range of cluster numbers and then plotted to identify reduction in variation, hence determine the optimal number of clusters. To discern the natural patterns and groups within the rated problems, a k-means clustering approach is administered. K- means clustering algorithm partitions *n* data points into *k* clusters where each data point belongs to a cluster with the nearest sum [151]. The mean of the data points in s cluster is referred to as the "centroid". The goal of k-means algorithm is to minimize the within-cluster sum of squares (WCSS). Mathematically represented as:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

Where:

- J is the total WCSS
- C_i represents the i-th cluster
- x is a data point within cluster C_i
- μ_i is the centroid of cluster C_i
- $||x - \mu_i||$ is the Euclidean distance between data point x and centroid μ_i

To determine the optimal number of clusters (k), the within-cluster sum of squares (WCSS) is plotted against a range of k values. The Elbow Method runs the k-means clustering in a given dataset for a wide range of k values, followed by computing the sum of squared distance from each point to it's assigned center for respective k values. The objective is to select a k value at "elbow" point in the plot representing the optimal value of k [152].

To establish the cluster quality and validity, a silhouette score is employed. A silhouette score measures how well each data point in a cluster fits with its respective cluster compared to the adjacent clusters [153]. It is represented by:

$$s(i) = \frac{b(i) - a(i)}{\max\big(a(i), b(i)\big)}$$

Where:

- a(i) is the average distance from the i^{th} data point to the other data points in the same cluster
- b(i) is the smallest average distance from the i^{th} data point to data points in a different cluster.

The silhouette score ranges from -1 and 1 for each data point. The higher values indicate better-defined clusters. The following are silhouette score interpretation:

- -1: Clusters are assigned wrongly
- 0: Clusters are indifferent and the distance between them is insignificant
- 1: Clusters are apart from each other and distinguishable

Drawing results from the described analysis technique allows for a comprehensive review of the rater agreement and classification of design problems for phase 3.

3. Problem Preference

The "Problem Preference" study is the final study (Phase 3) of the research. This neurocognitive lab experiment was designed to collect real-time brain imaging data of participants. The brain imaging data was collected in conjunction with a selection-based design task. Participants rated various design problem statements on the screen on a scale of 1 to 5, 1 indicating least interested and 5 indicating most interested. Design engineering scenarios are commonly used as educational material in engineering education in to enhance the problem-solving skills of undergraduate engineering students [2]. Exploring the real-time neurofeedback from students has been used to assess the education material and items in engineering education [154]. Design preference study applies this neurological approach in developing the design of engineering scenarios that will benefit engineering education practices in higher education settings [155]. The participants are enrolled in engineering program at UGA, including but not limited to agricultural engineering, biochemical engineering, biological engineering, civil engineering, computer systems engineering, electrical & electronics engineering, environmental engineering, and mechanical engineering. This study includes undergraduate and graduate engineering students. 8 females and 12 males participated in the experiments.

This study could not accommodate participants with a history of neurological disorders such as epilepsy, brain injury, and schizophrenia. Also, a medication history of anxiety, depression, and seizures are not eligible for this study. In the recruitment email sent to students, a screening survey was provided to determine their status and to ensure absence of the exclusion criteria. A $100 incentive was offered for participation.

This study investigated neurocognitive responses to various types of engineering design problems. The experiment was designed for engineering students to rate twenty unique engineering design problems on a Likert scale (1 to 5), indicating their preference for working on that problem. The neurocognitive data is collected using an electroencephalography (EEG) device.

The research design consists of three activities: pre-EEG experiment survey, EEG experiment and post-EEG experiment interviews. For the pre-EEG experiment survey, participants were asked to complete a demographic survey, followed by EEG experiment. During the experiment, participants rated 20 design problems on a five-point Likert Scale on a computer screen while wearing EEG device. The EEG device is a silicone cap with 32 electro-measuring channels that can collect frequency range of 0 – 100 Hz. During the experiment, the administered EEG device collected neurocognitive data. The design scenarios presented to participants during the EEG experiment differ on their level of social values and constraints. The EEG device used in this study is commercially available [156]

Figure 10 illustrates the Compumedics EEG 32-channel cap and hardware-software setup for the experiments. It includes the EEG Curry Data Acquisition and Chronos E-prime 3.0 for the stimuli and response mapping. The device is intended to be used as a tool for the engineering research study.

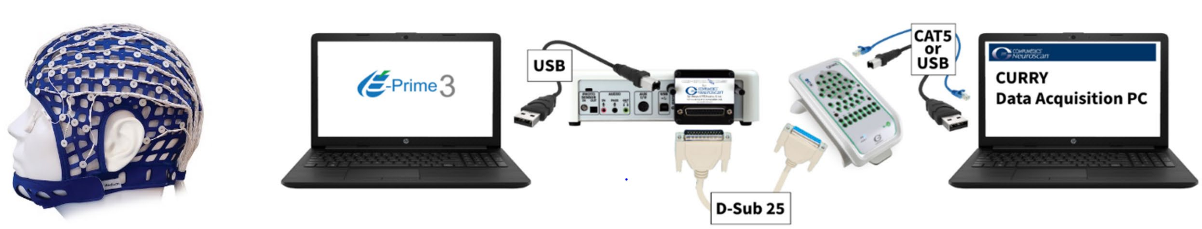

Figure 10 : EEG 32-channel Cap and Hardware Device [156]

This study is not intended to measure the safety or effectiveness of the tool itself. This was not time-based study. The total duration of the study is expected to be within the range of 120- 125 minute.

Table 6: Problem Statements Phase-3

Develop a solar-powered vehicle as a solution to the Earth's energy crisis. The vehicle should be affordable, with a total price not exceeding $20,000. It should accommodate at least four individuals of average height and weight, with a variable maximum speed of 30 miles per hour. Essential features include turn signals, brake lights, and headlights. The vehicle should have a minimum continuous range of 200 miles and be capable of storing power.
1 **2** **3** **4** **5**
Least Likely Most Likely
To combat nicotine addiction and its impact on American youth, design a device that tracks nicotine levels and motivates users to reduce and ultimately quit. The device allows regular vaping while providing an app-connected UI. The app displays vaping habits, trends, and progress, helping users gradually break free from nicotine.
1 **2** **3** **4** **5**
Least Likely Most Likely
The alto saxophone's cork has been a source of frequent complaints due to leakage during play, where the user's saliva seeps through the cork's bottom. This issue leads to premature cork failure and necessitates unwarranted repairs for the users. An engineer has been assigned to identify the cause of this leakage, such as manufacturing defects or adhesive failure, and devise a solution for the next product line to ensure high product quality and customer satisfaction.
1 **2** **3** **4** **5**
Least Likely Most Likely
The UGA College of Engineering aims to renovate the Fab Lab, focusing on achieving a net zero energy profile within spatial constraints of adding only 150 ft^2. The design must house existing machinery and incorporate an energy recycling process. Deliverables include a research document on net zero strategies, a floor plan for the facility, and a net zero strategy explanation.
1 **2** **3** **4** **5**
Least Likely Most Likely

In the “Problem Preference” study, the focus is shifted to an in-depth evaluation of participant’s cognitive response to the selected design problems. The survey data was analyzed using statistical tools such as AIC, ANOVA/t-test. The EEG data was analyzed using the EEG CURRY software. CURRY multimodal neuroimaging software is a source localization software for electroencephalograph (EEG) classified as a Class II according to FDA regulation CFR 882.1400.

The collected data is first examined for artifacts such as eye blinks, muscle contractions, or even electrical interferences, along with extraneous disturbances and noises. Using the Curry Compumedics software, both automatic and manual inspections are implemented to ensure the high quality of clean data. EEG signals are contaminated with noise from various sources, thus filtering process ensures the frequency bands of interest are preserved [157]. Some of the filtering process includes:

- Low-pass filter: Allows frequencies below a certain cutoff to pass though, removing high-frequency noises.
- High-pass filter: Allows frequencies above a specific threshold, eliminating slow artifacts.
- Band-pass filter: Combines both low-pass and high-pass filters, permitting only a specified frequency range.

Electroencephalography data are very minute electrical potential that can range from microvolts (V) to millivolts (mV). Given the diminutive nature of these signals, the data requires amplification of signals to a magnitude that can be processed and analyzed. Amplifiers boost the signal’s strength by avoiding significant noise addition. The raw EEG data is in the analog signal format (continuous in time and amplitude). Before this data can be processed, it is essential to convert it into a digital format. Common Average Reference is a technique employed to enhance signal-to-noise ratio and reduce the effects of reference electrode locations. This step is essential in isolating genuine neural activity from extraneous interference. The EEG data is meticulously segmented into specific event-related intervals known as Epoch. Epoching is a crucial step in the event-related potential (ERP) analysis where the continuous [158]. EEG data is divided into smaller and shorter segments calls epochs. Epochs typically include time intervals before and after the event. The three epochs/timestamps are: pre-stimulus, post-stimulus, and pre-response.

- Pre-stimulus: Representing the neural activity 3 second before the presentation of the design problem stimulus.
- Post-stimulus: Captures the immediate neural response after viewing the design problem on the screen.
- Pre-response; Denotes the neural activity 3 seconds before the participant rates the problem on the Likert scale.

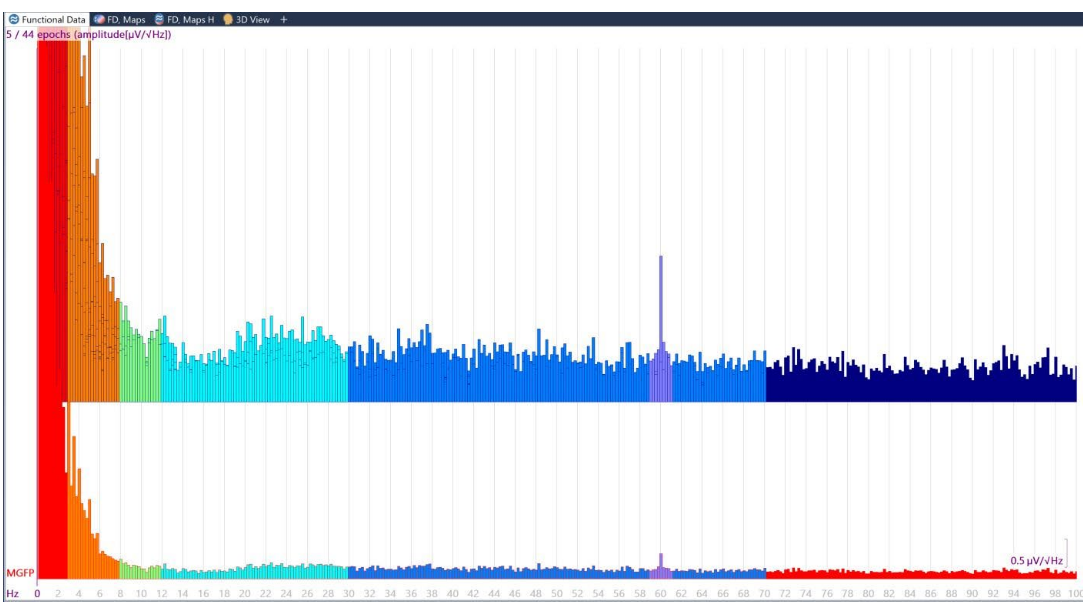

Figure 11: Epoching Events

Adjusting the EEG signal based on a baseline period ensures that any observed activity during and post stimulus is relative to the baseline. The processed EEG data further undergoes a Fast Fourier Transformation (FFT). The FFT is a mathematical algorithm that decomposes time-domain EEG signals into the frequency domain, unveiling domain frequency bands [159]. It is mandatory to transform the time-domain signals into frequency domains to examine the oscillations in the brain. FFT is an efficient implementation of the Discrete Fourier Transform (DFT). The DFT is represented by[160]:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi}{N}kn}$$

Where:

- $X(k)$ represents the k^{th} frequency bin's value in the frequency domain.
- $x(n)$ is the n^{th} value of the time-domain signal.
- N is the total number of points.
- j is the imaginary unit.

For the EEG data analysis, FFT assists with the decomposition of a complex-time domain signal into its constituent sinusoids, each with its amplitude and phase. This decomposition helps in the understanding of power and phase relationship of specific frequency bands. For the "Problem Preference" study, power values for each electrode across five frequency bands are obtained. FFT serves a foundational step in further analyzing EEG data. FFT reveals specific frequency bands – like alpha, beta, or theta waves – that may be dominant or exhibited variations when participants are rating the design problems. The significance of the observed EEG patterns, changes, and effects are further tested using ANOVA, t-tests, and Akaike Information Criterion (AIC). AIC measures the relative quality of statistical models for a given set of data. The central principal of AIC is the trade-off between the goodness-of-fit of the model and the complexity. AIC functions of the information theory, where it aims to establish a best balance between fit and simplicity., in a sense that describes the data well and with a minimal number of parameters, to avoid overfitting [161]. AIC is represented by

$$\mathrm{AIC} = 2k - 2\ln(L)$$

Where:

- k is the number of parameters in the model
- L is the maximum value of the likelihood function for the model

In addition to EEG data analysis, other variables and its interaction with EEG are also analyzed.

- Participant's scores for the design preference on 5-point Likert-Scale
- Gender of the participants
- Constraint values of associated with the respective design problem
- Social values associated with the respective design problem

For each of the above dependent variable, a separate regression model is generated and AIC value is calculated. The model with lowest AIC value is deemed most fitting. The coefficients in the regression models represents the change in the dependent variable for a unit change in EEG average power value, with the assumption that all other predictors remain constant. T-values gauge the significance of the predictor, p-values less than 0.05 generally indicating statistical significance.

The methodologies employed for the Phase 3 study, from spectral analysis to AIC model optimization, underscores the complexity and potential of EEG analysis in understanding the cognitive process behind the design preferences.

CHAPTER 6

RESULTS

The results from the data and analysis are discussed in three subchapters referencing the three phases of the research. The results chapter is an amalgamation of statistical analysis as well as qualitative interpretations. The multi-modal study includes various forms of analysis techniques, results interpretation and illustrations. The results begin with a topic modeling approach for Phase 1, agreement and cluster analysis for Phase 2, and lastly signal processing and regression analysis for Phase 3.

6.1 PROBLEM FORMULATION

The problem formulation study examines a textual data set containing 177 unique design problem statements generated by the engineering students. This data set is almost impossible to be solely analyzed using a qualitative approach. Maintaining a code book for an enormous dataset would be tedious and risks the quality and reliability of the results, hence a machine learning algorithm is administered to identify themes, patterns and novelty in the Phase 1 results. Table 7 shows a comprehensive grid search was conducted over the hyperparameters of LDA to establish an optimal setting. The model was subjected to a 5-fold cross-validation, iterating over 64 different parameter combinations. Thus, leading to a total of 320 fits. The following are the optimal parameters identified in the model:

Table 7: Best Model Parameters

Document-Topic Prior (Alpha)	0.6
Number of Components (Topics)	20
Document-Word Prior (Beta)	0.9
Best Coherence Score	0.45

The alpha value of 0.61 suggest each document is likely to contain a mix of several topics, this parameter influences the distribution of topic within each document. A beta value of 0 .91implies a broad variety of words within the document. The coherence score of 0.45 indicates moderate coherence, where the topics are moderately consistent and understandable.

Figure 12 displays an “Intertopic Distance Map” generated with the help of LDA visualization tool, pyLDAvis. The circles in the quadrants represent topics. The map also helps is visually representing the distances between the topics in a 2-dimensional space. The distance between the bubbles indicates the similarity or dissimilarity between topics. The map represents 20 distinct topics identified from the corpus and labelled as Topic 1, Topic 2, and Topic 3 and so on. The distance between all three topics is significantly larger, indicating distinct content in each of them.

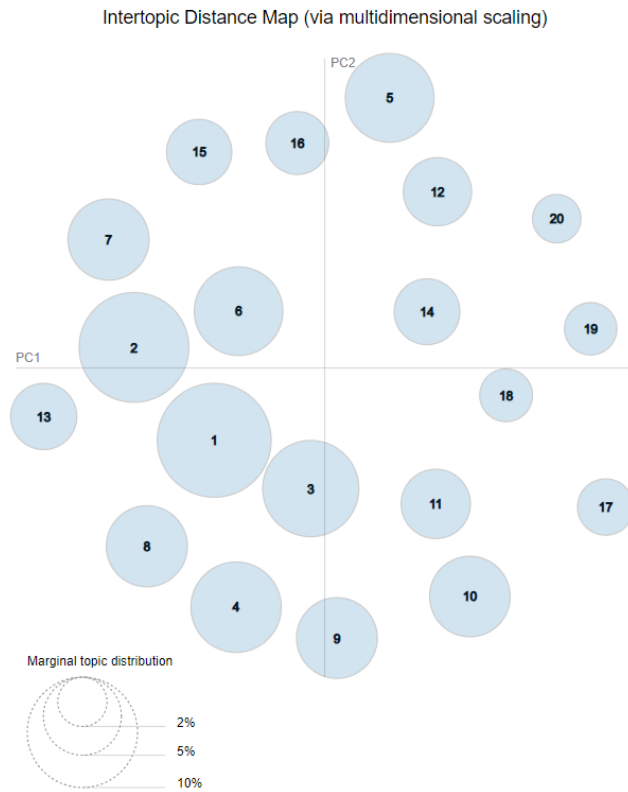

Figure 12: Topic Modeling LDA Results

Principal Component Analysis (PCA) is a statistical measure commonly used in machine learning algorithm such as LDA for dimensionality reduction. The PCA in large datasets allows for a large variance to be captured. The correlation between the variables is captured by first transforming them into new set of variables, which is a combination of variables and attributes to retain the maximum variation. This combination of attributes is called Principal Components (PCs). The component that captures maximum variation is called Dominant Principal Component. The order of retention of variation is PC1>PC2>PC3. PCA follows multiple steps such as standardization, covariance matrix calculation, eigen value decomposition and conversion to eigenvectors. That results in PC axes, x axis labeled PC1 and y axis labelled PC 2. Principal Components are linear combinations of the original variables., the position of data points on the axes indicate the scores on each component. Using LDA techniques, axes are determined via multidimensional scaling.

MSD is used to illustrate distance information between high dimensional points into a lower dimensional space. The size of bubbles indicates the prevalence of topic in the dataset. The most relevant topic in Figure 13 is Topic 1.

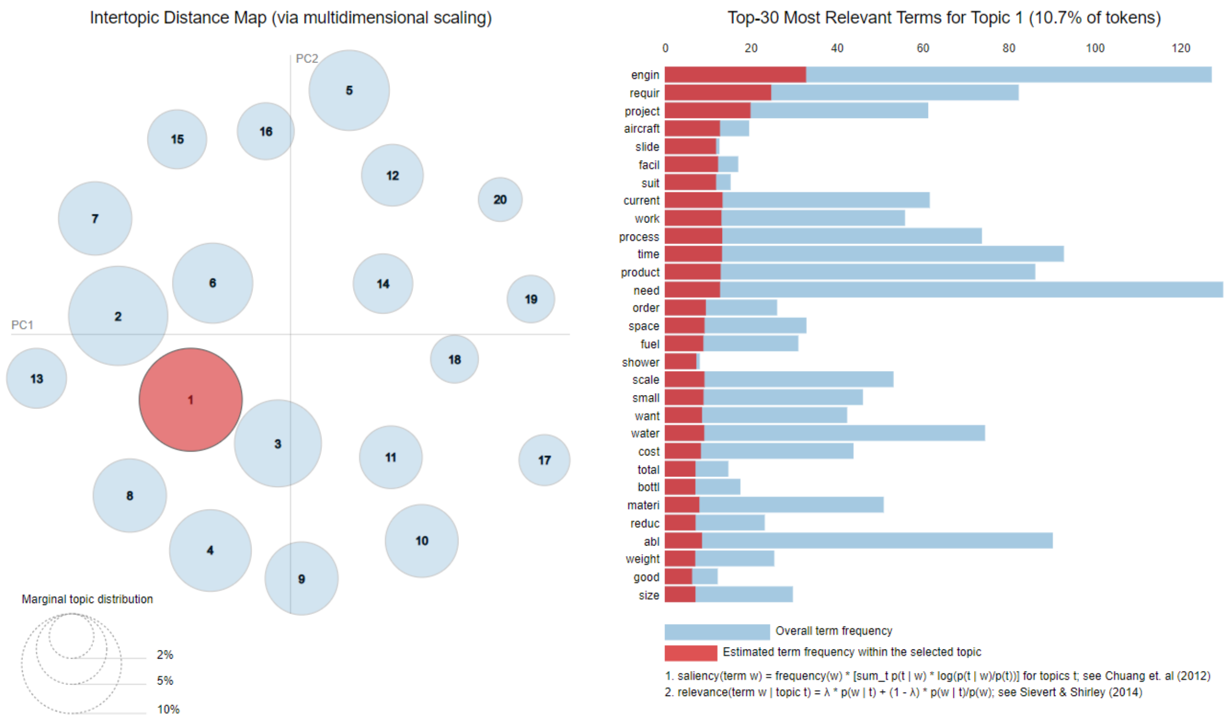

Figure 13 : LDA Analysis-Topic 1

The spatial distribution of topics in Figure 13 is determined by their word distribution. As seen, topics 1, 4, and 8 are closer potentially sharing more similar words. Topic 1 bubble is the largest of the group and dominates the data set indicating the bubble encompasses a significant portion of relevant words. The right-hand side of Figure 13 displays the top 30 most relevant topics within the bubble selected. The visualization differentiates between the word frequency in the corpus (in blue) and frequency within a topic (in red). The ranking is determined by the combination of word frequency within the topic but also exclusivity to the selected topic [162]. This ensures that the terms presented are uniquely associated with the selected topic. The top terms in Topic 1 include "engine", "project", "aircraft", "facility, "time", "process". The top five terms hint at a central theme of engineering and project management. The other frequency terms also include “order”, “work”, “product”, further hinting at the stages and logistics of project management. The problem formulation study required students to generate design problems, topic 1 reflects the practical aspect of engineering a student may have encountered. It represents the tangible, hands-on part of engineering.

The other adjacent topics are topic 4 and topic 8. The words in topic 4 circles lean towards the theme of industrial engineering and design of systems. Words include “pallet”, “conveyor”, “lift”, “dryer” and “colander” indicating elements of a manufacturing or production environment. Along with terms like “combustion”, “engine”, “sensor” hinting at the technical depth of the problems. This topic potentially represents the student’s exposure to factory floor operations, material handling and workflow optimization.

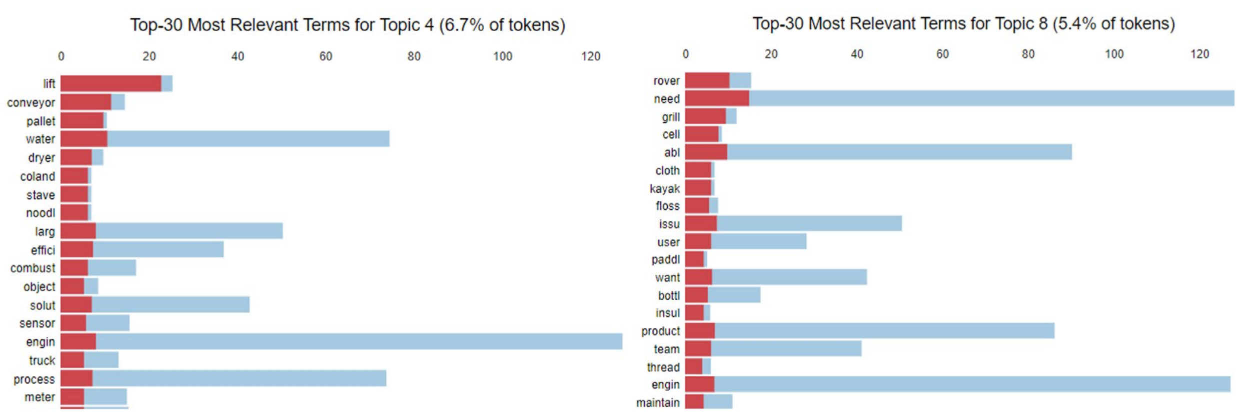

Figure 14: LDA Analysis - Topics 4 and 8

Topic 8 lists the words like “need”, “product”, “user”, “want”, “team”, thus hinting towards product development and consumer products. The more specific terms include “rover”, “grill”, “cell”, “kayak”, “cloth”, and “bottle” may suggest a diverse range of products. The specific-product related term may hint at particular design challenges or projects students may have experienced. Topics 1, 4 and 8 are situated in the same quadrant, and the proximity suggest some degree of overlap or similarity in the content or themes.

The next topic modeling analysis is results of Topic 6 and adjacent bubbles as shown in Figure 15. On the Intertopic Distance Map, topic 6 is closer to topics 2 and topic 15. Topic 6 has a prominent bubble signifying its substantial presence in the data analysis with 6.4 % tokens. The dominant terms in topic 6 are “water”, “project”, “need”, “student”, “vehicle”, “book” hinting at the school projects or initiatives related to sustainability and transportation.

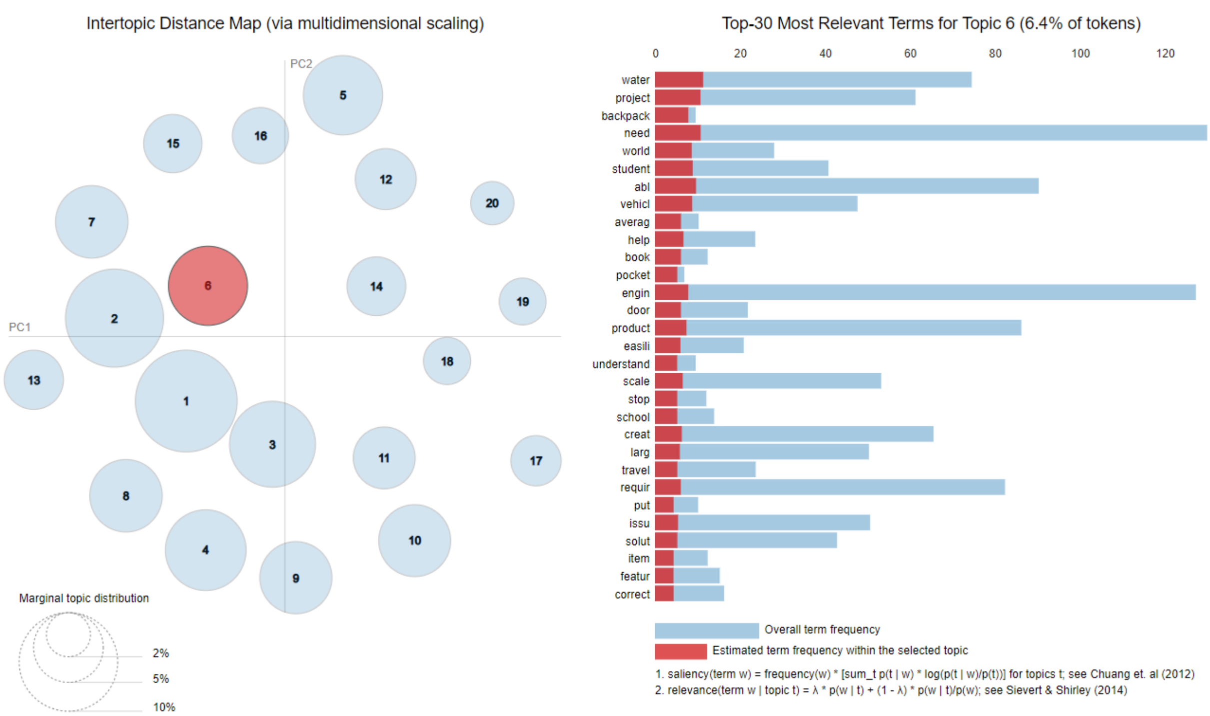

Figure 15 : LDA Analysis - Topic 6

The other relevant terms observed are “world”, “water”, “book”, and “travel” further reiterating the theme of broader impact or significant of the projects or global scale products. The adjacent topics to Topic 6 are topic 2 and topic 15. Topic 2 consists of a mixed set of terms such a s “lock”, “door”, “locker”, and “device” relating to electrical devices or systems. The other relevant words are “food”, “home”, “intone”, “temperature” indicating theme around global humanitarian issues and climate issues.

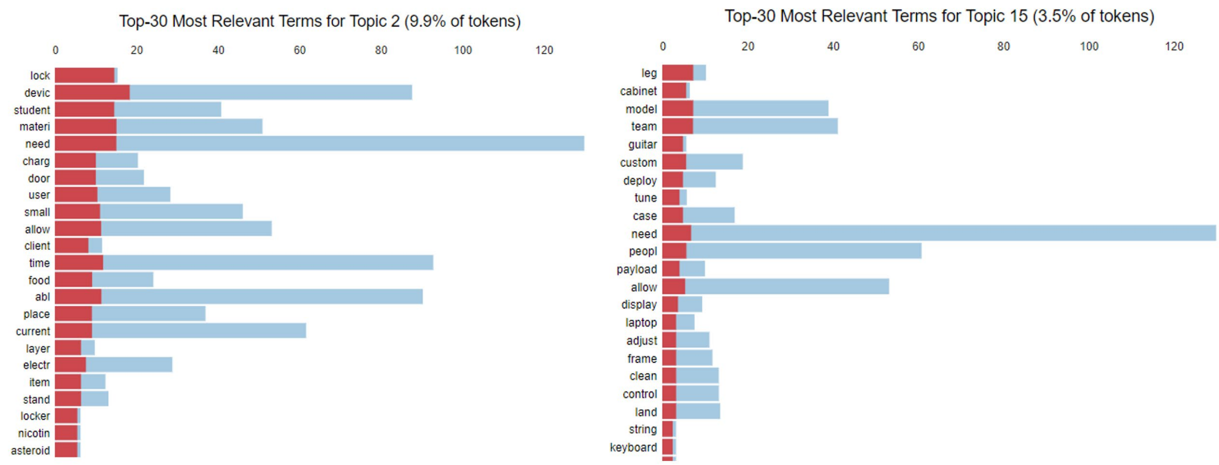

Figure 16: LDA Analysis - Topics 2 and 15

Topic 15 includes terms like “leg”, “cabinet, “model”, “guitar”, “string”, “case”, “laptop” related to musical instruments, furniture and electronics. The terms “team, and “people” hint at some collaborative aspects. The quadrant with topic 6, 2 and 15 consists of a wide variety of topics, hinting at everyday things that students experience or read about in news.

The next quadrant consists of 5 topics, and topic 5 is the most prominent bubble. The terms in topic 5 are “run”, “pool”, “drone”, “access”, “process”, “reality”, “virtual”. Topic 5 indicates presence of both physical and virtual domains. Words like “drive”, “traffic”, “park” suggest themes around transportation, potentially consisting of urban transportation systems, park and recreation areas, and racing activities. The terms “drone, and “sensor” suggest discussions related to modern transportation technologies or surveillance systems.

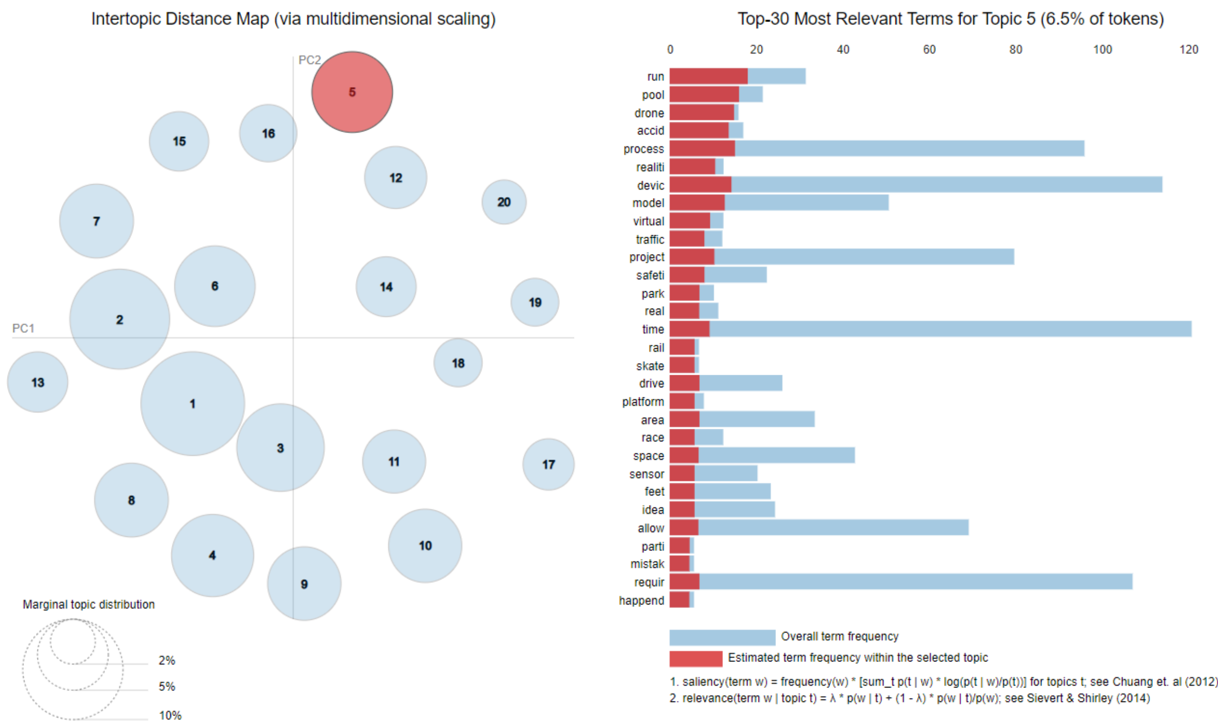

Figure 17: LDA Analysis - Topic 5

The terms like “virtual”, “reality” and “device” suggest discussions around virtual reality, possibly related to simulations of traffic or modeling transportation systems. Topic 5 represents a discourse about modern transportation, recreational activities, combines with elements of virtual reality or simulation technologies. The adjacent topics in the same quadrant include topic 12 and topic 14. Topic 12 centers around manufacturing, product development, and tools and processes associated with it. Core terms present in topic 12 are: “engine”, “worker”, “holder”, “wire”, alluding to hands-on, industrial environment. Phrases like “manufacture”, “capillary”, “product”, “determine” reinforces the themes of iterative process of creating and production. Additional terms such as “fuel”, “loom”, “technician” hint at the diverse elements and professionals in manufacturing processes. This topic contains technical as well as human aspect of manufacturing process.

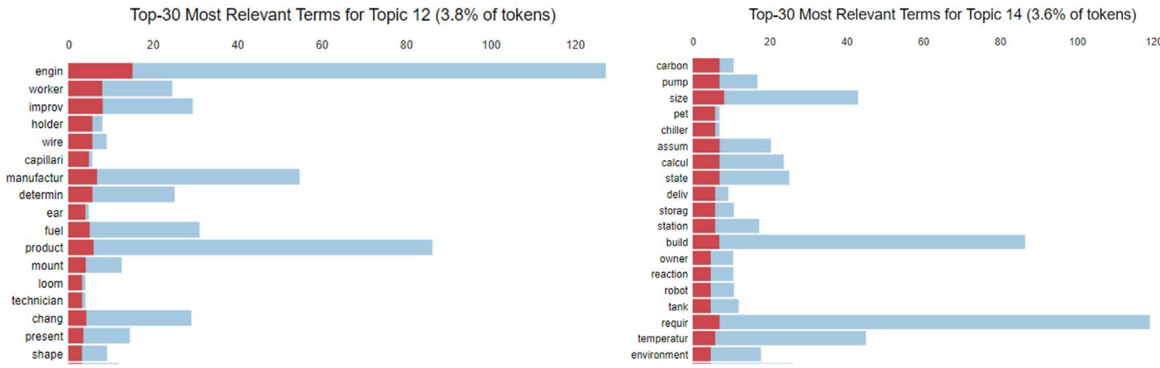

Figure 18: LDA Analysis - Topics 12 and 14

Topic 14 suggests the theme of storage and maintenance. The topic terms gravitate towards storage, delivery, and association to machinery. Predominant terms are "carbon", "pump", "size", suggesting terms in industrial context. Words like "storage", "delivery", "state" pointing towards storage. Thus, the broader context about storage, facilities, delivery stations, or the state of items in these systems. Topics 5, 12 and 14 highlight the overarching theme of industrial process and infrastructure.

The last quadrant of the LDA analysis offers a clear perspective into its thematic essence and insights form adjacent topics. As shown in Figure 19 the prominent topic 10 consists of words such as "board", "assemble", "device", "tool", "part" implying machinery and equipment creation. The terms "work" along with "operation" and "instruction" can allude to guidelines and procedures in production line or similar setting. The word "space", "rover" and "terrain" could indicate problem statements formulated around space exploration.

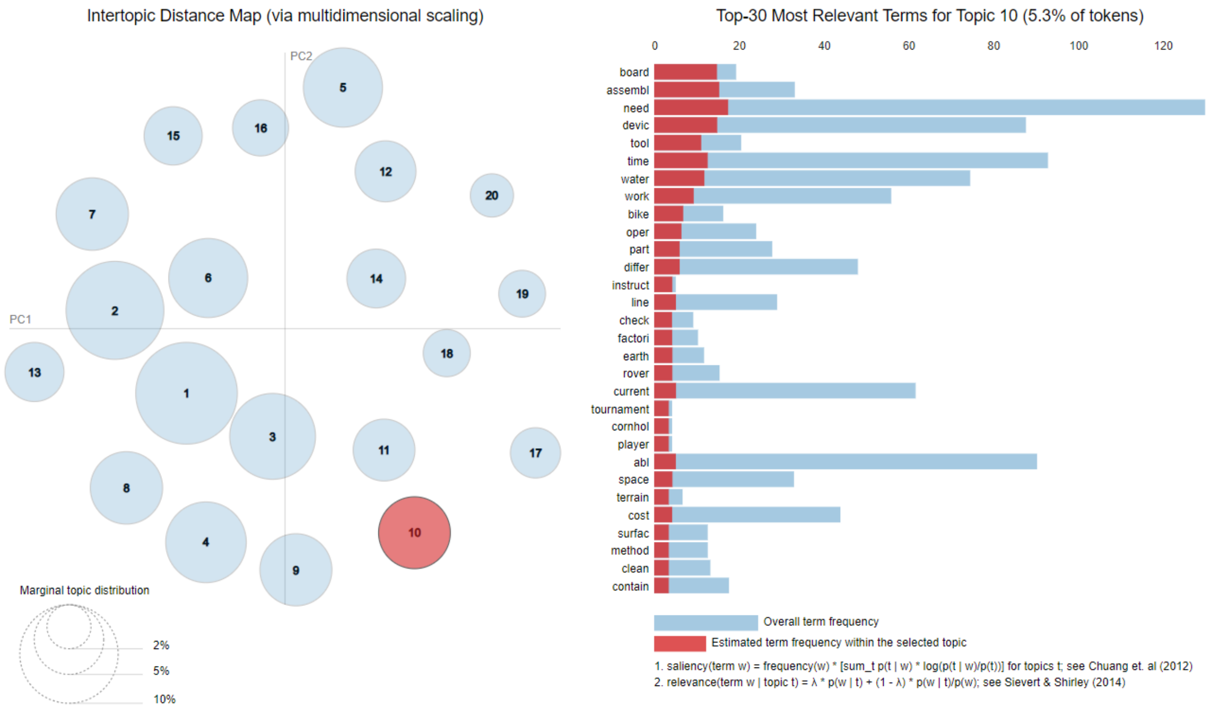

Figure 19: LDA Analysis - Topic 10

Topics 11 and 12 suggests the themes of thermal systems and infrastructure respectively. The top words in topic 11 are “engine”, “water”, “exchange”, “emission”, “reduction”, and “boiler” suggesting a theme related to thermal systems and environmental considerations.

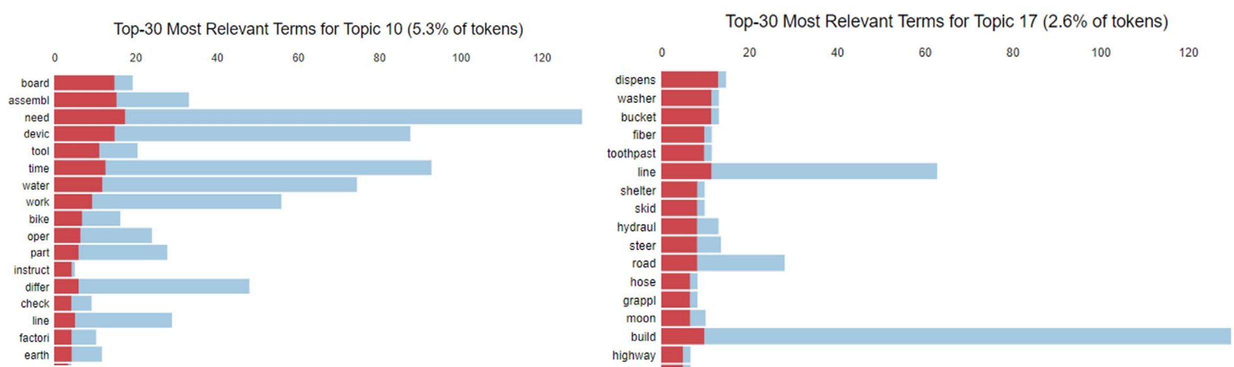

Figure 20: LDA Analysis - Topics 10 and 17

The top words in topic 17 are “dispense”, “washer”, “bucket”, “steer”, “highway”, “road” strongly hinting towards construction machinery and infrstructure development.

The process of determining the optimal number of topics for the LDA model is achieved through a systematic evaluation of model perplexity across the various topic numbers. Perplexity serves as an indicator of the model's predictive performnace, with lower values suggesting a better fit of the mdoel to the data. As seen in Figure 21, the perplexity of LDA mdoels is analyzed across a range of topic numbers, from 5 to 30. The perplexity values are plotted on the y-axis and the number of topics on the x-axis. As the number of topic increasses from 5 to approximately 10, there is a sharp decline in the perplexity score, indicating an improvement in model fit. Beyond this point, there are less significant fluctutaions. The lowest observed perplexity is around 20 and 25 topics.

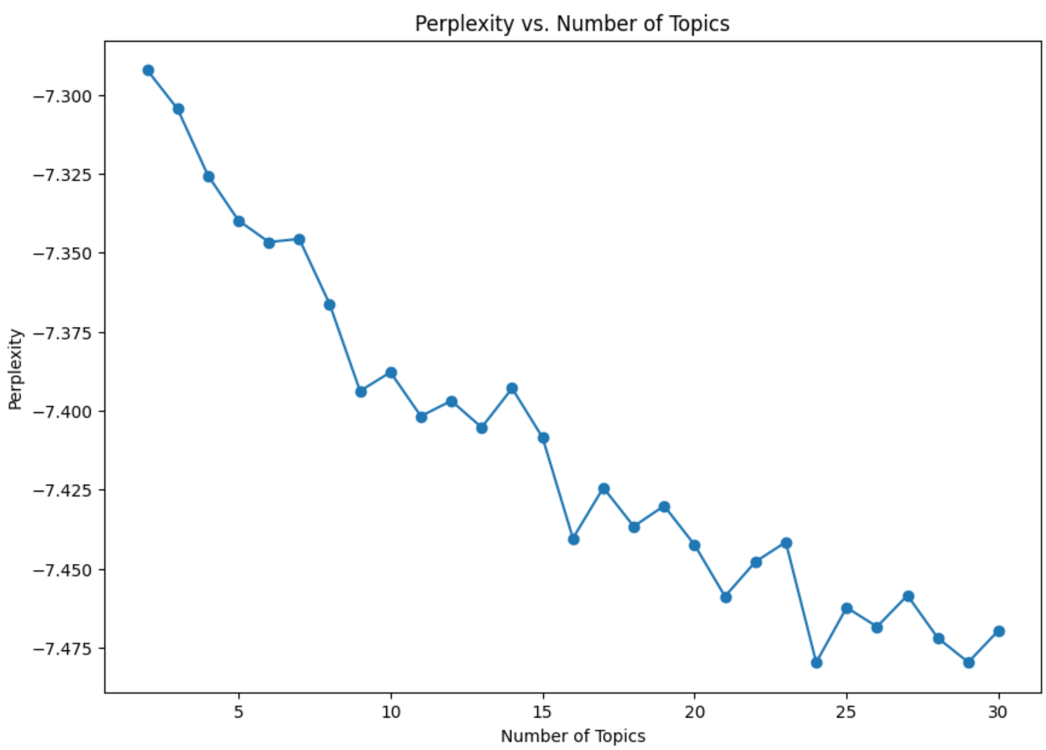

Figure 21 : Perplexity vs Number of Topics

While the perplexity provides insight into the model's predictive performances, the coherence score offers perspective on the quality and interpretability of the topics generated by LDA model. As seen in Figure 22, the coherence score is systematically evaluated across a spectrum of topic numbers, ranging from 5 to 35. For the initial range of 5 to 10 topics, there is a significant increase in coherence score. The steep indicates enhancement in topic quality and semantic clarity as the model begins to discern more distinct topics within the dataset.

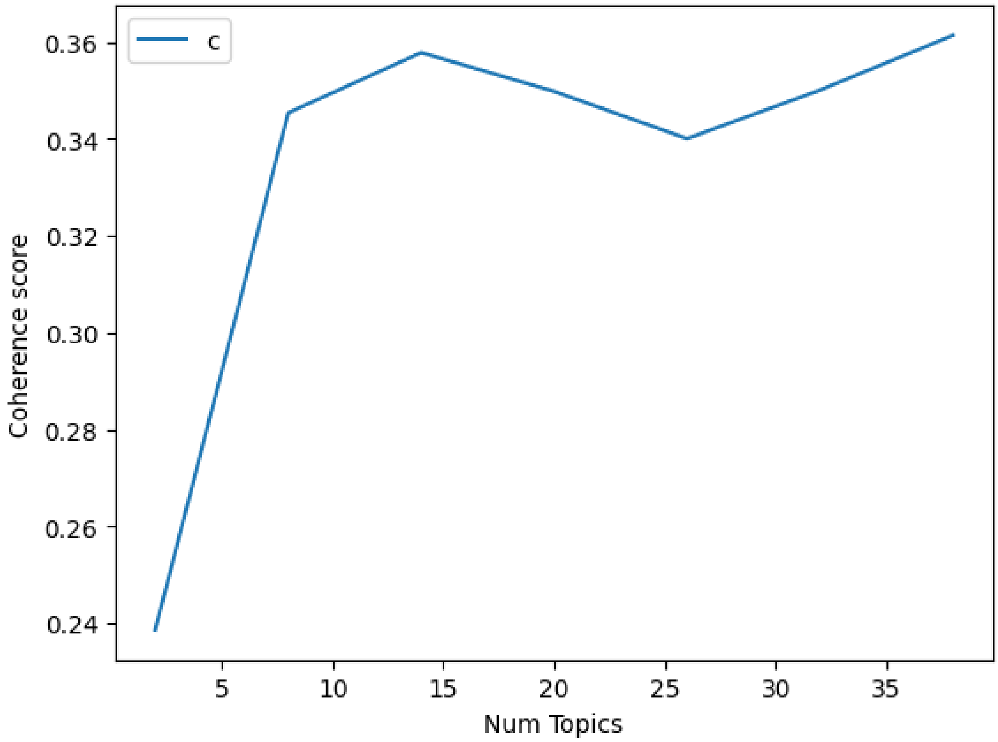

Figure 22: Coherence Score vs Number of Topics

Beyond 10 topics, and around 20 topics, the coherence score stabilizes, hovering consistently around a value of 0.32 and 0.34. This plateauing effect suggest addition of more topics may not yield significant improvements. As the number of topics increases from 20 to 25, there is a minor dip and rebounds at 30. Beyond 30, the coherence score remains relatively stable, suggesting that even with addition of more topics, the overall quality and clarity remain constant.

Table 8: Top topics from the LDA Analysis

Topic #	Topics (Inferred)	Words
1	Engineering/Project Management	Engine, project, aircraft, facility, time, process
2	Climate/Humanitarian	Food, home, temperature, device
3	Renewable/Infrastructure	Energy, build, satellite, beam, renew
4	Industrial Engineering	Pallet, conveyor, lift, dryer, engine, sensor
5	Urban Transportation	Drive, park, traffic, drone, access
6	School projects/global sustainability	Water, project, student, vehicle, book, world
7	Production/Product Design	Char, manufacture, submarine, device, company, product
8	Consumer Products	Need, product, user, cell, kayak, cloth

Table 8 shows the top words and inferred topics using the LDA analysis.

The Hierarchical Dirichlet Process (HDP) model is an extension of the Latent Dirichlet Allocation (LDA) method, offering an additional advantage of determining the optimal number of topics without pre-specifying them. The HDP results uncovers some of the underlying themes in the given dataset, providing valuable insights into the prevalent subjects. The coherence score, a measure of quality of topics, is found relatively low at 0.29, however, the results provide a secondary interpretation of the LDA analysis. The optimal topics identified by HDP are 100 topics which are significantly higher than the LDA analysis. There are several distinct themes that emerge from the HDP model. As seen in Table 9, the group of top words hint at 8 different themes.

Table 9: HDP Top Words

Topic	Top Words
1	speed, part, place, final, experiment, area, team, include, build
2	water, cost, area, build, capability, determine, process, operation
3	think, environment, limit, test, solution, team, impact
4	environ, travel, affect, speed, complete, maximum, power, model
5	reduce, best, come, process, hour, make, place, allow, provide
6	lead, water, final, go, speed meet, build, have, power, change
7	think, differ, increase, area, weight, maximum
8	want, size, affect, place, product, user, efficiency, lead

1. Topic 1 (Operational Efficiency): The terms in topic 1 are “speed”, “team”, “part” indicating a theme of operations, related to operational efficiency.
2. Topic 2 (Resource Management): Keywords suggest a focus on resources around water, building and cost.
3. Topic 3 (Environmental Impact): Focuses on environmental impact, with terms "affect", "solution", and "team" suggesting both environmental concerns and outlets for solutions.
4. Topic 4 (Power and Energy): The keywords suggest themes surrounding power and energy. Prominent terms like “environment”, “travel”, “power”.
5. Topic 5 (Process Optimization): The keys words hints at different facets of process, optimization and operationalization.
6. Topic 6 (Performance and Efficiency): Focuses around efficiency. Keywords like "power”, "change", and "speed" revolve around everyday environmental efficiency or performance.
7. Topic 7 (Variability and Parameters): Keywords suggest theme of device operation, with a possibility of topics on development of device or large-scale production.

8. Topic 8 (User-Centric Operations): Deals with aspects of user-oriented operation, words include “want”, “size”, “efficiency”.

Incorporating GSDMM model for further analysis of the problem statements has been instrumental in identifying latent patterns and topics. GSDMM was deployed to unearth potential clusters present within the dataset. The outcomes of the clustering technique are present in the Table 10 with inferred themes developed from the top words in each cluster.

Table 10: GSDMM Clusters and Top words

Topic	Themes (Inferred)	Top Words
1	Engineering Requirement	'engine', 'need', 'product', 'require', 'time'
2	Rover Mobility	‘terrain', 'rover', 'lift', 'need', air'
3	Space Exploration	'satellite', 'rocket', 'deploy', 'time', 'launch'
4	Security and Access	'door', 'food', 'people', 'lock', 'need'
5	Water Usage	'water', 'need', 'able', 'dish', 'marker'
6	Thermal	'heat', 'pool', 'temperature', 'grill', 'water'
7	Device Operation	'device', 'run', 'opener', 'model', 'conveyor'
8	Product Packaging	'product', 'company', 'vinyl', 'package', 'pfas'
9	Customization	'display', 'device', 'long', 'custom', 'shoe'
10	Fluids	'pump', 'tank', 'pipe', 'feet', 'water'

1. Topic 1 (Engineering Requirement): Revolves around requirements, particularly associated with specific product need. Keywords like "time", "need" suggest management.

2. Topic 2 (Rover Mobility): Keywords suggest a focus on challenges and mechanics related to rover movement and functionality on varied terrain.

3. Topic 3 (Space Exploration): Focuses on space exploration, with terms "satellite", "rocket", and "lift" suggesting both space technology and manufacturing advancement.

4. Topic 4 (Security and Access): The keywords suggest themes surrounding safety, accessibility, and adjacent to control mechanisms. Prominent terms like “door”, “people”, “lock” suggest security and home-based technologies.
5. Topic 5 (Water Usage): The keys words hints at different facets of water consumption, utility and management.
6. Topic 6 (Thermal Management): Focuses around temperature control. Keywords like "heat", "pool", and "grill" revolve around everyday environment or equipment.
7. Topic 7 (Device Operation): Keywords suggest theme of device operation, with a possibility of topics on development of device or large-scale production.
8. Topic 8 (Product Packaging): Deals with aspects of project management, cost evaluation, and tools used in engineering projects.
9. Topic 9 (Display and Customization): The top words indicate some form of customization to an existing product or technology.
10. Topic 10 (Fluids): Keywords like "tank", "pump", and "water" indicate topics related to fluid mechanics and also lean to a traditional academic problem.

The coherence score for the three model are shown in Table 11. indicating GSDMM have a higher coherence score of 0.53, suggesting the model is the most effective of the three at generating coherent topics. A high coherence score indicates the words within a topic are more semantically related.

Table 11: Model and Coherence Score

MODELS	Coherence Score
Latent Dirichlet Allocation	0.46
Hierarchical Dirichlet Process	0.30
Gibbs Sampling Dirichlet Mixture Model	0.53

These results help in the selection of the best topic modeling technique, GSDMM is the preferred model in terms of the coherence score. Coherence scores play a crucial role in validating the quality of topic models, as they directly impact the usability of the generated topics.

6.2 PROBLEM EVALUATION

Phase 2 of the research study entails rating the 177 problem statements on 2*2 design dimension scale. The problem statements are a direct result of phase 1: problem formulation study. The 177 problem statements were divided among 12 raters representing the "experts" in the field. Thus, each problem statement is rated by 3 raters. In the quest to understand the intricate correlation between the constraints and social value of problem statements, a comprehensive statistical analysis is presented in this section. Each problem statement holds unique characteristic as they are student generated problems with a wide range of topics and interest. The primary objective of this study is to identify patterns, similarities, or dissimilarities in the dataset and plot them on the design dimension scale. The results for Phase 2 are discussed in two parts:

1. All Data: The overview of all the data points
2. Agreement: Data points with rater's agreement

6.2.1 All-Data

Social Value is plotted on y-axis and Constraint is plotted on x-axis. Average z scores. The scatter plot shows the natural distribution of problems and segmented into four clear quadrants.

Figure 23 displays a scatter plot of ‘All-Data” points i.e. average z-scores of 177 problem statements.

Quadrant 1 (Q1) - High Constraint and High Social Value: The first quadrant is represented by blue dots exhibiting both high constraint and social values of a problem statement. There is a dense congregation of points in the Q1 especially closer to the center region, suggesting a significant number of problems hold considerable social importance despise having high constraints.

Quadrant 2 (Q2) - Low Constraint and High Social Value: The second quadrant represented by orange dots identifies problems with high social value but fewer constraints. The distribution is more scattered in Q2 region compared to Q1, a notable cluster is observed towards the higher social value axis.

Quadrant 3 (Q3) - Low Constraint and Low Social Value: Represented by the grey dots, this quadrant highlights problem statements with low constraints and low social value. A uniform distribution is observed in Q3, with some closer to the center.

Quadrant 4 (Q4) - High Constraint and Low Social Value: The yellow dots in Q4 denote problems with low social importance but high constraints. The Q4 region shows a significant number of points clusters in the mid to higher constraint levels suggesting problems with very low societal value.

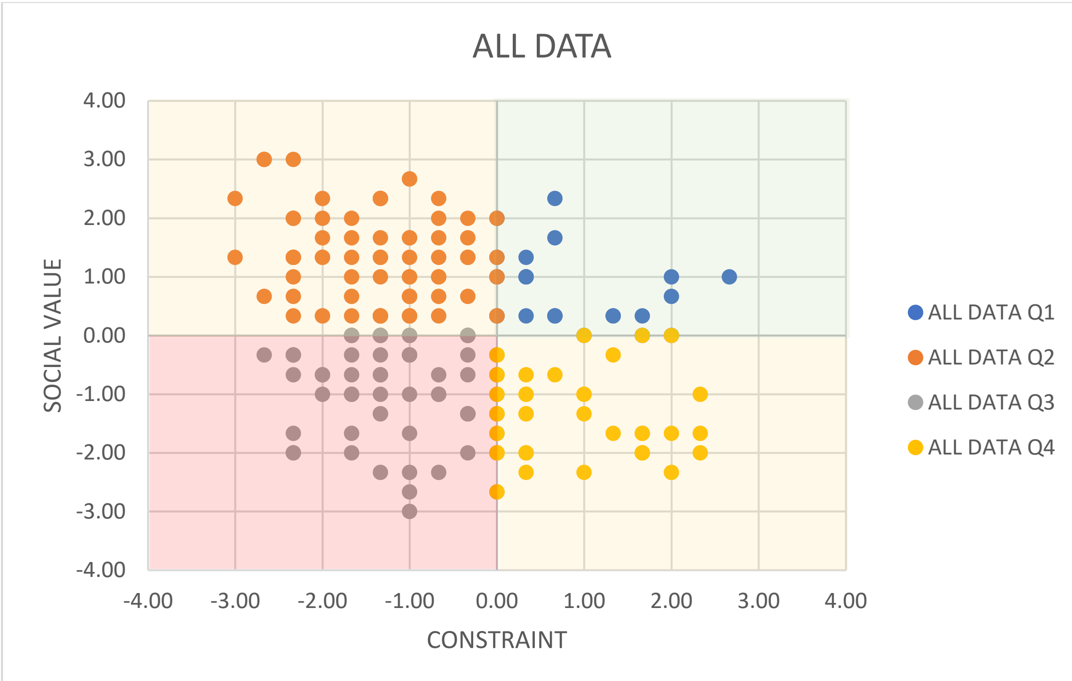

Figure 23: Scatter Plot of All-Data

As seen in Figure 24, a noticeable inflection is seen around k=4 cluster mark. This suggest that increasing the number of clusters beyond four may yield significantly better outcome.

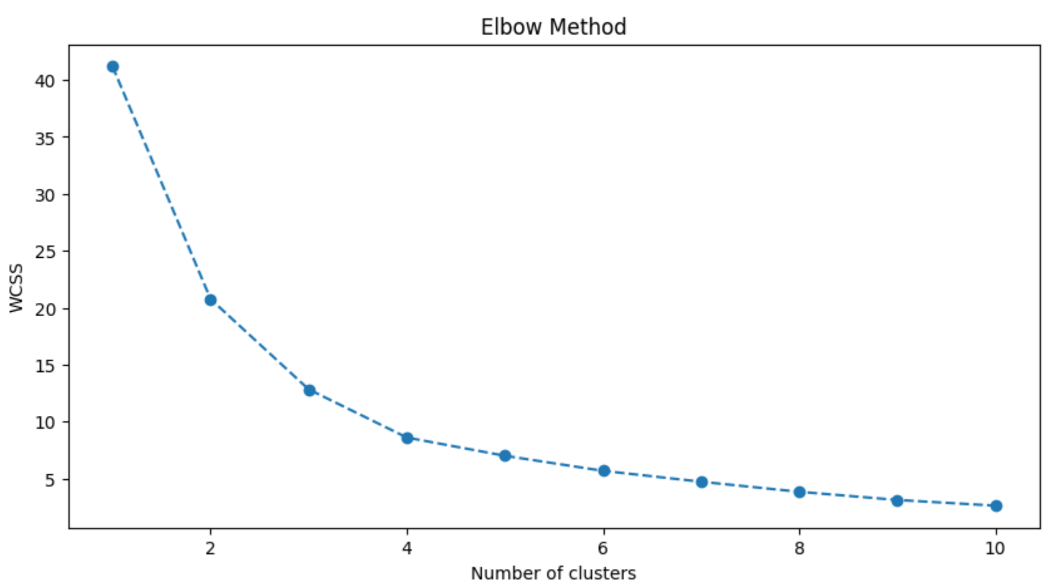

Figure 24 : Elbow Method for All-Data

From the insights of Elbow Method, K-means clustering analysis is performed on the All-Data dataset. For K-means clustering with k=4, the results as shown in Figure 25 four distinct cluster for constrains and social value are obtained.

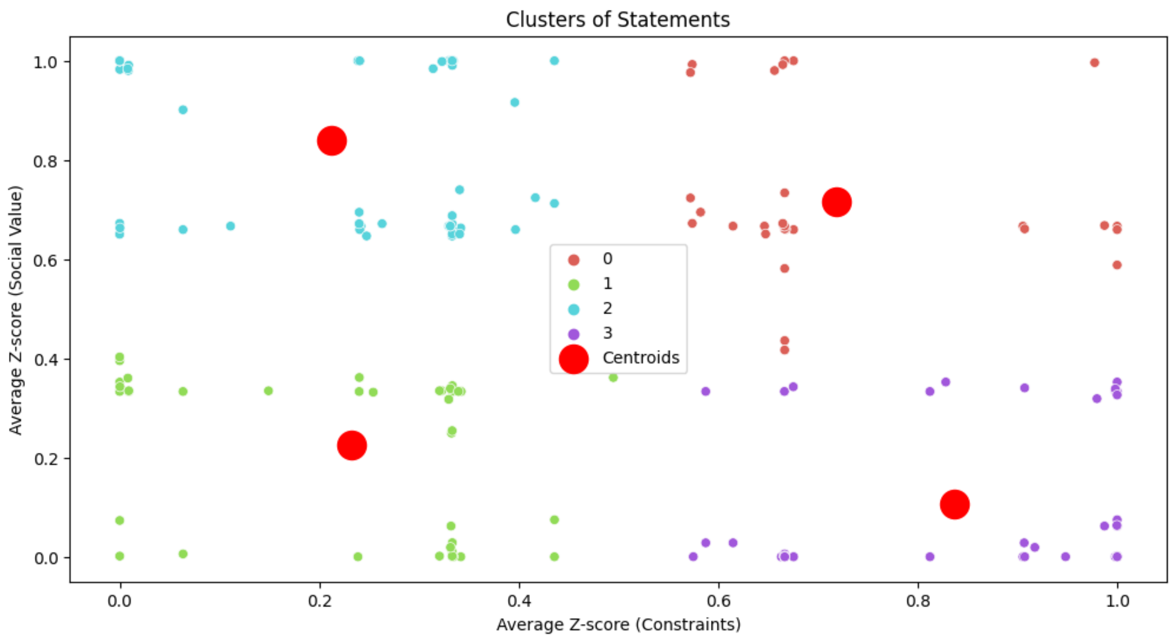

Figure 25 : K-means Clustering for All-Data

Centroids are the centers of clusters represented by large red dots, serving as a reference point for the average location of each cluster. Cluster 0 (denoted with cyan color dots) predominately populates the top left quadrant. The group shows datapoints high in social value and lower constraint. Centroid 1(denoted by green color dots) is present in the lower left quadrant, where the data points have lower constraints and lower social value. Cluster 2 (denoted with red color dots) spans across a broad range but dominant in the right half of the plot. These indicate datapoints with higher constrains. And lastly Cluster 3 (in purple) covers the top right quadrant with high constraint and high social values.

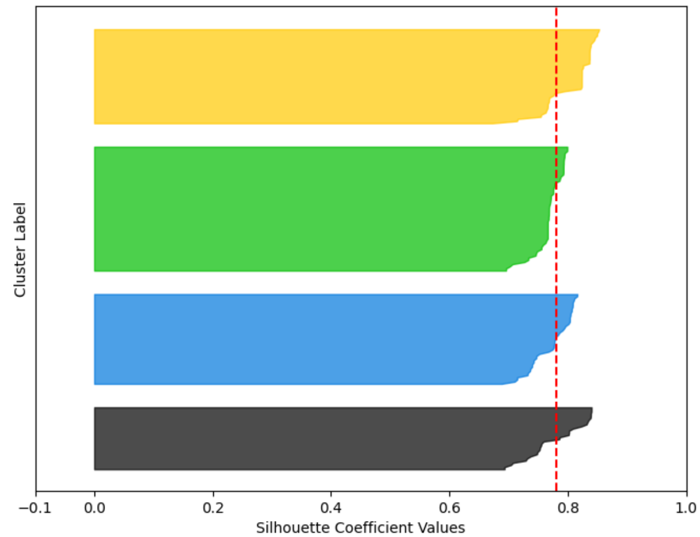

Figure 26: Silhouette Score for All-Data

As seen in Figure 26, the average silhouette score for All-Data clustering is 0.781. The colors in the silhouette plots represents different clusters that have been identified in a dataset, where each bar represents an individual data point.

6.2.2 Agreement

To explore the dynamics of agreement between the rater and within the dataset, a multi-faceted approach is employed. The intent of this approach is capturing the inherent structure, relationship and variability of agreement data thus enabling informed decision and insights into the *Problem Evaluation Study*.

Table 12 shows the number of problems statements agreed among raters on the constraint and social value design dimensions. Raters had the highest agreement on the social value scale with 85 problem statements agreed upon. And 68 problem statement agreed for their constraints. And 36 problem statements had rater's agreement on all design dimensions which are considered as final results for this study.

Table 12 : Agreement Count and Overlap

	Constraints	Social Value
Agreement	68	85
Overlap	36	

First a z-score of all the agreed problem statements is plotted as seen in Figure 27. The X-axis showcase "Constraints" and Y-axis showcase "Social Value." Utilizing z-scores data provides a standardized way of understanding the distribution of agreement data.

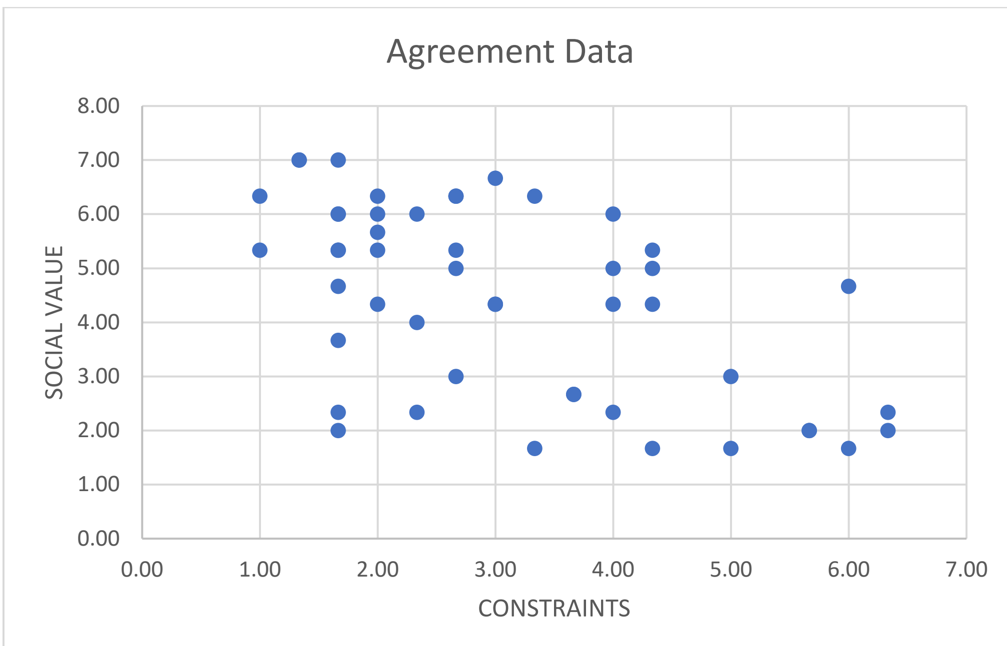

Figure 27: Scatter Plot of Agreement Data

Figure 28 titled "Agreements" shows the data points divided across the four quadrants. The constraints and social value are divided across ranges -4.00 to 4.00/ The bi-dimensional spaces helps in visualizing the relationship between the two design dimension metrics for each quartile of agreement.

1. Q1: High Constraint and High Social Value

   Denoted by blue markers, predominately reside in the central region with slight emphasis towards positive constraint values. The results of agreement of Q1 datapoints indicate a balanced view on constraints with a moderate social value score. There are relatively few data points Q1.

2. Q2: Low Constraint and High Social Value.

   The quartile showcases data points colored in orange mainly in the positives of both axes. Thus, suggesting that majority of data points lean towards higher constraints and a more positive social value.

3. Q3: Low Constraint and Low High Social Value.

   Scattered in the bottom-left quadrant, depicts negative values for both metrics. These agreements are associated with both low social value and low constraint of given problem statements.

4. Q4: High Constraint and Low Social Value

   Denoted by yellow markers, the agreements classified under Q6 predominately fall in the positive constraint region and extend across a wide range on social value axis. This spread indicates variability in the social value aspect of these agreements but a consistent lean towards positive constraints.

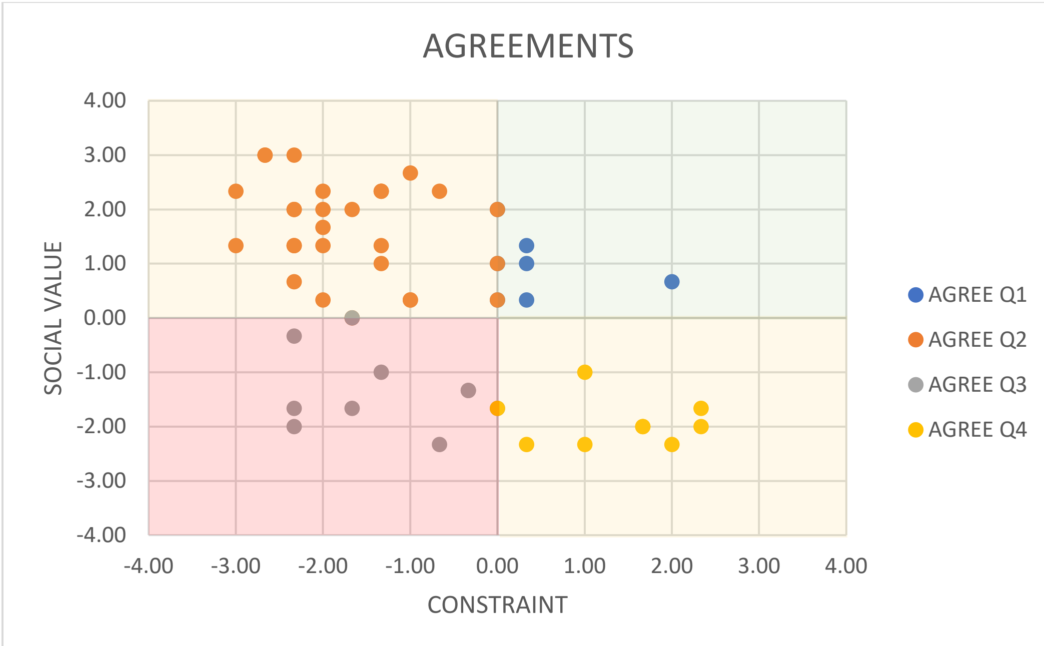

Figure 28: Agreement Data in Quadrants

The Z-score plot for "Agreements" presented in the results, offered a visual representation of the dispersion of problem statements across two design dimensions: constraints and social value. Each point represented problem statement's relative position based on average scores from two scales. While the z-scores plot provided a descriptive outlook of the data, it didn't inherently categorize or group the problem statements into meaningful clusters. The data's distribution suggested potential underlying patterns that might be present, indicative of similar characteristics or relationships among certain problem statements. K-means clustering was employed to delve into the suggested potential. K-means clustering technique portioned the data into groups based on similarity. By applying this method to the z-scores of the problem statements, the goal is to uncover naturally occurring groupings in the data. This aids in a more structured analysis of the dataset.

The ICC analysis dives into the consistency and reliability of the ratings for the agreement data. By gauging the extent of data correlation, ICC offers insights into the level of agreement among rater and reliability of the rating per dimension. It is a key metric for ensuring the robustness of findings. Table 13 represents the Interclass Correlation Coefficient (ICC) values for assessing the reliability of ratings for constraints. The ICC value for single rater absolute is 0.259, with an F-statistic of 2.049 (df1 = 176, df2 = 354). The p-value is statistically significant at 0, indicating the variability between constraints is indeed greater than the variability within constraints. The 95% confidence interval for the ICC value ranges from 0.17 to 0.361. The ICC values of single random raters is 0.263 with an F-statistic of 2.094 (df1= 176, df2 =352), this consistency is slightly higher than the single rater absolute. The confidence interval ranges between 0.17 and 0361. For the single fixed rater, ICC value is 0.267 and an F-statistic of 2.094 (df1=176, df2=352), suggests a marginal increase in agreement among the raters. The confidence interval lies between 0.17 and 0.361. For the ICC1k category, ICC value is substantially higher at 0.512, reflecting a higher level of consistency when considering the average ratings. The F-statistic remains at 0.249 (df1=176, df2=354), and the confidence interval lies between 0.37 and 03621. The consistency level rises for ICC2k with a value of 0.517. F statistic is 2.094 (df1=176, df2=352) with a consistent p value of 0. The confidence interval lies between 0.38 and 0.63. And lastly, the ICC value for ICC3K i.e. Average fixed raters is 0.523 with an F-statistic value of 2.094 (df1= 176, df2 = 352) with a p value of 0. The confidence interval lies between 0.39 and 0.63. Overall, the single rater categories demonstrate modest ICC values, indicating moderate agreement. The average rater's categories showcase higher ICC values, emphasizing improved consistency. The statistically significant p-values across all categories confirm the reliability of the observed ICC measurement for constraints.

Table 13 : ICC for Constraints

Type	Description	ICC	F	df1	df2	pval	CI95%
ICC1	Single raters absolute	0.259	2.049	176	354	0	[0.17, 0.36]
ICC2	Single random raters	0.263	2.094	176	352	0	[0.17, 0.36]
ICC3	Single fixed raters	0.267	2.094	176	352	0	[0.17, 0.36]
ICC1k	Average raters absolute	0.512	2.049	176	354	0	[0.37, 0.62]
ICC2k	Average random raters	0.517	2.094	176	352	0	[0.38, 0.63]
ICC3k	Average fixed raters	0.523	2.094	176	352	0	[0.39, 0.63]

Table 13 delineates the Interclass Correlation Coefficient (ICC) values pertinent to the reliability of ratings centered around social value. The ICC metrics shed light on the internal consistency or agreement of measurements within the specified groups. The ICC value for single rater absolute is 0.305 with a F-statistic of 2.319 (df1= 176, df2 = 352) and significant p-value of 0 confirming the premise that the variability between different social values exceeds the variability within the same social values. The ICC2 of single random raters demonstrates ICC value of 0.31 and F-statistic of 2.394 (df1= 176, df2 = 352), the consistency observed in this category is slightly heightened when juxtaposed against the single raters absolute. The confidence interval for this measurement is 0.22 and 0.41. The single fixed raters (ICC3) category has an ICC value of 0.317 with a minor increment in agreement from the previous categories. The associated F-statistic is 2.394, and the confidence interval encompasses a range from 0.22 and 0.41. The ICC value for the average raters absolute is 0.569, indicating a pronounced consistency when evaluating the average ratings. The F-statistic remains consistent at 2.319 (df1 = 176, df2 = 354) with the confidence interval extending from 0.45 to 0.67. For ICC2k, the ICC value is 0.575, the consistency in this category is marginally superior to the average raters absolute. The concurrent F-statistic is 2.394, and the confidence interval between 0.45 and 0.67. The ICC value for average fixed raters is 0.582, suggesting most formidable agreement or consistency among averaged fixed raters. The f-statistic is recorded at 2.394 with the confidence interval range from 0.46 to 0.68.

Table 14: ICC for Social Value

Type	Description	ICC	F	df1	df2	pval	CI95%
ICC1	Single raters absolute	0.305	2.319	176	354	0	[0.21, 0.4]
ICC2	Single random raters	0.31	2.394	176	352	0	[0.22, 0.41]
ICC3	Single fixed raters	0.317	2.394	176	352	0	[0.22, 0.41]
ICC1k	Average raters absolute	0.569	2.319	176	354	0	[0.45, 0.67]
ICC2k	Average random raters	0.575	2.394	176	352	0	[0.45, 0.67]
ICC3k	Average fixed raters	0.582	2.394	176	352	0	[0.46, 0.68]

The single raters' category for the social value agreement indicate modest ICC values, hence moderate reliability. The unanimous statistical significance of p-values across all categories corroborates the dependability of ICC measurements in the context of social value.

The visualization of problem statements provides critical insights into the intricate dynamics between constraints and social values across the defined agreement quartiles. The distinct clustering pattern underline individual attributes and offer an understanding on the multi-faceted nature of agreements. To further explore this, a k-means clustering technique was employed to segment the agreement data based on variables "constraints' and "social value".

The Elbow Method is first employed to visualize the Within-Cluster Sum of Squares (WCSS) against the number of clusters. This technique helps in determining the point where the rate of decrease sharply changes suggesting a balance between precision and computational cost. As illustrated in Figure 29, the WCSS begins to level off after n=4 clusters, hinting the optimal number of clusters.

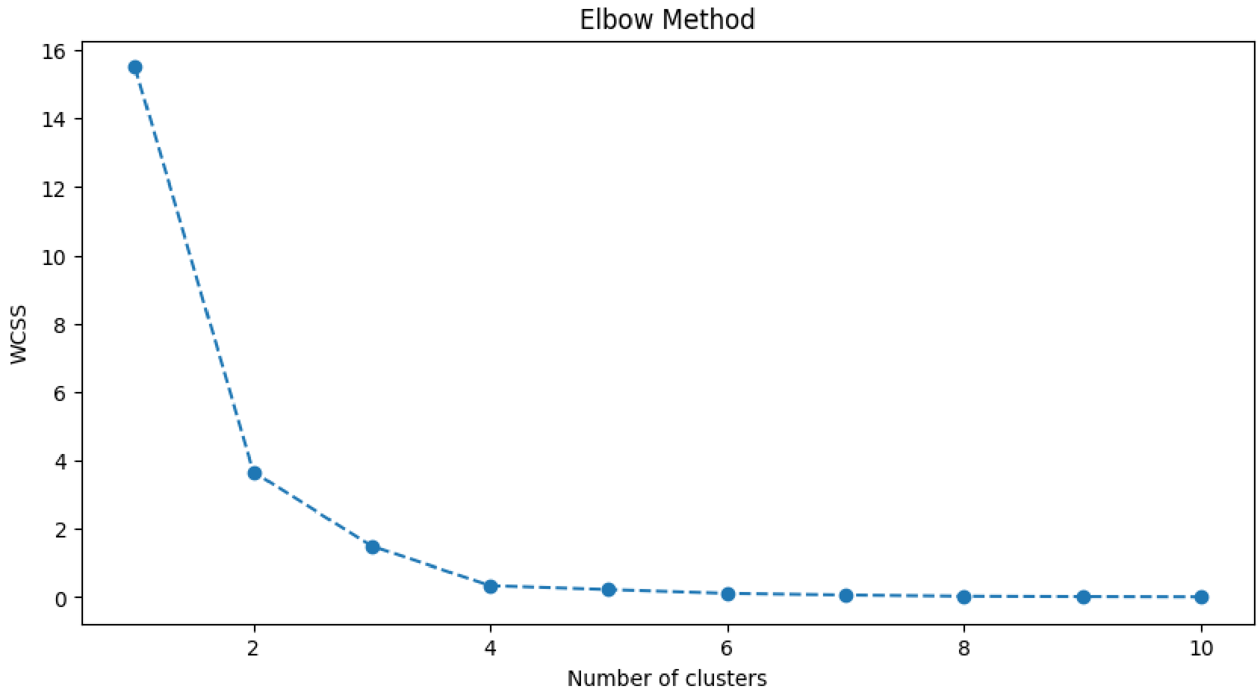

Figure 29 : Elbow Method for Agreement Data

The K-means clustering scatter plot represents the agreement data points on two variables: average z-score (constraints) on the x-axis and average z-scores (social value) on the y-axis. As seen in Figure 30, K-means clustering results for n=4. The centroids represent the mean value of the data points in each cluster. Their position offers a central reference point for interpreting the overall behavior of the statements within the cluster.

Cluster 0: Denoted by orange dots in the upper left corner encompasses statements with lower constraints but higher social values.

Cluster 1: Denoted by the green dots, dispersed in the bottom right quadrant signaling higher constraints but lower social values.

Cluster 2: Denoted by the turquoise dots, this cluster represents the statements with lower constraints.

Cluster 3: And lastly cluster 3, denoted by purple dots, located in the upper right quadrant indicating higher constraint and social value scores.

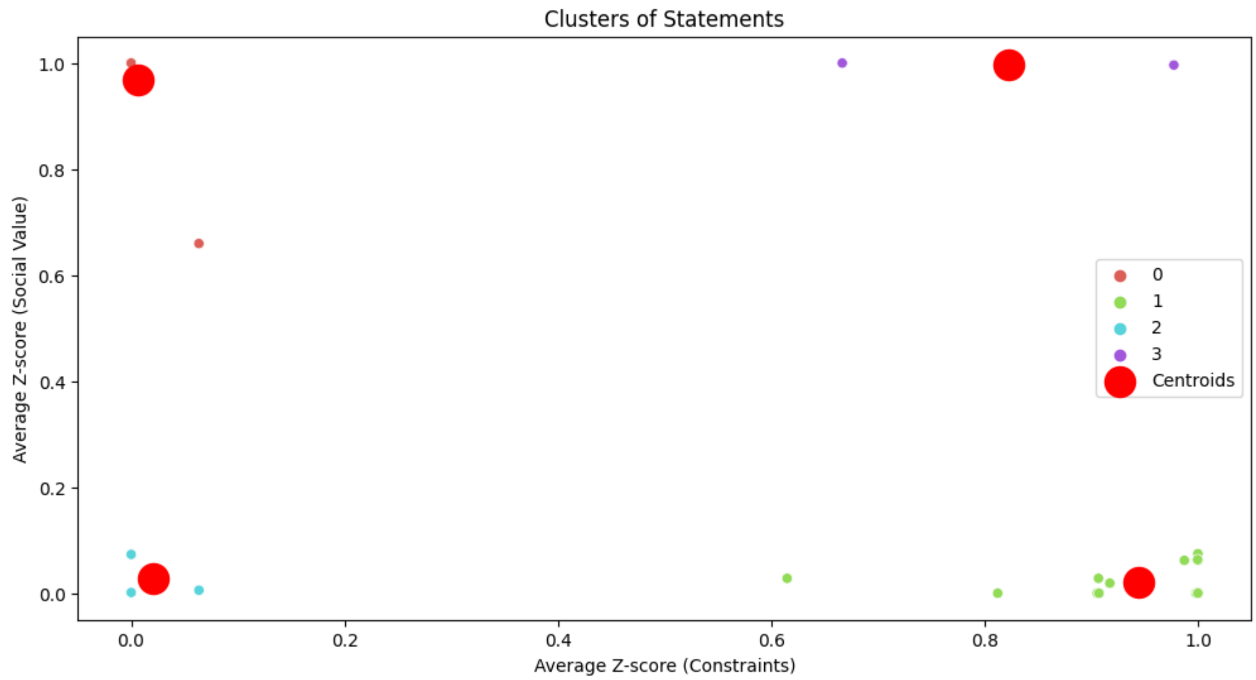

Figure 30: K-means clustering for Agreement Data

Post k-means clustering, the silhouette average score is utilized to quantify the quality of clusters formed. The Silhouette score range between -1 and 1, where a high value indicates well separated clusters. Table 14 displays silhouette scores for the different cluster numbers:

Table 15 : Silhouette Scores

Number of clusters	Silhouette score
n = 2	0.722
n = 3	0.799
n = 4	0.943
n = 5	0.926

It is evident that the silhouette score is highest at n=4 reinforcing the choice of four as the optimal number of clusters.

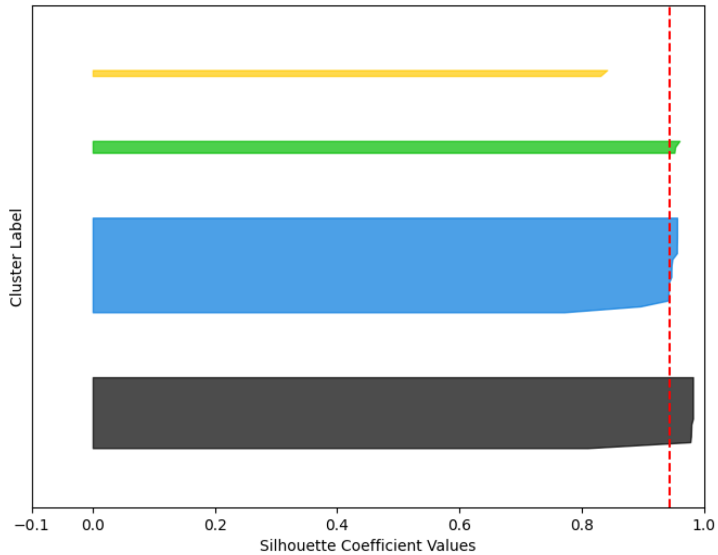

Figure 31: Silhouette Score for Agreement Data

The average silhouette score is 0.943 for the selected k-means clustering as seen in Figure 31. Taken together, the elbow method and the silhouette average analysis converged on the decision that dividing the data into four distinct clusters is the most appropriate approach. The clusters formed at n=4 not only minimized the within-cluster variance but also ensured demarcation between clusters, as evident with the high silhouette score.

The qualitative analysis shows the emergence of themes such as "expert's experience," "motivation," ill-defined," and "relatable. Experts found the questions to be ill-defined and vague many times, thus hinting at the outliers that did not find agreement on the two design dimension constraints. The problem statements were also found to be motivating as they highlight not only everyday issues but also big engineering challenges. Experts found the problem statements to be relatable. Expert's personal experiences played a role in identifying the familiarity in certain problem statements and relatability.

6.3 PROBLEM PREFERENCE

6.3.1. Preference – Design Dimensions

The analysis evaluates the relationship between preferences, design dimensions and gender. As seen in Table 15. The model intercept, represents the baseline preference when all other predictors are zero, is statistically significant at 2.69354 ($t = 15.29$, $p < 0.001$) thus suggesting a robust baseline for the model. The coefficient of social value is 0.08208 and approaches statistical significance ($t=1.951$, $p=0.051$). This effect suggests that social values indeed play a considerable in shaping preferences. The model shows a negative relationship between constraint and preferences when considered against gender. Female students showcase a negative reaction to constraints of a problem in comparison to their male counterparts. The gender variable is statistically significant with a coefficient of 0.78089 ($t=2.718$, $p=0.00685$). The interaction between gender and constraint is statistically significant with a coefficient of -0.14947. The findings highlight the intricate interplay between social values, gender, and constraints in shaping the preferences towards a particular design. Social value significantly influences preferences, this effect further modulated by the gender, particularly in context of constraints.

Table 16: Coefficient for Design Dimension and Preference

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	2.69354	0.17611	15.294	< 2e-16 ***
Social	0.08208	0.04206	1.951	0.05173
Gender	0.78089	0.28729	2.718	0.00685 **
Gender: Constraint	-0.14947	0.06467	-2.311	0.02133 *

While examining the relationship between EEG frequency and preferences, two statistical AIC models are considered for assessment. The first model incorporates the interactions between different brain waves and potential predictors. The second model is focused on the relationship and interaction between brain waves and problem preferences, i.e., the scores for each quadrant.

Table 17 : Coefficient for Interactions

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	3.20406	0.13983	22.914	< 2e-16 ***
Constraint: Delta	0.02651	0.01434	1.848	0.068589
Constraint: Theta	-0.15007	0.05733	-2.617	0.010765 *
Theta: Gender	0.16572	0.06477	2.559	0.012575 *
Gender: Beta	-0.50042	0.13806	-3.625	0.000532 ***
Gender: Gamma	0.23592	0.06947	3.396	0.001109 **
Gender: Social	0.40340	0.24785	1.628	0.107919

As seen in Table 16, the coefficients represent the relationship between the predictor and the response value, and controlling all the remaining variables in the model. The 'estimate' informs the amount of change in response variable for one-unit increase in the predictor, assuming all other variables remain constant. AIC Model with Interaction Effects:

1. Intercept: The model yields a significant intercept (estimate = 3.020406, t = 22.914, p < 0.001), stating that in the absence of predictors, the expected preference value is approximately 3.20406.
2. Constraint – Delta: The interaction displays a marginally significant relationship between preference (estimate = 0.02651, t = 1.848, p= 0.0686). The positive estimate suggests the effect of 'constraints' on preference increases as 'delta' increases.
3. Constraint - Theta: There us a significant negative association between the constraint and theta values with an estimate of -0.15007 (t = -2.617, p = 0.0108). This indicates the combined effect of 'constraints and theta tend to decrease preference prediction.

4. Theta – Gender: The is a positive significant relation between the interaction of theta values and the gender inputs and preferences. Estimate value of 0.016572 ($t = 2.559$, $p = 0.0126$). This result indicate that ‘theta’ has an impact on preference across al the genders.
5. Gender – Beta: A significant negative association is observed with an estimate value of -0.50042 ($t = -3.625$, $p < 0.001$). This implies as the ‘beta’ value increases for female population, preferences decreases.
6. Gender – Gamma: A positive and significant ‘gamma’ and ‘gender’ association is observed with an estimate value of 0.23592 ($t = 3.396$. $p = 0.0011$), indicating a differential effect of ‘gamma’ on preference depending on gender.
7. Gender – Social: No significant interaction is observed between ‘Gender’ and ‘Social’ variables on predicting preferences.

6.3.2. Brain Frequencies and Design Preferences

AIC Model with Direct Relationship between Brain Waves and Preferences is delineated in Table 17. The Coefficients for the Delta, Theta and Gamma frequencies are observed to decipher the relationship between frequencies and participant’s preferences for various design problems. The Intercept with a coefficient of 2.89, signifies the expected preference score when all the other predictors are held constant. The intercept is significant at the 1% level ($p<0.01$), suggesting a robust association with participant’s preferences.

Table 18 : Coefficient for Brain waves

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	2.89967	0.30469	9.517	1.37e-14 ***
Delta	0.02443	0.01337	1.827	0.0716
Theta	-0.12903	0.05573	-2.315	0.0233 *
Gamma	0.04077	0.02575	1.584	0.1175

The Theta coefficient is -0.129. The negative value for theta indicates that the likelihood or preference of participants to work on the design problem decreases. The relationship is significant at the p value of 0.02. The Delta and Gamma brain waves exhibit coefficients of 0.0244 and 0.0407, respectively. These values may suggest that as the activities of delta and gamma waves increases, there is a corresponding increasing in the preference score, however not statistically significant. The results underscore that among the three observed frequencies, Theta waves across all the brain regions demonstrate a significant negative relationship with the preferences. The AIC value of the model is 176.75. It is significantly lower than the mean value of 180.33, indicating a good fir.

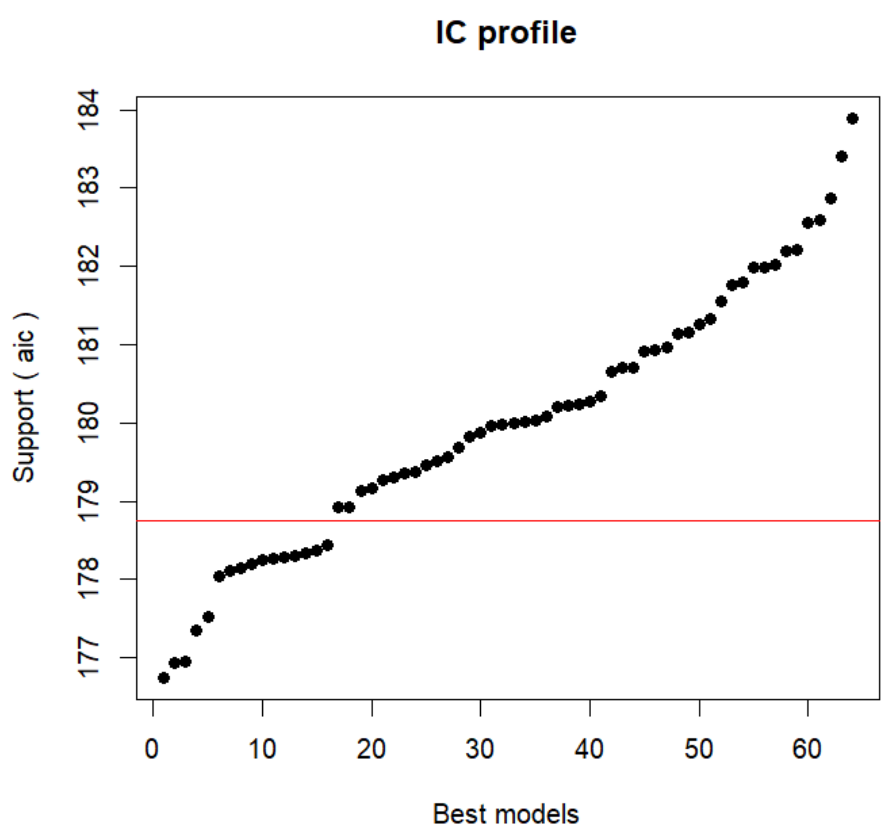

Figure 32: AIC Model for all frequencies

6.3.3. Brain Lobes and Design Preferences:

All the images of brain lobes are attributed to the Society of Neuroscience (2017).

Lobe F

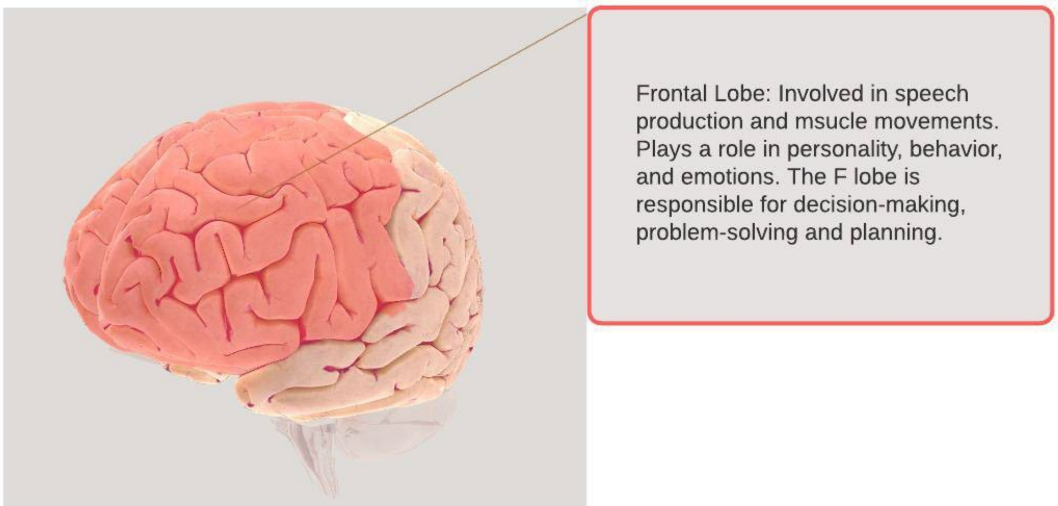

Figure 33: Frontal Lobe

Lobe F plays a pivotal role in a wide array of cognitive and motor functions. It is principally involved in controlling thinking processes, planning, organizing, problem solving and short-term memory within the brain's functional anatomy. As seen in Table 18, the effects of various predictors are observed for Lobe F. The coefficient for delta is 0.11, with a p-value of 0.07, not statistically significant. Alpha waves show a significant negative relationship with preference, indicating decrease in likelihood of problem preference with increase in alpha frequencies. Gamma waves and social values of a problem indicate a positive relation however lacks statistically significant evidence.

Table 19: AIC for Frontal Lobe

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	3.026587	0.309376	9.783	< 4.9e-15 ***
Delta	0.011978	0.006566	1.824	0.07209
Alpha	-0.287597	0.101355	-2.838	0.00584 **
Gamma	0.045533	0.024382	1.868	0.06574
Social	0.251215	0.153702	1.634	0.10636

In summary, Lobe F plays a crucial role in cognitive and motor functions, it's EEG interactions in the context of design problems suggest a nuanced relationship. Alpha frequency is a significant predictor, while delta and gamma lack significant evidence.

Lobe P

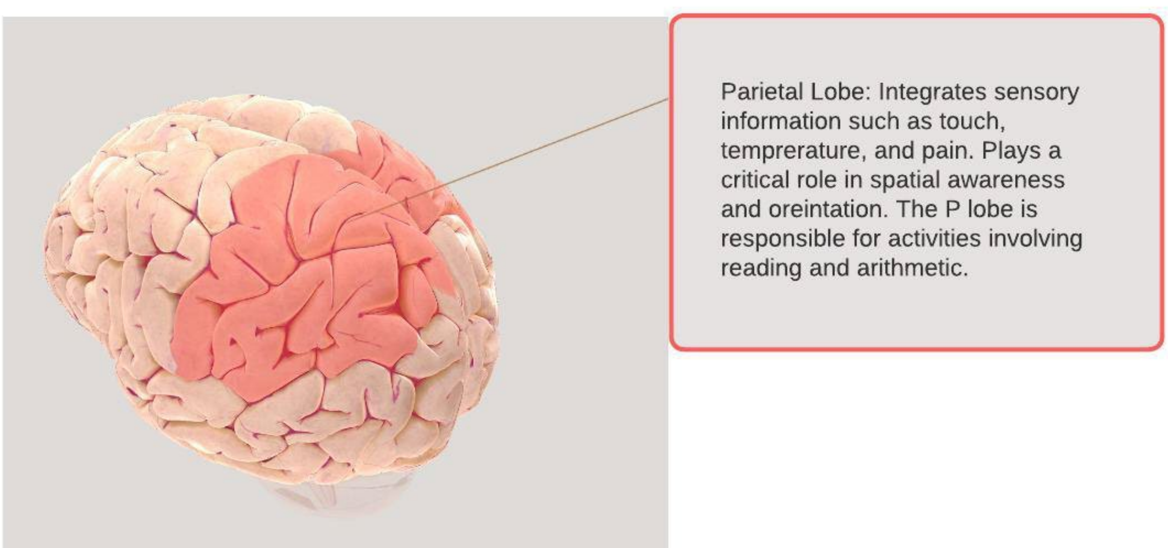

Figure 34: Parietal Lobe

Lobe P is associated with the interpretation of various sensory inputs and perception, such taste, temperature, touch, and working memory. The coefficient for the intercept as seen in Table 19 is 3.008, with a standard error of 0.360 and highly significant p-value. This indicates significant baseline activity in the parietal lobe, when participants are first presented with the design stimuli.

The estimated coefficient for theta frequencies is -0.137 with a p-value of 0.0330 suggesting a negative relationship between theta frequencies and design stimuli. This implies that the decrease in theta activity can impact design preferences. The coefficient for gamma waves is 0.069 with a p-value of 0.0312. The positive relationship indicates the increase in gamma activity can be a predictor for the changes in design preferences.

Table 20: AIC for Parietal Lobe

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	3.00893	0.36016	8.354	2.31e-12 ***
Theta	-0.13707	0.06310	-2.172	0.0330 *
Gamma	0.06939	0.03161	2.195	0.0312 *
Social	0.27591	0.15473	1.783	0.0785

In summary, the theta and gamma waves in the parietal lobe play a significant role in influencing design decision. The trending influence of social dimensions suggests a subtle bias or preference towards design problems.

Lobe O

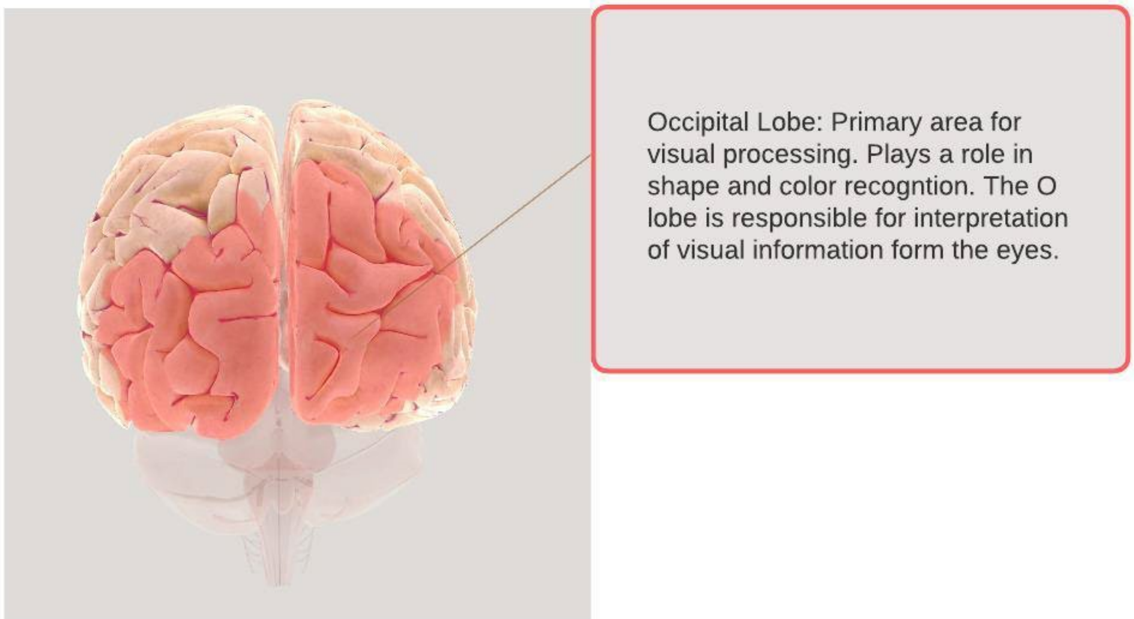

Figure 35: Occipital Lobe

The occipital lobe plays a critical role in processing images and associating visual information with memory. As shown in Table 20, the intercept coefficient is 3.0744 with a p-value of less than 0.05. This signifies a prominent baseline activity in the Occipital Lobe when participants are presented with design stimuli. The coefficient for theta frequency is -0.084, indicating one-unit increment in theta, the expected outcome decreases by about 0.084 at a 10% level. Gamma has a positive coefficient of 0.0156 with a statistically significant p-value of 0.0477. The positive coefficient indicates increase in gamma wave activity with particular design preferences.

Table 21: AIC for Occipital Lobe

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	3.074406	0.307076	10.012	1.58e-15 ***
Theta	-0.084065	0.048890	-1.719	0.0896
Gamma	0.015643	0.007772	2.013	0.0477 *
Social	0.287785	0.155635	1.849	0.0683

The Occipital Lobe indicates gamma waves may have statistically significant influence on design decisions. Additionally, the theta frequencies and social dimension of design problems may have a subtle yet noticeable role in shaping participants' design preferences. The comprehensive analysis of the Occipital Lobe results provides insight into the potential neural mechanisms underpinning design preferences.

Lobe T

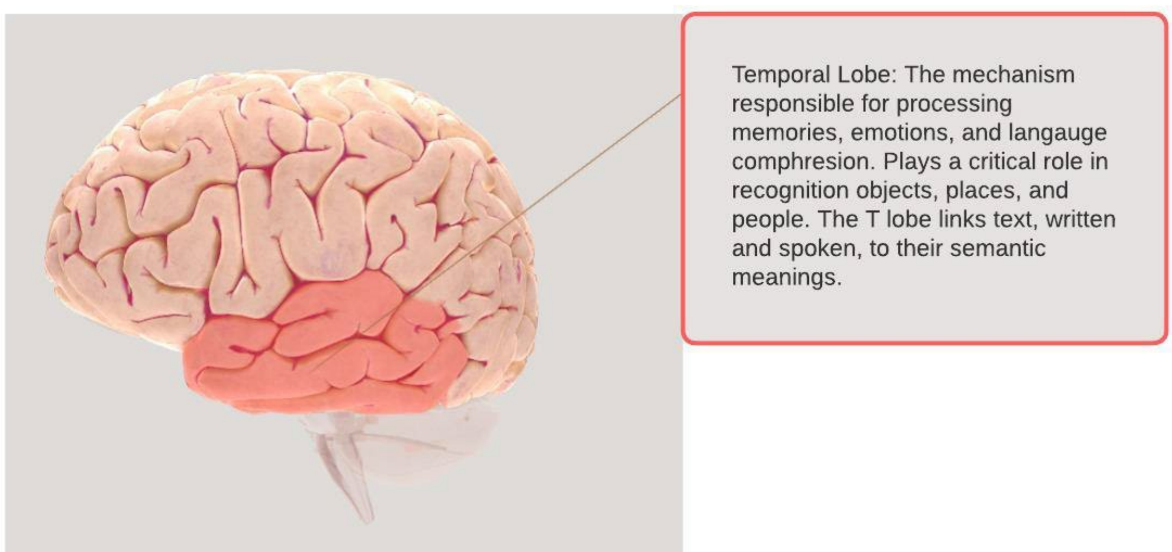

Figure 36: Temporal Lobe

The relation between observed frequencies in Lobe T and its interaction with variables such as preference score and gender are shown in Table 21. The temporal lobe is typically associated with memory and emotional processes. With an estimate value of -0.211 and significant p-value of 0.00159, beta waves have a negative association with the preference scores. As the beta activities increases, the likelihood of participants preferring a design problem decreases. The positive coefficient of 0.0755 suggest that as gamma wave activity in Lobe T increases, there is an increase in preference score. The positive coefficient of 0.3352 and p- value of 0.4497 indicate a statistically significant effect of gender on preferences scores, implying that different genders may exhibit varying preferences when presented with different design problems. And lastly, the intercept shows a statistically significant coefficient (estimate = 3.39).

Table 22: AIC for Temporal Lobe

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	3.39315	0.23036	14.73	< 2e-16 ***
Beta	-0.21178	0.06461	-3.278	0.00159 **
Gamma	0.07553	0.02651	2.849	0.00567 **
Gender	0.33529	0.16443	2.039	0.04497 *
Social	0.26161	0.15246	1.716	0.09029

The IC profile plot displayed in Figure 37, as the “Best models” grows, the support (AIC values) for the model also increases. The most competitive models are within the range of 0-20, with a discernible AIC threshold close to 174.

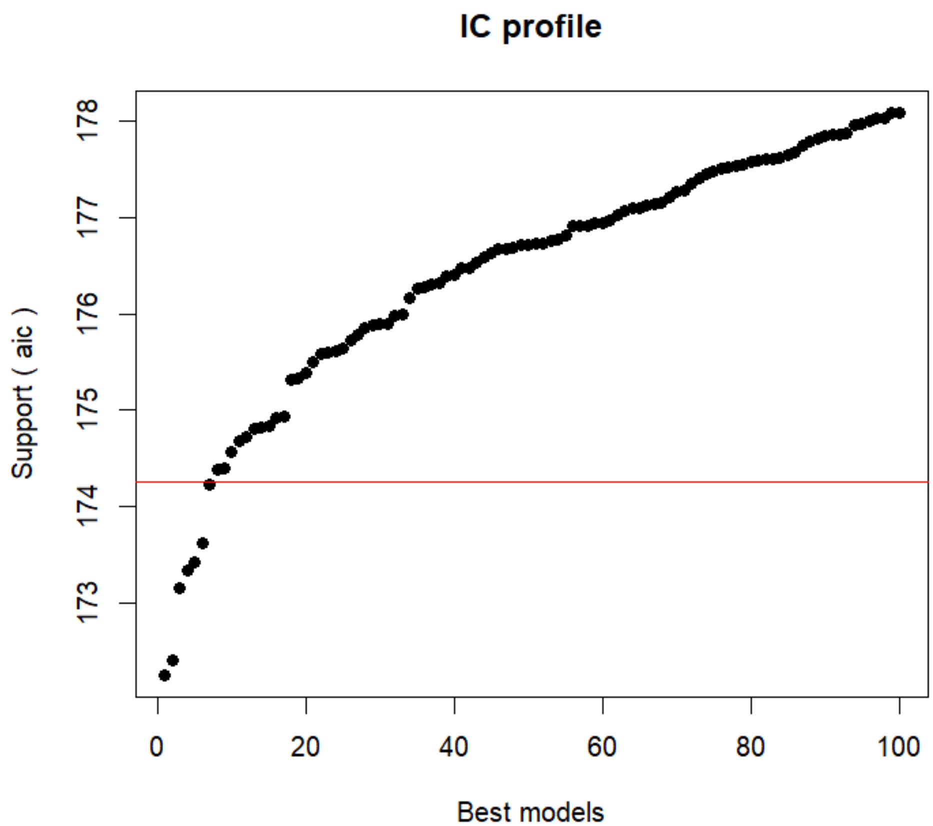

Figure 37: AIC Best Model for Lobe T

A lower value of AIC indicates a better model. After consideration of 250 models for preference prediction concerning design problems based on social values and constraints, the best model identified for preferences in relation to Lobe T is presented by the equation:

$$\text{Preference (Pref)} = \beta_0 + \beta_1 \times \text{Delta} + \beta_2 \times \text{Theta} + \beta_3 \times \text{Beta} + \beta_4 \times \text{Gamma} + \beta_5 \times \text{Gender} + \beta_6 \times \text{Social}$$

The criterion value, a measure of the goodness-of-fit, for the model is 844.863. The mean criterion value is 856.29. Comparing the two values, the model's criterion value is lower than the mean value suggesting the model provides a better fit to the data compared to the average of all the models considered.

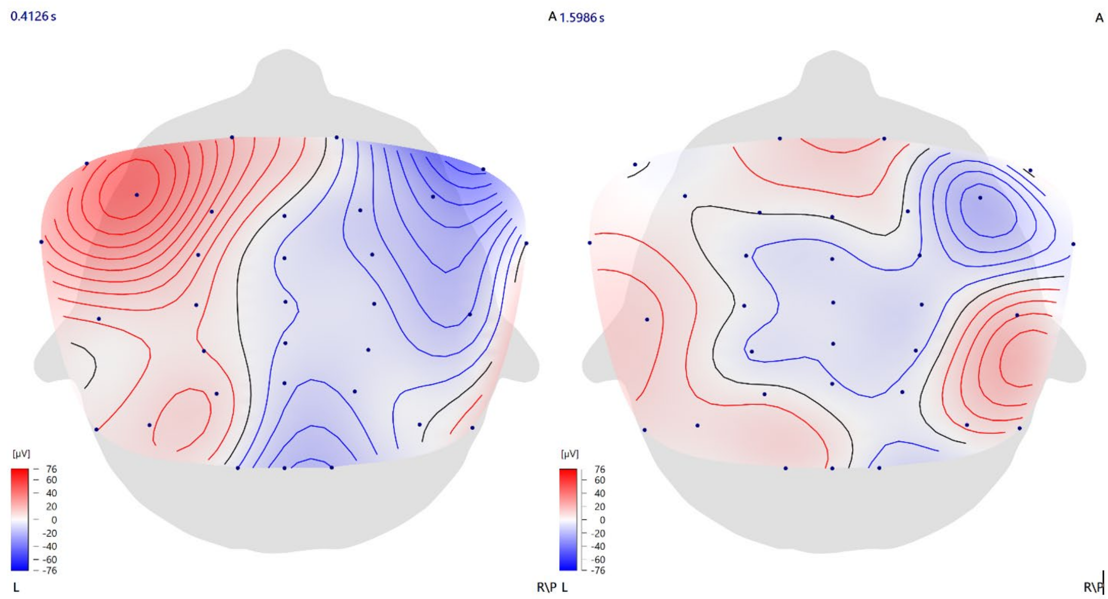

Figure 38: Frequency Contour Map of High and Low Social Value Problems

Figure 38 shows the frequency contour map of a single brain during high social value stimuli and low social value stimuli.

Providing a positive indication of the model's relative quality and potential utility in explaining the response variable. The results revealed that students' preferences are intricately influenced by cognitive and emotional responses, as evidenced by distinct patterns in EEG frequencies. Additionally, notable gender-based differences in preferences emerged, underscoring the importance of incorporating diverse cognitive and emotional considerations into design education.

CHAPTER 7

CONCLUSION AND FUTURE WORK

Phase 1: Problem Formulation Study

The problem formulation study showcases the intricate thought process of the engineering students when formulating design problem statements. Topic Modeling techniques such as Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP) and Gibbs Sampling Dirichlet Mixture Model (GSDMM) incorporated in this study elucidates the underlying themes and topics by providing a glimpse into the general perspective on design along with the trending areas of design challenges identified by an undergraduate student. The application of the three models provided a multi-faceted perspective on the problem statements formulated by students. The analyses reveal a dual influence in these statements, reflecting a synthesis of academic rigor and real-world influence.

The core engineering principles, along with a focus on project and operational management, were prominently featured in the problem statements, as illuminated by the topic modeling analysis. The academic drive, observed in all three models, is indicative of a strong foundational understanding in technical aspects of engineering. However, the influence of socio-environmental contexts is equally compelling. Themes of sustainability and environmental impact consistently emerged, underscoring the students' capacity to intertwine academic learning with pressing global and humanitarian challenges.

Phase 1 findings highlight a paradigm shift in engineering problem formulation, where the emerging generation of engineers exhibits a heightened sense of social awareness. The problems formulated were not only theoretically robust but are also imbued with the complexities of human experience and social consciousness. These findings are critical in understanding the evolving landscape of engineering education and underscore the importance of nurturing an education system that is as responsive to societal needs as it is to academic excellence.

Phase 2: Problem Evaluation Study

In the Phase 2, a comprehensive assessment was performed on the 177 student-generated problem statements. This involved standardizing ratings using Z-scores to normalize the responses and conducting variance analysis to eliminate outliers, ensuring the focus was on the most consistent problem statements. Followed by K-Means clustering, the problem statements were categorized into four distinct clusters. This approach was aligned with the hypothesis that the problems naturally fall into quadrants reflecting their constraints and social value. Silhouette scores further validated the clustering outcomes, confirming the adequacy of categorization and the natural grouping of the data.

And lastly the raters' agreement is statistically analyzed using the Interclass Coefficient. A significant overlap was observed, with 36 problem statements showcasing strong consensus across both constraint and social value dimensions. This indicated a shared understanding among the raters. Phase 2 results are instrumental in refining and understanding the problem statements, providing insights into the types of issues deemed significant in design and engineering.

Phase 3: Problem Preference Study

The intellectual merit of this research lies in fundamentally understanding the neurocognitive response and student preference toward design problems. The results phase 3 highlight landmark findings into the emotional inclination toward problem preferences as observed from activities in the temporal lobe. The neurocognitive study was centered on understanding the underlying cognitive and emotional mechanisms that guide an individual's preferences towards specific design problems. It is evident that the lobe 'T' activations, which are closely associated with emotional processing, play a significant role in shaping these preferences. The results hint at an intriguing interplay between emotional processing and design dimensions, particularly constraints and social values. For instance, design problems that impose constraints might evoke feelings of challenge or restriction, impacting their desirability. Similarly, design problems with strong social values might be perceived as more emotionally rewarding or fulfilling.

In summation, the study illuminates the intricate nexus between emotional processing in the lobe 'T' and preferences towards design problems. Understanding these dynamics is paramount for designers, educators, and industry professionals aiming to craft design problems that resonate emotionally and cognitively. Future endeavors require dissecting this interrelationship and exploring strategies to harness these insights in real-world design contexts. Current practices in design problem formulation do not consider student preferences and the impact of the type of problem on student motivation. In practice, this research has the potential to impact how design teams are formed by adding the design problem preference as a dimension that could ultimately lead to a higher performance team. The findings of the research will guide the design education community in understanding the complex process of design problem formation and design cognition. The education path to design as a discipline forces us to consider the nature of the design challenges offered, its' interpretation and impact on the designer and how this understanding can be structured for learning.

The research has the potential to open a pathway for studying design research from a student-centered lens. Educationally, this research provides insight and recommendations that ensure are providing the appropriate type of design problems to students in a manner that promotes persistence in engineering.

Some recommendations for the design and engineering education community:

1. Integration of socio-environmental contexts into the curriculum: Given the student's demonstrated interest in global issues and sustainability, new design curriculums could benefit students with the addition of topics that resonate with the current generation of engineers.
2. Interdisciplinary learning avenues: Study suggests that students could benefit form an interdisciplinary approach, incorporating learning and application-based elements from the field of social sciences and environmental studies can equip students with a well-rounded approach in tackling modern-day engineering challenges.
3. Promoting awareness of personal experiences and surroundings: Inculcating more fieldwork, community engagement projects and reflective assignments can encourage students to draw more inspiration from surrounding and tap into personal experiences.
4. Focusing on gender-sensitive education: This study finding recommends a review on how gender dynamics can be addressed in newer curriculums. This includes upgrading teaching materials with every new cohorts of students and classroom activities tailored to create a more inclusive and gender sensitive content.

CHAPTER 8

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APPENDIX 1: INTERVIEW PROTOCOL

Script for the interview Good morning, My name is Devanshi Shah, I am a Ph.D. candidate in Model Lab. I 'd like to thank you for participating in my research interview today. As mentioned in the consent form, my research aims to understand engineering student's learning experiences, motivation, and cognition in a design setting. The goal of the research is to have a better understanding of how students think in a designing exercise and their design experiences in the program, thus improve the project options and opportunities. The interview will last approximately 45 minutes. I will be asking you questions on your educational background, interest, experiences, and ideas about yourself and your identity as a designer. You have completed a consent form indicating I have permission to audio record our conversation today. All the comments will stay confidential, and will not reveal your identity or any individual mentioned by you. The interview will be transcribed and used for research purposes only. Do I have your permission to audio record this interview? If Yes: Thank you! Please let me know if at any point you want me to turn off the audio recorder or say something off the record. If No: Thank you for letting me know. I will only take notes from the interview. So, before we begin, do you have any questions? If yes: Address them before the interview. If No: If any questions arise during the interview, please feel free to ask me. Let us proceed to our interview!
1. How would you describe your motivation to be an engineer? *Probe: Was there any high school experience that impacted your decision to join engineering?* *Follow up: Was there an influence/role model you looked up to before choosing mechanical engineering?*
2. What excites you the most about the mechanical engineering program? *Probe: Was there any course/project/internship* of particular interest? *Follow up: Could you describe to me any cherished memory as an engineering student?*
3. Could you describe your experiences in design courses vs other engineering courses?

Follow up: How different was your experience in cornerstone vs capstone? *Probe:* Do you have an area of interest?
4. How do you view a design problem? Probe: Could you walk me step by step through your process of solving a design problem?
5. What type of project did you pick in Senior Design Class? Probe: Industry vs Non-Industry project? Follow up: Why did you choose the particular projects?
6. Were you anxious in your design classes? Follow up: What factors added to your anxiety?
7. How would you describe your experience in cornerstone vs capstone course?
8. What were some of the challenges as a mechanical engineering student?
9. Do you see yourself as an engineer? Follow up: Do your friends and family see you as an engineer?
10. What are your plans after graduation? Follow up: graduate school/industry/business.
This concludes our interview. Thank you very much for your time and participation. Again, your responses will remain confidential and you will not be individually referenced in any publications moving forward. If you have any questions, please feel to reach out to me at Devanshi.Shah@uga.edu. I would be happy to answer them.

The interview protocol matrix helps in identifying the research questions to the interview questions. This exercise is beneficial for a pilot study.

APPENDIX 2: MSLQ SURVEY

Motivated Strategies for Learning Questionnaire

Name ______________________ Team: ______________

1. Student ID Number (e.g. 800XXXXXX): ________________________________
2. What is your academic standing?

O Freshman

O Sophomore

O Junior

O Senior

3. Were you a transfer student? O Yes O No
4. Are you a domestic or international student? O Domestic O International
    a. If international, state your country: _________________________
    b. If domestic, what is the Zip Code of your permanent home address (back home)? _______________
5. What is the highest degree earned by your parents? _________________________
6. What is your gender? O Female O Male O Do not want to report
7. What is your age group? O 17-20 O 21-24 O 25 and above O Do not want to report
8. With which racial group(s) do you identify? (Mark ALL that apply)

O African-American or Black O Caucasian or White

O South Asian (e.g. Indian, Pakistani, Bangladeshi, etc.) O Other Asian

O East Asian (e.g. Chinese, Korean, Japanese, etc.) O Native Hawaiian or Pacific Islander

O American Indian or Alaskan Native O Do not want to report

Rate the following items based on your behavior in this class. Your rating should be on a 7-point scale where **1= not at all true of me** to **7=very true of me**.

Question	Not True						Very True
(IV) I prefer work that is challenging so I can learn new things.	1	2	3	4	5	6	7
(SE) Compared with other students in senior design I expect to do well	1	2	3	4	5	6	7
(PA) I am so nervous during a presentation that I cannot remember facts I have learned	1	2	3	4	5	6	7
(IV) It is important for me to learn what is being taught in this class	1	2	3	4	5	6	7
(IV) I like what I am learning	1	2	3	4	5	6	7
(SE) I'm certain I can understand the ideas taught in this course	1	2	3	4	5	6	7
(IV) I think I will be able to use what I learn in this class in my life	1	2	3	4	5	6	7
(SE) I expect to do very well in this class	1	2	3	4	5	6	7
(SE) Compared with others in this class, I think I'm a good student	1	2	3	4	5	6	7
(IV) I often choose research topics I will learn something from even if they require more work	1	2	3	4	5	6	7
(SE) I am sure I can do an excellent job on the problems and tasks assigned	1	2	3	4	5	6	7
(PA) I have an uneasy, upset feeling when I present	1	2	3	4	5	6	7
(SE) I think I will receive a good grade in this class	1	2	3	4	5	6	7
(IV) Even when I do poorly, I try to learn from my mistakes	1	2	3	4	5	6	7
(IV) I think that what I am learning in this class is useful for me to know	1	2	3	4	5	6	7
(SE) My study skills are excellent compared with others in this class	1	2	3	4	5	6	7
(IV) I think that what we are learning in this class is interesting	1	2	3	4	5	6	7
(SE) Compared with other students in this class I think I know a great deal about the subject	1	2	3	4	5	6	7
(SE) I know that I will be able to learn the material for this class	1	2	3	4	5	6	7

(PA) I worry a great deal about presentations	1	2	3	4	5	6	7
(IV) Understanding the design process is important to me	1	2	3	4	5	6	7
(PA) When I present I think about how poorly I am doing	1	2	3	4	5	6	7
(CV) When I do homework, I try to remember what the teacher said in class so I can answer the questions correctly	1	2	3	4	5	6	7
(SR) I ask myself questions to make sure I know the material I have been studying	1	2	3	4	5	6	7
(CV) It is hard for me to decide what the main ideas are in what I read	1	2	3	4	5	6	7
(SR) When work is hard I either give up or study only the easy parts	1	2	3	4	5	6	7
(CV) When I prepare for a presentation I put important ideas into my own words	1	2	3	4	5	6	7
(CV) I always try to understand what the teacher is saying even if it doesn't make sense.	1	2	3	4	5	6	7
(CV) When I prepare for a presentation I try to remember as many facts as I can	1	2	3	4	5	6	7
(CV) When preparing for a presentation, I copy my notes over to help me remember material	1	2	3	4	5	6	7
(SR) I practice presentations even when I don't have to	1	2	3	4	5	6	7
(SR) Even when study materials are dull and uninteresting, I keep working until I finish	1	2	3	4	5	6	7
(CV) When I prepare for a presentation, I practice saying the important facts over and over to myself	1	2	3	4	5	6	7
(SR) Before I begin studying I think about the things I will need to do to learn	1	2	3	4	5	6	7
(CV) I use what I have learned from previous classes to do prepare for project work	1	2	3	4	5	6	7
(SR) I often find that I have been reading for class but don't know what it is all about.	1	2	3	4	5	6	7
(SR) I find that when the teacher is talking I think of other things and don't really listen to what is being said	1	2	3	4	5	6	7
(CV) When I am studying a topic, I try to make everything fit together	1	2	3	4	5	6	7

(SR) When I'm reading I stop once in a while and go over what I have read	1	2	3	4	5	6	7
(CV) When I read materials for this class, I say the words over and over to myself to help me remember	1	2	3	4	5	6	7
(CV) I outline the relevant topics to help me prepare for a presentation	1	2	3	4	5	6	7
(SR) I work hard to get a good grade even when I don't like a class	1	2	3	4	5	6	7
(CV) When reading I try to connect the things I am reading about with what I already know.	1	2	3	4	5	6	7