An Exploratory Analysis of Technical Communication and Spatial Skills Among Engineering Students

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Abstract

Modern engineering graduates enter a highly globalized and cross-cultural workforce where they must maintain technical competencies alongside communication skills with various audiences and stakeholders. These engineering graduates typically have strong technical skillsets; however, industry comments that recent engineering graduates' communication abilities are weak. Prior research into engineering revealed that spatial skills are an empirically validated and significant indicator of an individual's decision to major in engineering and subsequent success in the degree. Conversely, industry has continued to report a gap in engineering graduates' technical communication ability since the late 1990s.

This research applied a unique examination of this phenomenon via the exploration of interactions between spatial skills and technical communication skills via methods adopted from gestural research; the hypothesis explored whether skills that academia promotes and states are critical for engineers interact, perhaps negatively, with communication skillsets. Data was collected in two phases from first-year engineering students (n = 86) enrolled in a two-semester introductory engineering course at the University of Cincinnati where participants completed a team-based robotics project in the previous semester. Participants completed a battery of spatial, verbal, and communication tasks across two phases of interviews. Sketches produced revealed no consistent patterns in sketch quality by spatial visualization skill. Other results revealed that high spatial visualizers outperformed low and medium spatial visualizers on written and oral communication tasks; furthermore, high spatial visualizers produced fewer gestures overall but gestured more meaningfully.

Factor analysis revealed two latent constructs of non-verbal cognition, composed of spatial skills and verbal analogy skills, and verbal cognition, composed of fluencies. Non-verbal cognition significantly predicted written scores, while verbal cognition significantly predicted oral scores. Non-verbal and verbal cognitions were statistically significantly and positively correlated with each other. Results imply that different cognitions may be relied on by engineering undergraduates based upon the communication task being completed. Furthermore, cognitions typically associated with technical content, such as spatial skills, are not the inverse of verbal cognition, which has been theorized by previous research. It is likely both cognitions operate in a symbiotic relationship, with the combination of the two resulting in stronger communication skills.

Final results indicate that the intelligences extolled for engineering students are connected to intelligences of communication, and spatial visualization skills can improve other aspects of cognition beyond technical content knowledge, such as communication. These reaffirm the critical need for spatial skills in engineering education. Industry's statements on the lack of communication skills may be more related to inter/intra personality traits, rather than the actual skillsets of writing a technical document, drawing a sketch, or explaining engineering projects orally. Recommendations on how academic institutions, accreditation boards, and industry can help improve aspects of engineering identity, culture, and personality traits are made; future directions for similar research are suggested.

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Chapter 1. Introduction

This document used the dissertation by publication methodology. It is the culmination of three journal articles which have been submitted to three separate journals; an engineering design graphics journal (sketching skills), a journal of technical and written communication (written skills), and an engineering education journal (oral skills / gesture production).

1.1 Study Objectives

The purpose of this study was to explore the persistent phenomenon reported by engineering industry that new engineering graduates are entering industry with acceptable to strong technical content knowledge but weak communication skills; this occurs despite concentrated efforts by academia to enhance various aspects of communication The hypothesis is that these are negatively correlated; high spatial visualizers have poor communication skills, especially when writing or speaking about things they view as inherently spatial.

The following research questions guided this project:

- What is the relationship between spatial skill levels and technical communication skills (oral, written, and sketching skills) for engineering undergraduate students when describing their first-year design projects?
    - Is the relationship similar for high / low visualizers, women / men, domestic / international students?
- What is the relationship between spatial skill levels and gesture production when engineering students are describing their first-year design project products orally?
    - Is there an interaction between semantic / phonemic fluency and spatial skill levels in gesture production?

- Is the relationship similar for high / low visualizers, women / men, domestic / international students?

The final results of this study indicate through validated quantitative and qualitative analysis that spatial visualization skills and communication skills are positively and more deeply connected than previously assumed. It is likely that spatial visualization skills can cause marked improvements in other cognitive domains beyond just technical content knowledge and engineering success and are useful in aspects of communication and recollection of information. The reported poor communication skills of recent engineering graduates is likely not their specific written documentation style or oral communication in one-on-one contexts, rather inter / intra personality traits that industry is not seeing in new graduates. Previous stereotypes and assumptions that verbal skills and non-verbal skills (such as spatial) are cognitive opposites have likely harmed overall communication expectations and experiences for the engineering population; stagnant engineering curricula potentially reinforce these stereotypes which could explain the persistent complaints from industry. Recommendations for ways to improve and foster personality traits which industry desire are provided, and further explorations of how spatial skills interact with communication skillsets are suggested.

1.2 Dissertation Document Organization

To minimize repetition of information between the chapters, one should read this document with the following guidelines. Chapter 2 should be read in its entirety to understand the full scope of the literature review between all research domains analyzed in this project. Chapter 3 contains the entire methodology used in this research project; the data of which was divided among the articles. Chapters 4 through 6 are each of the journal articles; for each of those chapters, one should focus on the findings, discussion of results, and conclusions, which help provide a deeper analysis of each specific communication skill. Chapter 7 should be read in its entirety to examine how all journal findings interact with the main hypothesis.

Chapter 2. Literature Review

This chapter is a literature review which provides an overview of the three research domains of spatial visualization skills in engineering, technical communication skills, both broadly and in specific engineering contexts, and gesture research. The reason these three specific domains have been examined is that, to the author's best knowledge, only gesture and linguistic research have previously explored spatial skills and verbal communication skills, a subset of technical communication skills. There has been little to no research that specifically examines spatial visualization skills and the specific competencies of engineering writing and oral communication skills in engineering education contexts; sketching has been related to spatial skills, but typically associated with training and coursework, not in the context of how it is used in communication contexts in industry.

Gesture and linguistic research have focused on the types of gestures produced during verbal communication tasks; while an important aspect of communication, these are likely not the forms of communication industry states new engineering students lack. The extensions of methodologies used in these domains can provide deeper insights into communication of new engineers. The following section provides a brief review and definition of spatial skills in engineering, technical communication skills in engineering, and gesture production; this is followed by a hypothesized model of interactions amongst the three areas. Finally, an overview of the research methodology, the data of which was subdivided across the three journal papers, is provided.

2.1 Spatial Skills in Engineering

"Success in the work of an engineer does seem to be related to spatial aptitude" (Super & Bachrach, 1957, p. 61)

In the mid-1900s literature began to report that spatial aptitude was critical for engineering success (Smith, 1964; Super & Bachrach, 1957). At this time spatial aptitude was often ignored by educational institutions in favor of general intelligences, where institutions' often "over-value[d] the verbal type of ability at the expense of its psychological opposite–spatial ability" (Smith, 1965, p. 5). An abundance of research has since empirically validated spatial skills as key predictors behind students' decisions to major in STEM disciplines alongside subsequent success in those fields (Kell & Lubinski, 2013; Lane & Sorby, 2022; Ramey & Uttal, 2017; Shea et al., 2001; Uttal & Cohen, 2012; Yoon & Mann, 2017). Research has revealed marked differences in spatial skills based on gender and socioeconomic status (Casey et al., 2011; Newcombe & Shipley, 2015; Wai et al., 2009), however as spatial skills are malleable and trainable through interventions (Ramey & Uttal, 2017; Sorby, 2007; Sorby, 2009; Uttal et al., 2013), these differences can be mitigated which could lead to improved representation for more groups in engineering.

A recurring aspect throughout the literature is that the phrases *spatial ability* (sometimes referred to as spatial aptitude) or *spatial skills* are often used interchangeably. One definition of spatial ability is an intelligence comprised of two components: one component being *spatial orientation*, which involves mental representations and operations on visual stimuli, and *spatial visualization*, which is an individuals' ability to picture spatially arrayed elements from various perspectives (Bednarz & Lee, 2011). Spatial ability has also been defined as "[t]he ability to make use of simulated mental imagery to solve problems…recalling images in the mind's eye" (Reid, 2022, p. 29), and a person's capability of imagining in their mind visual stimuli and applying manipulations or transformations to that stimuli (Raju & Sorby, 2024). A distinction between spatial ability and skill is that one's ability is typically viewed as innate, but evidence from prior research indicates that spatial skills can be trained and improved (Reid, 2022, p. 32). Therefore this research will use the term spatial skills, defined as an individual's skill to use mental representations and visualizations in their mind to solve problems that involve manipulations and transformations of visual stimuli.

2.2 Technical Communication Skills in Engineering

"Words, then, are not only the instruments for the expression of thought, they are also the instruments of the thinking process itself ... No act of thinking is complete till its products have been set forth in words" (McLellan & Dewey, 1889, p. 217).

Technical communication in engineering discusses two areas of skills termed *hard skills* and *soft* or *professional skills*. This terminology can be traced to the early 1960s when the United States Army required engineers in settings where teamwork and leadership contributed to effectiveness (Chaibate et al., 2019; Durelli et al., 2024). This shift caused work done on physical machinery to be termed *hard skills* and other operations critical to but not physically involved with the machinery to be termed *soft skills* (Durelli et al., 2024), henceforth referred to as *professional skills*. A shift began during the turn of the century for engineering students to have stronger professional skills due to a more globalized economy and infrastructure that would require modern engineers "to work in teams [and] communicate with multiple audiences…more effectively in the future" (National Academy of Engineering, 2004, p. 43). More recently this focus was re-emphasized by the Accreditation Board for Engineering and Technology (ABET) which stated in the third criterion for student outcomes that graduates must have "an ability to communicate effectively with a range of audiences" (2025). Surveys that analyzed online descriptions for engineering jobs found communication skills (oral, written, and/or generic) in the top three skills desired for new hires (Chaibate et al., 2020; Durelli et al., 2024; Jaimes-Acero et al., 2023; Lancetti et al., 2023; Zaharim et al., 2009). This is consistent with sentiments from engineering industry personnel, executives, and hiring managers who have emphasized the importance of technical communication skills (Ford et al., 2021; Katz, 1993; Karimi & Pina, 2021), even stating graduates "need to learn basic people skills combined with technical communication skills or they will fail horribly" (Sageev & Romanowski, 2001, p. 690). This demand for technical communication skills has resulted in myriad methods being implemented in higher education to improve communication skills for engineering students.

Specific books have targeted communication and presentation within engineering contexts (Alley, 2013; Stone, 2015). Researchers and faculty of engineering lab-writing courses have experimented with more consistent and constructive feedback loops and communication workshops for students (Badran et al., 2022; Berthouex, 1996; Boyd & Hassett, 2000; Cox et al., 2009; Masoud & Muhtaseb, 2021; Yalvac et al., 2007). Some faculty have added self-reflective sections within written assignments (Selwyn & Renaud-Assemat, 2020), used flipped-classroom models, or examined the impacts of co-curricular activities on communication skills (Baytiyeh, 2017; Boelt et al., 2022; Garrett et al., 2022), and attempted to recreate authentic industry experiences for students (Kaewpet & Sukamolson, 2011). Engineering students themselves voice technical communication as a critical skill. Students in civil engineering and computer science rated communication and teamwork skills as critical to success in their fields (Bielefeldt, 2018 Polmear et al., 2020; Naiem et al., 2015), and general engineering students rank communication ability within their top four skill sets (Carberry et al., 2013; Itani & Srour, 2016). Despite the consensus that technical communication skills are important, there exists a disparity between industry expectations and the perceived skills of new graduates. One explanation could be that technical communication is ill-defined in engineering contexts, which has been debated since the mid-1960s.

Research around this topic categorizes communication into two distinct forms. One stems from Aristotle's concept of rhetoric in which one attempts to persuade an audience through discourse and debate about a topic (Davis, 1999). The other form of communication is where the "author conveys one meaning and only one meaning in what they say" (Britton, 1965, p. 114). The rhetorical form of communication has been stated as inconsistent and unethical with engineering, as one should not be persuaded about objective reality and life-critical systems (Davis, 1999). The objective form of communication has been defined as the written representation of physical reality to contribute to shared-knowledge (Winsor, 1990), or the effective communication of expert knowledge, skills, or judgements to an audience (Davis, 1999). This 'written' aspect of information does not only mean a typed document, but rather any form of information that is specific to that field, whether it be measurements, tools, code, or any other element of information that can be shared (Winsor, 1992).

Aller's research (2002) examined practicing engineers and conducted interviews on their thoughts of writing for the workplace; practitioners considered effective technical writing to be "concise, clear, and to the point in order to be useful", alongside the process of writing as something that "never takes place in isolation but rather proceeds through a complex network of individuals and departments" (2002, p. 132). Specifically, Aller found that engineers recognize that when writing "[y]ou're trying to persuade the decision makers to take action or convince your boss that your work is correct," leading Aller to recognize that "[t]he rhetorical concept [of persuasion] is not foreign to them; just the lexicon" (2002, p. 134-135). These findings present a counterpoint to both Davis's and Winsor's findings about persuasive undertones in scientific technical writing. Aller's findings state that an effective written document in an engineering workplace is some form of a document provided through the written medium that is "concise, brief, and clear; it must be accurate and well-organized; it will consider its audience and the social exigencies that shape and arise from it; and it will, coincidentally, use appropriate style, format, and mechanics" (2002, p. 135).

It is not useful to place an explicit division between aspects of technical communication, such as lab reports, and persuasive communication, such as argumentative essays, as there exists overlap between the two styles. With this context, technical communication skills are defined as an individual's competency to provide expert knowledge about objective reality to an audience through oral, written, and graphical (visual / sketching) mediums.

2.3 Gesture Production in relation to Spatial and Technical Communication Skills

"We can therefore look at gesture as a special window on underlying spatial cognition" (Alibali, 2005, p. 313)

Research into gesture has explored different theories on the origin and meaning behind gestures in relation to speech. The majority of these utilize the concept of working memory, which refers to "a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" (Baddeley, 1992, p. 1). The three components of working memory involve a central attentional-controlling system, and two subsystems, one that manipulates visual imagery and the other which stores speech-based information (1992). One theory of gesture, called the Lexical Gesture Process Model, states a speaker's working memory begins the process of generating a propositional representation, or a pre-verbal message, which are sometimes reflected in lexical gestures when a concept is being explained. The authors of this model suggest that "gestures are a product of the same conceptual processes that ultimately result in speech, but the two production systems [visual imagery and speech-based subsystems] diverge very early on" (Krauss et al., 2000, p. 17). The Interface Model theory by Kita & Ozyurek explains that gesture production occurs simultaneously through the language of the speaker and non-verbalized spatial information about the subject discussed (2003). The spatio-motoric processes that are simultaneously occurring with speech production generate gestures, which in turn chunks information to be verbalized later. This can help organize the verbal messages for the speaker (2003). The Growth Point Theory proposes that the start of a sentence involves the combination of "linguistic and imagistic information together to initiate the dynamic cognitive processes that organize thinking for speech and results in co-speech gesture" (Clough & Duff, 2020, p. 2). Interestingly, these gesture theories seem to align with the Dual Coding Theory, where individuals code and store non-verbal and verbal information (Paivio, 1991). Some information is more likely to be coded visually (objects) while others are coded more verbally (concepts) (1991). Coding concepts mentally with spatial and speech patterns has resulted in gesture research exploring spatial skills and verbal speech ability.

Various research has linked spatial skills to gesture production ability (Alibali & Goldin-Meadow, 1993; Alibali, 2005; Wakefield et al., 2019). Gestures are also related to verbal ability (spoken communication), in which the combination of gesture and verbal speech generate new meaning (Alibali & Goldin-Meadow, 1993); however, these skillsets were found to be negatively related. Hostetter and Alibali have explored the three areas of verbal skills, spatial skills, and gesture production by measuring how phonemic and semantic fluency abilities interact with gesture production and found participants with low phonemic fluency, but high spatial skills produced the most gestures (2007). Gesture production was also examined in groups of participants verbally describing an event, one with no visual cues and one with, and found that "speakers do gesture more when they are describing events that they have witnessed visually than when describing events they have only heard about" (Hostetter & Skirving, 2011, p. 220). Analysis of only verbal utterances found that speakers with higher motivational and general-purpose cognitive abilities, rather than strong visuo-spatial abilities, had more understandable and easily interpreted verbal utterances (Boer et al., 2013). These results may corroborate previous sentiments that the verbal type of ability is the 'psychological opposite' of the spatial ability (Smith, 1964). While the relationship may not be linear, there may be a trend that if someone has stronger imagistic mental cues or spatial skills, they are likely to gesture more at the cost of effective verbal speech. From this context, gesture production is defined as a person's movements with their body parts that can be redundant / non-redundant (representational / beat, or meaningful / non-meaningful) typically accompanying oral communication about a specific topic being discussed that can either detract, improve, or add no further information to the topic of oral discussion.

2.4 Intersections between Spatial Skills, Technical Communication Skills, and Gesture Production

It is tempting to see the relationships in gesture research among verbal and spatial skills and assume they are consistent across individuals, however Hostetter and Alibali state that a potential reason that some relationships between these skills are ambiguous could be the "expectation that the relationship between verbal skill and gesture production is linear" (2011, p. 75). A further complexity is that the technical communication skills defined in this research include three forms; oral, written, and sketching (i.e., drawing), all components that comprise daily communication tasks for engineering students. While verbal skill and gesture productions in relation to spatial skills have a breadth of research, there is less research on how these two domains interact with writing or sketching skill.

Spatial skills have been researched within engineering drawing and graphical design, where drawing activities are used to improve spatial skills (Olkun, 2003; Stringer, 1975) and spatial skills can impact shapes of drawings (Machuca et al., 2019). Research about spatial skills and writing ability have shown a slightly positive relationship. In an English course researchers provided spatial cues to discuss document design and students mentioned it improved conceptual understanding as a subconscious learning experience (Kothalawala & Kothalawala, 2021). A total of 833 kindergarten children that were provided with visuo-motor and visual-spatial training were found to have significant relations between visual-spatial skill and letter writing, reading, spelling skills, and later literacy achievement (Mohamed & O'Brien, 2021). Further relationships between spatial skills and writing skills were examined by Bourke and Sumner:

> "The findings suggest, that, after controlling for the effects of reading in the first order correlations, as well as phonological WM [working memory], the variation in ability to produce shapes correctly on paper (visual perceptual processing) and the transcription of upper and lower case letters of the alphabet in further analyses, visuo-spatial WM is able to account for a unique proportion of the variance in children's spelling and independent text writing skills" (2014, p. 17).

These results are likely to be related to the actual penmanship of the participants and may not extend to how an engineer would generate a written document in industrial contexts. Drawing from these explored relationships between spatial skills, technical communication skills, gesture production, gestural theories and the Dual Coding Theory, a model has been created that hypothesizes how these various forms of skills may interact among each other in engineering communication contexts as shown in Figure 1.

Figure 1. *Hypothesized model of the relationships between spatial skills, technical communication skills, and gesture production.*

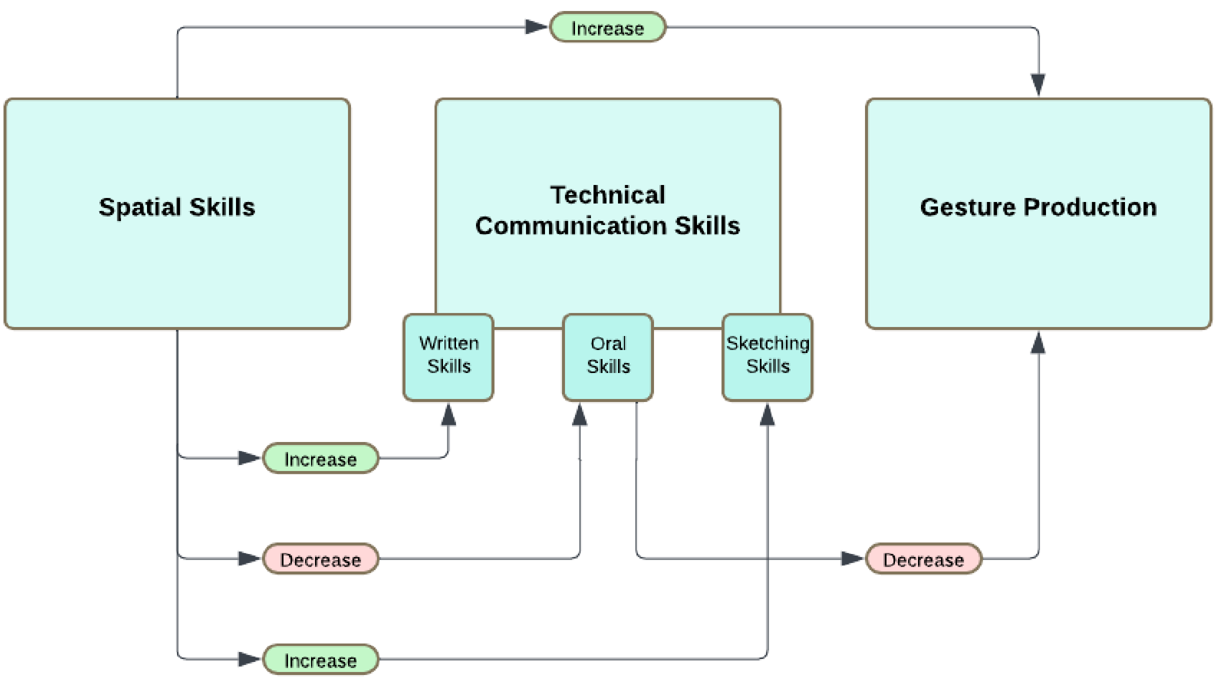


Figure 1 does not include other aspects that could impact communication such as personality traits, environmental effects, or cultural backgrounds; however, it provides a baseline to explore potential relationships in these skills which are typically considered separate from each other.

Chapter 3. Methodology

The following chapter contains all data collection conducted through the Spring 2023 semester. The specific forms of analysis conducted are described in each respective journal chapter as each analysis varied. The following research questions guided this project:

- What is the relationship between spatial skill levels and technical communication skills (oral, written, and sketching skills) for engineering undergraduate students when describing their first-year design projects?
    - Is the relationship similar for high / low visualizers, women / men, domestic / international students?
- What is the relationship between spatial skill levels and gesture production when engineering students are describing their first-year design project products orally?
    - Is there an interaction between semantic / phonemic fluency and spatial skill levels in gesture production?
    - Is the relationship similar for high / low visualizers, women / men, domestic / international students?

To answer these questions a mixed-method approach was used to obtain quantitative and qualitative data for collection and analysis.

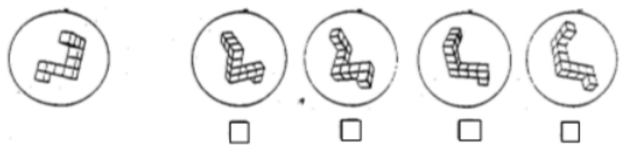
3.1 Data Collection

Data was collected from first-year engineering students at the University of Cincinnati in the Spring 2023 semester. The students were enrolled in the second course of a two-course sequence taken by all engineering majors at the university. Students explicitly practiced spatial thinking skills in the first-semester course through two weeks of in-class activities and graded assessments. Their training and practice with communication came from their experiences prior to college as well as any communication courses they may have enrolled in in their first semester at the university. Both of the engineering courses in the sequence involve a semester long team-based robotics project that students must demonstrate at an end of year event; the teams are composed of three to four individuals, typically divided into the roles of coder, builder, and project manager. Students were incentivized with a gift-card at the beginning of the second semester to complete an online proctored Zoom survey over Qualtrics hereafter referred to as Phase One. Students that successfully completed all Phase One instruments were invited to participate in Phase Two, an approximately hour-long one-on-one interview with a member of the research team that involved technical communication tasks and discussions of their robotic project from the previous semester.

3.2 Phase One Instruments

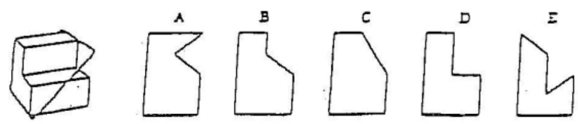
Spatial factors for students were measured with the Mental Rotation Test (MRT) (Vandenburg & Kuse, 1978) and the Mental Cutting Test (MCT) (CEEB, 1939). The MRT is a timed exam where students complete 24 questions in 6 minutes. In the MRT, participants are presented with a criterion figure on the left and are instructed to find the two figures on the right that are rotated views of the criterion object. Scoring for this is 1 point if they identified both rotated views of the object, and 0 points if they fail to identify both. This was included as mental rotation skills have been related to overall success in engineering (Sorby, 2009) and speeded mental rotation tasks have the largest gender differences in spatial skills (Voyer, 2011). An example question of the MRT is shown in Figure 2.

Figure 2. *Sample problem from the MRT (Correct answer is 1 & 3)*



In the MCT, students are shown a figure with an imaginary cutting plane through it and are asked to determine the resulting cross-section from the choices given. Students are given a total of 20 minutes to complete 25 questions with a total of 25 points possible, 1 point per each correct cross-section selected. An example MCT question is shown below in Figure 3.

Figure 3. *Sample problem from the MCT (Correct answer = D)*



A Verbal Analogy instrument was also administered to the students to measure verbal skill. This instrument had a total of 16 items with no time limit and consisted of three words with one missing, and students' had to determine the relevant word based on the three provided. An example verbal analogy task question is shown in Figure 4 below.

Figure 4. *Sample problem from the Verbal Analogy Task (Correct answer = Saw)*

WOOD : (______) :: BUTTER : KNIFE

a) String b) Paper c) Saw d) Drill

Two final instruments included a self-reported confidence questionnaire and self-reported general demographic information (e.g. gender, parent's education, GPA). The self-reported confidence questionnaire included the following 4 prompts on a 5-point Likert scale. (1=Strongly Disagree, 2=Somewhat Disagree, 3=Neither Disagree nor Agree, 4=Somewhat Agree, 5=Strongly Agree).

- Q1: “I am confident that I am able to follow the instructions to efficiently put together a dresser from Ikea”. (Image of a cabinet shown)
- Q2: “I am confident that I am able to come up with appropriate words or phrases when I am in a conversation with someone talking about my non-technical ideas”.
- Q3: “I am confident in my ability to communicate my engineering ideas using verbal descriptions (words) that non-engineers can easily understand”.
- Q4: “I am confident that I am able to express my thoughts, in writing, so that other engineers can easily understand my ideas”.

3.3 Phase Two Instruments

Students who successfully completed all Phase One tasks were invited to complete another set of instruments in a face-to-face video recorded interview session with a member of the research team. The participants completed four fluency tasks (two phonemic, two semantic), a written communication task, in which a sketch could be optionally generated by the participant if desired, and an oral communication task. The written and oral communication tasks shared the same set of prompts for the participant provided below.

For the writing portion of this study, reflect back on your robot from ENED1100 and please write a document that describes:

- *What problem were you trying to solve?*
- *What task was it supposed to do?*
- *What did it look like?*
- *How did it operate?*
- *What features of your robot solved the problem?*
- *How did your robot perform in the demo?*

If you need to include a figure in your document, please use the blank sheets of paper provided and hand-sketch the figure. Do not spend a great deal of time trying to make a computer-generated sketch either in Word or elsewhere.

Table 1 below provides the order that the participants completed tasks in for Phase Two.

Table 1. *Process of phase two communication tasks*

Task	Description	Approximate Time
Phonemic Fluency Task (letter "s")	Name all of the words you can think of that begin with the letter "s".	60 secs (enforced)
Semantic Fluency Task (animals)	Name all of the animals you can think of.	60 secs (enforced)
Written Communication Task	Describe your ENED1100 project on a written document (see Appendix B).	15-20 Minutes
Phonemic Fluency Task (letter "t")	Name all of the words that you can think of that begin with the letter "t".	60 secs (enforced)
Semantic Fluency Task (fruits and vegetables)	Name all of the fruits and vegetables you can think of.	60 secs (enforced)
Oral Communication Task	Describe your ENED1100 project orally (see appendix A).	5-10 Minutes
Pathway Description Task	Please describe the pathway (or route) you took from your home to your high school.	2 Minutes
Present Wrapping Task	Please describe orally how you would wrap a present (research member may potentially gesture a present size).	4 Minutes

3.4 All Data Analysis

All data was analyzed with RStudio Build 2026.05.1 Build 225. A principal component analysis (PCA) was applied to the MRT/MCT scores of participants to create a single spatial score that categorized students into low, medium, and high spatial visualizers. Verbal analogy scores from phase one were left unmodified. Validated Likert-scale rubrics generated by members of the research team that have expertise in technical communication and sketching in engineering contexts were created to grade the oral (see Appendix A), written (see Appendix B), and sketch (see Appendix C) artifacts created by students in Phase Two. The individual journal articles describe the specific descriptive statistics as sample size varied based on the report created and any technical issues during collect. A total of n = 86 written reports, n = 81 oral reports, and n = 35 sketches were successfully collected. Average scores on the semantic fluency measurements (production of words that belong to categories of things) and phonemic categories (words that begin with specific letters) were calculated. These measures were based on previous research conducted in neuropsychological assessments (Hostetter & Alibali, 2007). Categorical, nominal data examined for the students included self-described gender, self-described student status (domestic / international), and spatial visualization rank (determined by the PCA).

For gestural analysis, the thematic coding scheme developed by Hostetter and Alibali (2007) was applied to the project discussion, pathway, and present tasks. Counts of representational (gestures that imply semantic meaning) and beat (gestures that imply no clear semantic meaning) were tallied manually. An example of a representational gesture is "if a participant moved her right index finger around in a circle several times while saying 'the mouse swung around the bar,' this motion was counted as one representational gesture" (2007, p. 85). Simple and rhythmic motion that occur with specific words and phrases with no specific semantic depiction were counted as beat gestures. An example of this can be an individual having their left hand make a small circular motion while attempting to remember a word. There are various coding schemes for gestures; however, the interactions between the student and interviewer in the collected data was kept infrequent; this scenario aligns with the Hostetter & Alibali coding scheme (2007). To identify the gestures per 100 words, all three oral tasks (project, pathway, present) were transcribed using Microsoft's One Drive built in transcription software and *Vibe*, an online transcription service. Two sets of transcripts were generated and cross checked to ensure similar outputs. All interviewer comments, prompts, and interjections were removed alongside all timestamps to create a document with only the participant's oral responses. This document had a word count. After, the author analyzed each of the video responses and, to the best of their skill, marked a gesture as representational or beat. The analysis of gestures was kept simplistic; if an engineering student motioned that their robot moved "like this" and proceeded to place their palms facedown and move them forward and back repeatedly parallel to the ground and away from their chest, this was counted as a *single* representational gesture. If an individual stated that their robot was a "box with a square bottom" (gestured a square bottom) and was "this tall" (gestured two vertical pillars), that was counted as *two* representational gestures. Conversely, if an individual was thinking aloud, and moving their hand around with no context, this was categorized as a single beat gesture. Every time either of these gestures occurred, a tally was placed in the respective representational or beat location. After all n = 86 participants were analyzed, their total number of gestures (representational and beat combined) was divided by their total word count then multiplied by 100 to generate a numerical value of gestures generated per 100 words. This allowed a comparable variance of gesture production across all participants in their oral communication tasks (see Appendix F and G for examples of these tallies).

In summary, the variables of spatial visualization score, verbal analogy score, semantic fluency, phonemic fluency, gesture production rates, with nominal characteristics of gender, status, and spatial rank, were used to predict final written, oral, and sketch communication scores of undergraduate engineering students. The following three chapters are the individual journal articles written from this dataset. The first journal article involves relationships between spatial skills and sketching quality, specifically the low / high spatial visualizers, to examine trends on both extremes of spatial skill levels. This is followed by the second journal article that examined spatial and written report scores; the final journal article involves spatial and oral report scores, with an accompanied focus on gesture production among the engineering students. These three chapters are followed by an overall conclusion and recommendations for future work.

Chapter 4. Journal Article 1: The Relationship between Spatial Visualization Skills and Sketching.

Engineering Design Graphics Journal (EDGJ) (Published)

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4.1 Abstract

Academia trains engineering students to have strong technical content knowledge through various courses, work experiences, or capstone projects. Two skillsets engineering students are likely to have utilized throughout these experiences are spatial visualization skills and sketching skills. Spatial skills are a key indicator of interest, decision to major, and later success in various fields of engineering. Sketching can aid in project design ideation, improve design conceptions over iterations, and can be an effective way to communicate complex information to different audiences. Spatial skills can be trained through explicit courses, interventions, and typically the natural progression through an engineering major. Likewise, sketching skills can be trained through courses and interventions; however, with the advent of more technological drawing tools such as CAD, these skills may not be adequately trained. This research examines relationships between spatial skills and sketching skills for first-year engineering students enrolled in a two-semester introductory engineering course at a large midwestern R1 institution. A total of 35 participants completed all spatial instruments and opted to generate a sketch. A principal component analysis was applied to categorize participants into low, medium, or high visualizers. The types of sketches the participants generated included orthographic, pictorial, and schematic sketches. Analysis of the low and high spatial visualizer sketches revealed that low spatial visualizers generated sketches with more details, annotations, and information regarding their project demonstration or their robot; conversely, high spatial visualizers provided sparser sketches of smaller, specific components of their robot, or opted to provide a simple overall view without as much detail. These results are then connected to prior literature that has explored sketching and spatial skills and implications are discussed.

4.2 Introduction

4.2.1 Spatial Skills in Engineering

Spatial skills are a strong indicator of an individual's decision to major in engineering and be successful in the discipline (Lane & Sorby, 2022; Loney et al., 2019; Ramey & Uttal, 2017; Shea et al., 2001; Uttal & Cohen, 2012; Yoon & Mann, 2017). Spatial skills are often defined as one's ability to "visualize objects and situations in one's mind, and to manipulate those images" (Sorby, 2007, p. 1). Spatial skills are important cognitive skills in general but are particularly important in engineering majors, which often rely on more mental imagery or the ability to generate and navigate multiple viewpoints compared to other fields. Spatial skills are not static, as multiple studies have shown that these skills are malleable and trainable through interventions (Ramey & Uttal, 2017; Sorby, 2007; Sorby, 2009; Uttal et al., 2013). Research has shown differences in spatial skills based on gender and socioeconomic status (Casey et al., 2011; Newcombe & Shipley, 2015; Wai et al., 2009); the training of these skills could lead to improved representation and success in engineering.

4.2.2 Sketching in Engineering

Another skill that research has demonstrated as important for success in engineering is the ability to sketch effectively. Sketching has been shown to be important to the engineering design process and as a way to physically represent complex aspects of engineering projects (Ishak et al., 2015; McGown et al., 1998; Schutze et. al., 2003; Song & Agogino, 2005). Sketching plays an important role in the early stages of project development and can be a useful tool for students who may have trouble fully conceptualizing project designs mentally (Yang & Cham, 2007). Sketching is just as powerful as written and oral communication (Rose, 2005; Westmoreland et al., 2011) and can aid in an engineering design team's productivity, their shared visual representations of projects (Booth et al., 2015; Goldschmidt, 2007) and provide a means to communicate information to other experts (Jeong, 2019). Other researchers have stated that sketching is the most "traditional and quickest way to communicate technical information…[and] creating and using drawings and sketches is the engineer's way to work" (Schmidt et al., 2012, p. 304). Despite the empirically validated importance of sketching skills and interventions that can improve them (Booth et al., 2016; Jeong, 2019; Weaver et al., 2022), there appear to be multiple factors that contribute to why sketching may not be used as much by engineering students. Some factors are access to computer-aided drawing software and a lack of comprehension of the role of sketching in design (Schmidt et al., 2012). Prompts are also a critical indicator of a student's decision to sketch, with specific guidelines and instructions impacting sketch generation and quality (Rose, 2005; Weaver et al., 2024). The decision to sketch is multifaceted and complex. Regardless, efforts have been made to return to pure free-hand sketching based courses through interventions and modifications, a particular one being for the improvement of spatial skills.

4.2.3 Intersections between spatial skills and sketching skills in engineering

Training spatial skills often includes a mixture of freehand sketching instruction, the introduction of 2D and 3D modeling, orthographic projection, perspective sketching, and isometric sketching either through workshops, lectures, or additional content provided to the students (Raju & Sorby, 2024; Sorby, 2022; Youssef & Berry, 2012; Weaver et al., 2022). It is important that this training provides multiple opportunities to sketch in various forms for students, as other research has found that "most of the improvements in spatial visualization occurs during the sketching instruction portion of the class, not the CAD portion" (Weaver et al., 2022, p. 1846). However, it has been hypothesized that well-developed spatial visualization skills may result in a student *not* sketching. Westmoreland, et al have stated that "today's students do not sketch as much as engineers of earlier generations…[instead] students prefer to visualize (and solve) design problems in their heads instead of on paper" (2011, p. 1). Yang & Cham explored sketching skill in the design process and found "a common complaint among some students is that they do not want to keep [sketch] logbooks because their work is already *all in their head*" (2007, p. 479-481). Overall, there are various ways to instruct and improve spatial and sketching skills, and often both skills are targeted simultaneously, potentially providing engineering students with an improvement to two proficiencies that will have broader impacts on their future engineering design processes and success in their engineering studies.

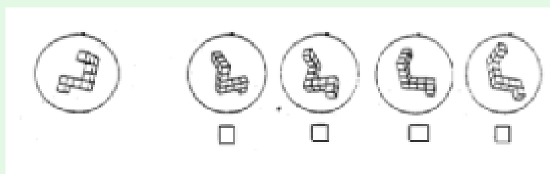
4.3 Methodology

Data was collected from first-year engineering students at a large midwestern US R1 institution. The participants were enrolled in the second course of a two-course sequence taken by all engineering majors at the university. Students complete a team-based project where they build an autonomous robot based on real world examples of disaster relief in the first semester. The students' robot must not use wheels, must navigate uneven terrain, be able to pick up waste objects in bins, determine what waste it is via weight, and have the robot drop off the waste at the proper location. Teams are made up of three to four students, with each student typically adopting a specific role of coder, project manager, builder, or documenter. Participants explicitly practiced spatial thinking skills and sketching in the first-semester course through two weeks of in-class activities and graded assessments. The data used in this research was collected across two phases; the first phase involved a monitored online video call where students completed a battery of spatial tasks, and the second phase involved an approximately hour-long one-on-one interview with a member of the research team that involved technical communication tasks and discussions of their robotic project from the previous semester.

4.3.1 Phase One Instruments

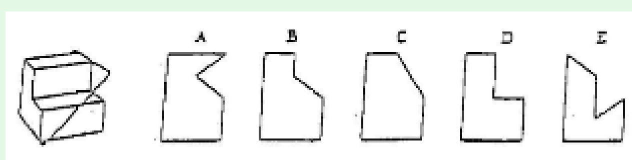
The spatial skills of the participants were measured with the Mental Rotation Test (MRT) (Vandenburg & Kuse, 1978) and the Mental Cutting Test (MCT) (CEEB, 1939). In the MRT, participants are given a criterion figure on the left and must select two of the four images on the right that represent the criterion figure in a rotated position; both selections must be correct in order to earn a point for the question. An example of an MRT question is provided in Figure 5.

Figure 5. *Example MRT Problem (Correct Answer = 1, 3)*



In the MCT, participants are shown a criterion figure with an imaginary cutting plane through it on the left and are asked to determine the correct resulting cross-section from the five choices given. Participants are given a total of 20 minutes to complete 25 questions with 1 point per each correct cross-section selected. An example of an MCT question is shown in Figure 6.

Figure 6. *Example MCT Problem (Correct Answer = D)*



4.3.2 Phase Two Instruments

Participants who successfully completed all Phase One instruments were invited to complete another set of instruments in a face-to-face video recorded interview session with a member of the research team. The sketching data was collected as part of a larger written communication task. Participants were tasked with generating a written document that described their robotic design project based on these questions:

- *What problem were you trying to solve?*
- *What task was it supposed to do?*
- *What did it look like?*
- *How did it operate?*
- *What features of your robot solved the problem?*
- *How did your robot perform in the demo?*
- *If you need to include a figure in your document, please use the blank sheets of paper provided and hand-sketch the figure. Do not spend a great deal of time trying to make a computer-generated sketch either in Word or elsewhere. Your document should be 2 pages maximum.*

Sketches that were generated by participants were gathered and categorized as described in the following.

4.4 Results and Analysis

All data analysis was conducted in RStudio 2026.01.1 Build 403 where appropriate. A principal component analysis was applied to participants' MRT and MCT scores to generate a single spatial visualization score; this score was used to categorize participants into the spatial ranks of low (n = 12), medium (n = 60), and high (n = 14) spatial visualizers. After rank categorization, all participants who generated a sketch (n=35) were analyzed. A system of rubric grading and rank categorization based on holistic quality was applied. All generated sketches were grouped into three categories: orthographic, schematic, and pictorial. Sketches that had at least one orthographic view or a 2D sketch of a specific part of the robot (i.e. a detail view) were placed into the orthographic category (n=22); sketches that displayed the pathways the robot had to take or how the project demonstration occurred were placed into the schematic category (n=7); sketches that displayed only a pictorial view of their robot were placed into the pictorial category (n=6). A rubric was developed and applied to the orthographic sketches. The rubric contained five Likert scale questions (1: Not Applicable, 2: Marginal, 3: Adequate, 4: Above Average, 5: Strong). Two members of research team applied the sketching rubric to all orthographic sketches. Cohen's squared kappa resulted in a kappa of 0.85 (z=8.96, p=0); the individual question kappa was 0.64, 0.95, 0.85, 0.81, 0.72 for questions 1-5 respectively. A two-way mixed-effects model for intraclass correlation resulted in an ICC(A,1) = 0.85, and ICC(C,2) = 0.92. Raters had moderate / substantial agreement on each question and very strong agreement on the final score of each orthographic sketch; non-orthographic sketches were ranked by both raters simultaneously.

4.4.1 Descriptive Statistics for all Participants

A total of 86 participants completed all phases, and 35 generated a sketch, of which a smaller portion were low and high visualizers. Gender was not considered as its variance was approximately equal between high and low visualizers that generated sketches; medium spatial visualizers were not examined to focus on how both ends of the spectrum of spatial visualization skill interact with sketching. Specifically, these two populations were examined to find trends on how individuals that may struggle with engineering (low visualizers) and those that may be more proficient in engineering (high visualizers) generate sketches for design problems. Other factors such as written report responses, prior reading / writing training, and comprehension of provided tasks were not examined as this research specifically focused on spatial skills and sketching. While these aspects likely impact motivations behind creation of a sketch or information deemed necessary to be included in sketches, those examinations are outside the scope of this work's research question; these could be considered when larger populations are examined.

Table 2. *Means (SD) of sketch participants spatial scores.*

Variable	Low Visualizers (n=5)	High Visualizers (n=6)

Spatial Score (out of 100)	6.26 (5.41)	86.21 (12.47)

High spatial visualizers had larger variations in spatial scores as some individuals scored near perfect, while others bordered just above the medium spatial skill level. All low spatial visualizers had similar scores. Overall, the power of this sample size was too small to generate meaningful quantitative results. The following discusses the set of sketches and provides the spatial score of the participant that generated their sketch and the sketch's rank or rubric score.

4.4.2 Schematic Sketches

These types of sketches focused on specific tasks for the robot, often the movements the robot had to complete during the demonstration. These sketches were labeled as schematic since they focused on the physical layout of the demonstration or task, with the robot either missing or simplistic. The following two schematic sketches were completed by low visualizers; no high visualizers elected to create a schematic sketch.

Figure 7. *Low Visualizer Schematic Sketch #1 (Sketch Rank: 1 out of 7, Spatial Score: 4%)*

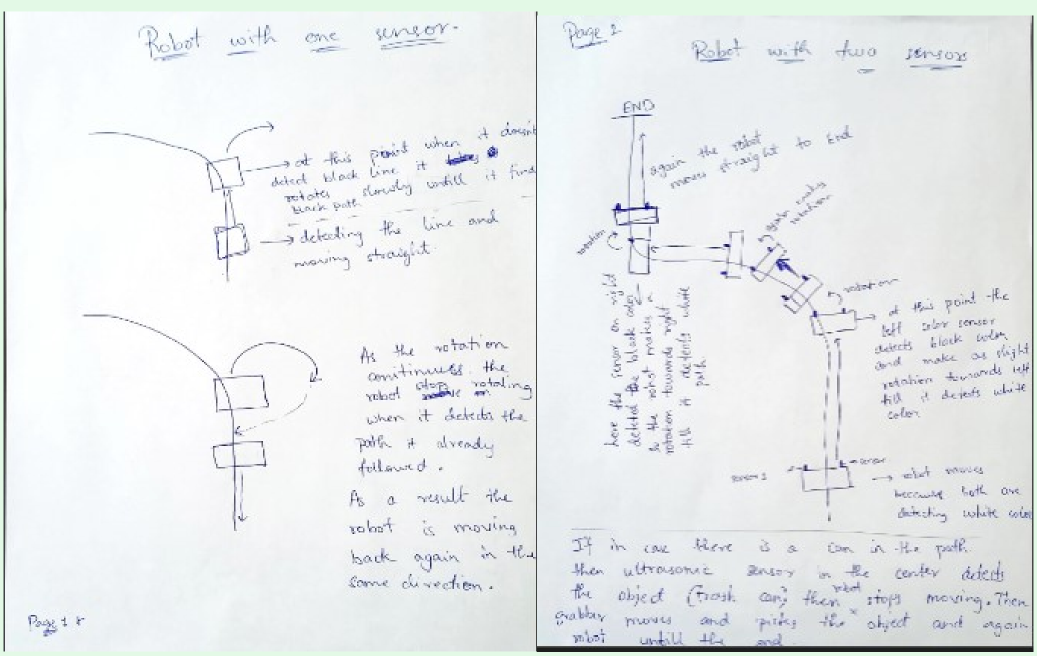
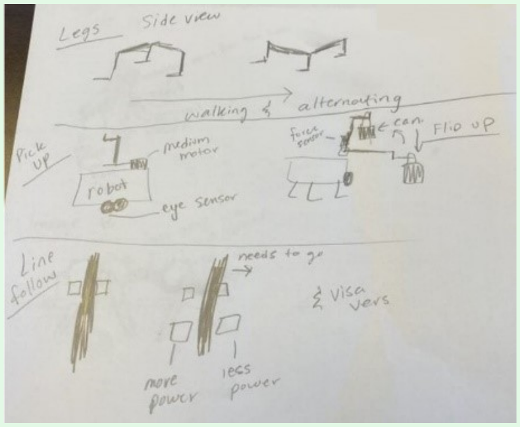


Figure 8. *Low Visualizer Schematic Sketch #2 (Sketch Rank: 3 out of 7, Spatial Score: 0%)*



For Figures 7 and 8 the text and arrows are necessary for these schematic sketches to be comprehensible. Furthermore, the annotations and labels go beyond pointing out key components of the robot and provide deeper insights for how operations of the robot were supposed to occur. Schematic sketches appear to represent one or more tasks to be performed by the robot, whether it be movement of legs, rotation, and operation of sensors, or grabbing operations.

4.4.3 Pictorial Sketches

Two high spatial visualizers opted to generate pictorial sketches during the communication task as shown in Figures 9 and 10 below. All participants had practiced isometric sketching in the previous semester and all pictorial sketches that were generated contained a single view of the robot.

Figure 9. *High Visualizer Pictorial Sketch #1 (Sketch Rank: 2 out of 6, Spatial Score: 100%)*

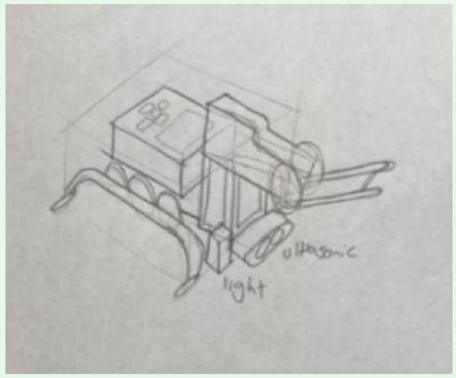
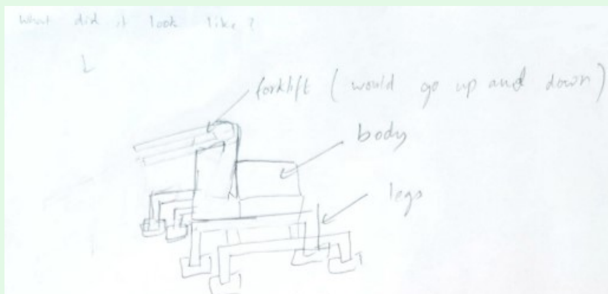


Figure 10. *High Visualizer Pictorial Sketch #2 (Sketch Rank: 5 out of 6, Spatial Score: 76%)*



Both sketches (Figures 9 and 10) have noticeably less text than the schematic sketches but illustrate an overall view of the robot the participants designed. The labels on both sketches point out the forklift and parts of the body; pictorial sketch 1 (Figure 9) shows the specific sensors used, ultrasonic and light, and while it does not point out the lifting mechanism, it can be understood easily from the image. While these two sketches have slightly neater lines and focus on the robot itself over the tasks the robot was meant to perform, it is harder to discern the precise leg movements of these robots from the sketches. Overall, the high visualizers' pictorial sketches do an effective job at giving a visual at-a-glance view of the entire robot and some aspects of the tasks, such as lifting an object; however, it is more difficult to visualize the movement of the legs without the inclusion of more arrows, labels, or further perspectives of these sketches. No low spatial visualizers created a pictorial sketch.

4.4.4 Orthographic Sketches

Due to the larger sample size in this sketch category, a validated rubric was applied. The following figures and descriptions detail the low and high visualizer orthographic sketches with scores from the sketching rubric (max score of 25 points). These sketches are ordered based on the total spatial visualization score for the participant acquired in phase 1 (out of 100%), from lowest to highest.

4.4.5 Low Visualizer Orthographic Sketches

Figure 11. *Low Visualizer Orthographic Sketch #1 (Sketch Score: 12.5 points, Spatial Score: 4%)*

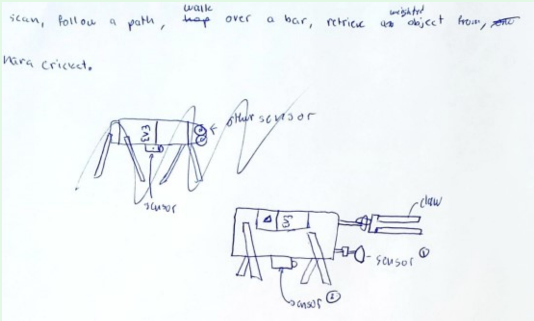


Figure 12. *Low Visualizer Orthographic Sketch #2 (Sketch Score: 13.5 points, Spatial Score: 9%)*

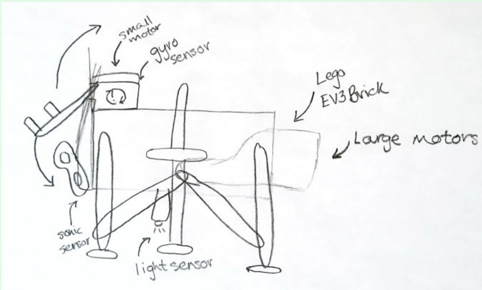
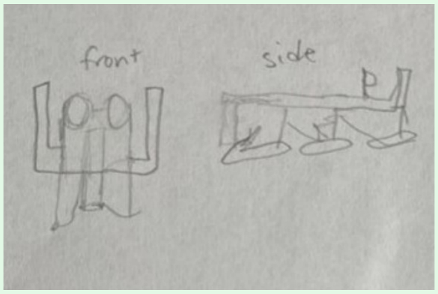


Figure 13. *Low Visualizer Orthographic Sketch #3 (Sketch Score: 8 points, Spatial Score: 14%)*



All low visualizer orthographic sketches did not include a detail view or a specific zoom in on elements of the robot to provide further information. Figures 11 and 12 are all a single orthographic sideview with all having a large number of labels. The annotation details in Figure 11 describe the specific tasks the robot was to perform and Figure 12 includes annotations to specify locations of sensors and has utilized arrows to signify motion of the claw. Figure 11 includes two orthographic projections, a front and side, but only label these views and provides no further detail; this figure is the weakest out of this group of sketches.

4.4.6 High Visualizer Orthographic Sketches

Figure 14. *High Visualizer Orthographic Sketch #1 (Sketch Score: 9.5 points, Spatial Score: 74%)*

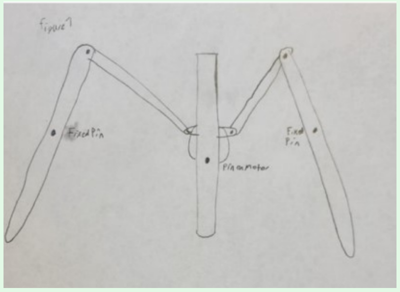


Figure 15. *High Visualizer Orthographic Sketch #2 (Sketch Score: 17 points, Spatial Score: 75%)*

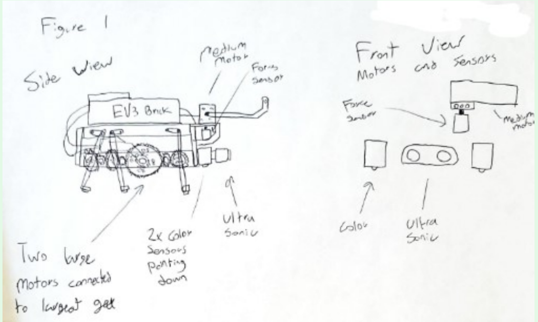


Figure 16. *High Visualizer Orthographic Sketch #3 (Sketch Score: 9.5 points, Spatial Score: 92%)*

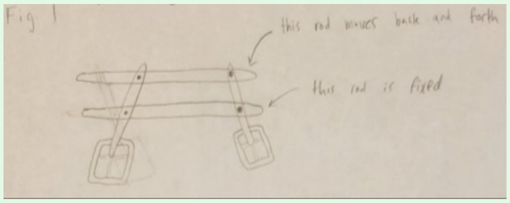
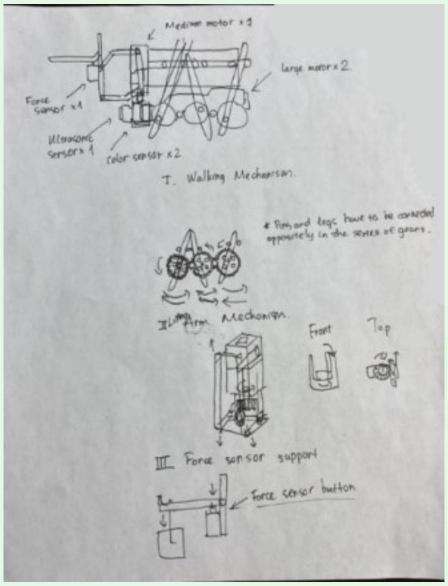


Figure 17. *High Visualizer Orthographic Sketch #4 (Sketch Score 18 points, Spatial Score: 99%)*



All four high visualizer orthographic sketches contained detail views, with Figures 14 and 16 consisting of only a single detail view. Figures 15 and 17 both used annotations to focus on the legs of the robot; while this does provide information on the movement operations of the robot, the overall robotic object is not discernable. There is a noticeable discrepancy in quality and focus between Figures 14 and 16 when compared to Figures 15 and 17. Figures 14 and 16 follow a similar pattern of the low spatial visualizers' orthographic sketches with a single side orthographic view and labels to point out specific sensors and mechanisms; this is followed by one or more detail views on mechanisms of movement and lifting, similar to Figure 8 (low visualizer schematic sketch) that grouped information on a single sketch. A simplistic tally was conducted to count the occurrence of three key components of the sketches: callouts or annotations that describe elements of the sketch through text (e.g. a phrase or sentence detailing information, or front / side); labels that specify specific components, sensors, or object in the robot (e.g. ultrasonic sensor, lifting-mechanism); arrows or lines that indicate motion, direction, functions. Table 3 presents the tallies for the schematic and pictorial sketches, and Table 4 presents tallies for both groups of orthographic sketches.

Table 3. *Schematic and Pictorial Sketch Tallies*

Sketch Figure	Spatial Rank	Annotations / Callouts	Labels	Motion Arrows / Motion Lines	Total
Figure 7	Low	12	2	14	28
Figure 8	Low	5	5	3	13
Figure 9	High	0	2	0	2
Figure 10	High	1	2	0	3

Low spatial visualizers used more annotations, labels, and motion lines as part of their schematic sketches to illustrate movement and task operations, with less focus on overall robotic appearance. Low spatial visualizers who created schematic sketches may have had less confidence in sketching the full robot, which would include aspects of lifting and leg mechanisms, and to compensate these participants relied on alternative ways to communicate information such as more annotations and labels. Conversely, high spatial visualizers generated pictorial sketches that used sparse labels and annotations and relied on a single 3D view of the robot to communicate information. The locations of the legs and lifting mechanisms were clear; however, the specifics of movement of the robot were difficult to discern. Further detail views or usage of movement lines or annotations could offset this; however, these participants may have felt it necessary to only provide a single view. Participants' written responses may have driven the focus of sketches; low spatial visualizers may have wanted to communicate further details that were difficult to describe through textual mediums; whereas, high spatial visualizers may have relied on sketches to enhance their written report.

Table 4. *Orthographic Sketch Tallies*

Spatial Rank	Sketch Figure	Annotations / Callouts	Labels	Motion Arrows / Motion Lines	Total
Low	Figure 11	1	3	0	4
	Figure 12	0	6	2	8
	Figure 13	2	0	0	2
High	Figure 14	0	3	0	3
	Figure 15	4	8	0	12
	Figure 16	2	0	0	2
	Figure 17	3	6	15	24

Larger variations were found in orthographic sketches within and between low and high spatial visualizers. For two of the three low orthographic sketches, general comprehension of movement and lifting of the robot could be derived, such as where the front was, sensor locations, some form of a claw or grip, and leg locations; labels and annotations were used for these sketches, with less reliance on motion lines. This was not the trend for all low orthographic sketches. High orthographic sketches were polarized, where Figures 14 and 16 focused only on a single detail view of the legs with annotations and labels, while Figures 15 and 17 focused on multiple aspects of the robot, with specific detail views which focused on sensors and used annotations to describe operations. Figure 17 notably utilized multiple arrows to convey movement and specific operations; this participant is likely strong in both spatial visualization and sketching skill.

4.5 Discussion of Results

In this research, low spatial visualizers, individuals who may have weaker mental visual imagery, often used more holistic and complex sketches with annotations to communicate information about their robot, whereas high spatial visualizers often only sketched portions of the robot. This could be interpreted as the low visualizers had to sketch out information they may not have been able to fully visualize, whereas the high visualizers only sketched information they felt important to point out, likely due to their stronger mental imagery of the robot. Previous literature has stated that individuals with difficulty recollecting complex mental imagery may rely on sketching to externalize designs and communicate information; conversely those that have stronger visual imagery rely on mental recollection and may opt not to sketch at all (Yang & Cham, 2007). Other confounding variables on the decision to produce a sketch involve self-perceived and actual drawing skills (2007). The data presented here does not support this notion 100%--some low spatial visualizers had poor sketch quality and sparse information, and two high spatial visualizers had more detailed sketches; however, this study lends more data to trends between spatial and sketching skills in engineering. Another result was the notable number of participants who opted not to generate any sketch at all (~59%). This may be due to recent trends where engineering students do not feel required to sketch as much (Marklin et al., 2013; Song & Agogino, 2004; Westmoreland et al., 2011) or due to a lack of prompts as prompts are important indicators of deciding to sketch (Rose, 2005; Weaver et al., 2024). This could explain why so many participants chose not to generate a sketch as they may have assumed the written document was enough and they weren't required to complete a sketch. These findings parallel the after-effects of some sketching interventions, where some participants that voiced concern about no mastery of sketching skills (Jeong, 2019), did not have long-term improvements in reducing their inhibition to generate sketches (Booth et al., 2016), and for students that did admit the sketching process does help with design, they maintained that design problems could be solved without needing to sketch (Schutze et al., 2003). Overall, the results from this research show a complex relationship between spatial and sketching skills, two very important skills for engineering students to master. Modern engineering students enter a curriculum that may progress spatial visualization skills naturally; this same curriculum has reduced the number of opportunities for freehand-sketching or replaced it with CAD or alternative software. Furthermore, the sketching opportunities in the curriculum are often more likely for specific majors, and with a growing number of engineering degrees in electrical, industrial, chemical, and software / computer engineering, the sparse opportunities for sketching may be reduced further for those majors. Such sketching opportunities may only be a workshop, intervention, or a few modules embedded in a larger course, often to aid or measure their spatial skills. This may reveal a self-limiting relationship between sketching and spatial skills, in which sketching skills are used by novice engineers to improve their spatial skills, but due to their heightened spatial skills, the more experienced engineers are then more likely to only utilize their superior spatial skills, reducing or completely removing their reliance on sketching.

4.6 Limitations and Future Work

This work used sketches that were collected as part of a larger written communication task that described a team design project. Future work should consider making a mandatory question that asks participants to generate a sketch about their team design project. This work only examined the low and high visualizer sketches; future work will examine the medium visualizer sketches which contained a larger variation in sketch quality that necessitates an individual examination and discussion. This research was conducted with participants who successfully completed several spatial visualization training modules a semester prior, so they were likely more familiar with sketching. This may vary based on institutional curriculum. Each participant was part of a team in the prior semester, which was comprised of 3 to 4 participants with individual roles that may have consisted of a builder, project manager, documenter, or coder. Individual experiences might have obvious implications for what is remembered by the participant and may have impacted their resulting sketches; however, team role data was not collected. The participants were interviewed inside a room with a researcher in a one-on-one recorded setting which may have impacted scores or sketching capability. Participant's standardized test scores were not collected but these could provide further insights into characteristics about engineers who opt to sketch. This work was conducted as part of a larger research study that examined how spatial skills are related to various communication skills. Future work will examine how the sketching communication discussed in this can interact with the written and oral communication of participants and further discuss implications that those interactions may have.

4.7 Conclusions

This research examined relationships between spatial skills and sketching skills, two important proficiencies for an engineer. Participants consisted of a variety of engineering majors in a first-year engineering course who had all practiced spatial visualization and sketching the semester prior. Participants completed spatial visualization tasks and an optional sketching task that described the robot their team generated in the prior semester. Results revealed variations within sketches by spatial rank, with some low visualizers generating more comprehensive sketches that showed tasks or overall pictures of the robot, whereas some high spatial visualizers opted for specific aspects of the robot to sketch. However, these sketches were generated in tandem as written reports of their robotic projects, which likely influenced information participants decided to sketch. These results reinforce prior research that hypothesized that individuals with strong mental visualization skills may not want or need to generate sketches, as information is already available in their mind; conversely, low spatial visualization ability may lead a participant to sketch more in order to have information in front of them to be able to think through their writing. Similar research should be conducted between spatial and sketching skills with the suggestions and limitations discussed in this research in mind to ensure more sampling opportunities and stronger representations of spatial visualization ranks.

4.8 Acknowledgements

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4.9 Biography

John William Lynch is a PhD candidate investigating relationships between spatial skills and technical communication skills of engineering students. He holds a Bachelor's and Master's degree in computer science and is currently obtaining a PhD in Engineering and Computing Education. He is interested in the creation and distribution of spatial visualization applications to improve spatial visualization skills and is interested in exploring how spatial skills interact with computer science comprehension and success. (University of Cincinnati*: lynch2j5@mail.uc.edu*)

Dr. Sheryl Sorby is a Professor of Engineering Education at the University of Cincinnati. Dr. Sorby has a well-established research program in spatial visualization, receiving her first grant from the NSF to develop a course and materials for helping engineering students develop their 3-D spatial skills; she has received numerous follow-up grants to further her work. Her spatial skills curriculum has been adopted by several engineering programs across the U.S. She has received numerous awards based on her work including WEPAN, ASEE, ASME, ABET and IFEES. She is a Fellow of ASEE, a fellow of the European Society for Engineering Education (SEFI) and is a Past President of ASEE. (University of Cincinnati: *sorbysa@ucmail.uc.edu*)

Chapter 5. Journal Article 2: Exploratory Research Examining links between spatial and written communication skills among engineering students.

Journal of Technical Writing and Communication (Submitted)

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5.1 Abstract

This research explores how spatial skills and written communication skills interact in engineering students. Participants completed tasks of spatial visualization, verbal analogy, lexical fluencies, and a written report. High spatial visualizers created the strongest written reports, and spatial and communication skills were positively correlated. Latent constructs of non-verbal skills were strong predictors of written scores; non-verbal / verbal skills were significantly and positively correlated. Results indicate that spatial visualization skills and verbal skills are more harmonious than previously assumed.

5.2 Background

An abundance of research in spatial skills and, separately, in written communication has generated terminology that is often used interchangeably in each domain. The following sections of this paper define spatial and technical communication writing skills in relation to the current research context, followed by an exploration of overlaps between the two skillsets and a theoretical model of how these skills interact. The guiding research question is: what is the relationship between spatial skill level and written communication skills for engineering undergraduate students when describing their first-year design projects?

5.3 Literature Review

5.3.1 Spatial Skills in Engineering

In the mid-1900s literature began to report that spatial aptitude was critical for engineering success (Smith, 1964; Super & Bachrach, 1957). At this time spatial aptitude was often ignored in favor of general intelligence; institutions often "over-value[d] the verbal type of ability at the expense of its psychological opposite–spatial ability" (Smith, 1965, p. 5). An abundance of research has empirically validated spatial skills as key predictors behind students' decisions to major in STEM disciplines as well as subsequent success in STEM fields (Kell &

Lubinski, 2013; Lane & Sorby, 2022; Ramey & Uttal, 2017; Shea et al., 2001; Uttal & Cohen, 2012; Yoon & Mann, 2017). Spatial skills have also been reported as an important component in mathematical word-problem solving (Duffy et al, 2024; Reid, 2021), engineering design problem solving (Raju & Sorby, 2024), creative design performance (Chang, 2014; Chang et al., 2016; Olkun, 2003), chemical engineering problem solving (Loney et al., 2019), computer programming success (Bockmon et al., 2020; Endres et al., 2021; Fincher et al., 2005; Fisher et al., 2006; Ly et al., 2021; Parkinson & Cutts, 2022), mechanical reasoning and engineering (Ha & Fang, 2016; Julià & Antolì, 2018), and as a highly relevant construct in the general structure of human intellect (Johnson & Bouchard Jr., 2005). Other research has revealed marked differences in spatial skills based on gender and socioeconomic status (Casey et al., 2011; Newcombe & Shipley, 2015; Wai et al., 2009); however, as spatial skills are malleable and trainable through interventions (Ramey & Uttal, 2017; Sorby, 2007; Sorby, 2009; Uttal et al., 2013), these differences can be reduced which could lead to improved representation for underrepresented groups in engineering.

An examination of the literature demonstrates that *spatial ability*, *spatial aptitude,* or *spatial skills* are often used interchangeably. One definition of spatial ability is an intelligence comprised of two components: one component being spatial orientation, which involves mental representations and operations on visual stimuli, and spatial visualization, which is an individual's ability to picture spatially arrayed elements from various perspectives (Bednarz & Lee, 2011). Spatial ability has also been defined as "[t]he ability to make use of simulated mental imagery to solve problems…recalling images in the mind's eye" (Reid, 2022, p. 29), and a person's capability of imagining in their mind visual stimuli and applying manipulations or transformations to those stimuli (Raju & Sorby, 2024). These definitions seem to agree that spatial ability, aptitude, or skill is the mental capability of an individual to both visualize an object in their mind and apply transformations to that object. A distinction between spatial ability and skill is that one's ability is typically viewed as innate, but evidence from prior research indicates that spatial skills can be trained and improved (Reid, 2022, p. 32). Therefore, this paper will use the term spatial skills throughout, defined as an individual's skill in using mental representations and visualizations in their mind to solve problems that involve manipulations and/or transformations of visual stimuli.

5.3.2 Written Communication Skills in Engineering

The ability to communicate technical information through written media is critical for an engineer's success. Attempts by academia and industry that target communication skills typically include written skills under an overall definition of technical communication and research has attempted to examine what specifically constitutes effective technical writing in engineering. Britton attempted to define technical writing by separating writing into two forms; associative thoughts to history, humanities, literature, which indicate chronological or emotional relationships, and sequential thoughts which belong to science, with concepts such as *because* or *therefore*, and general logical sequences (1965, p. 114). One goal for this definition was to acquire a measurable outcome for technical writing, which Britton explained as:

> *"[T]he effort of the author to convey one meaning and only one meaning in what they say. That one meaning must be sharp, clear, precise. And the reader must be given no choice of meanings; [they] must not be allowed to interpret a passage in any way but that intended by the writer. Insofar as the reader may derive more than one meaning from a passage, technical writing is bad; insofar as [they] can derive only one meaning from the writing, it is good" (1965, p. 114).*

Despite the goal of objectivity, Britton remarked that scientific technical writing would benefit from efforts to make it attractive for the audience, either through prose or genre specific writing (1965). Davis (1999) also defined technical writing in a way that paralleled Britton's view of a "persuasive style" and an "objective style"; however, Davis takes a stronger stance that the persuasive style for engineers is both harmful and unethical. The notion that scientific and persuasive writing were separate was also explored by Winsor (1992). Winsor's background was in writing and linguistics, and she posited that writing constructs all knowledge in all fields. In the context of engineering and its associated culture, this means all elements that are part of an engineer's task comprise writing, which include calculations, notes, lab reports, emails, code, and symbolic information (1992). Winsor also stated that engineers may find persuasiveness to be counterintuitive and against an engineer's goals (Winsor, 1996).

Aller's research (2002) examined practicing engineers and conducted interviews on their thoughts of writing for the workplace; practitioners considered effective technical writing to be "concise, clear, and to the point in order to be useful", alongside the process of writing as something that "never takes place in isolation but rather proceeds through a complex network of individuals and departments" (2002, p. 132). Specifically, Aller found that engineers recognize that when writing "[y]ou're trying to persuade the decision makers to take action or convince your boss that your work is correct," leading Aller to recognize that "[t]he rhetorical concept [of persuasion] is not foreign to them; just the lexicon" (2002, p. 134-135). These findings present a counterpoint to both Davis's and Winsor's findings about persuasive undertones in scientific technical writing. Aller's findings state that an effective written document in an engineering workplace is some form of a document provided through the written medium that is "concise, brief, and clear; it must be accurate and well-organized; it will consider its audience and the social exigencies that shape and arise from it; and it will, coincidentally, use appropriate style, format, and mechanics" (2002, p. 135).

It is not useful to place an explicit division between technical engineering writing, such as lab reports, and persuasive writing, like an argumentative essay, as there exists overlap between the two styles that may not be obvious to engineers. With this context, written communication skills in engineering are defined as an individual's competency in providing expert knowledge about objective reality to an audience through written or textual mediums for the purpose of instruction and expanding audience comprehension. Specifically, written communication in engineering provides facts, data, and findings on products and processes to inform and support recommendations for change.

5.3.3 Communication Skills in Engineering

Literature distinguishes between domain specific and general or transferable experiences, synonymous with "technical" and "non-technical" capabilities (Neeley, 2021). This resulted in specific technical skillsets, such as the ability to use a physical machine or code in a specific language, as a "technical skill," and other skillsets that may be difficult to define but crucial to performance as "professional skills." Professional skills were emphasized to be just as important as technical skills, and the distinction was therefore to define skills that are "important without being overly specific about what is being named" (2021, p. 4). Charles Mann's report, written more than 100 years ago, reinforced the importance of the two skillsets, where interviews with representative engineers and an analysis of recent engineering graduates in industry explored what makes a professional engineer (1918).

> *"personal qualities such as common sense, integrity, resourcefulness, initiative, tact, thoroughness, accuracy, efficiency, and understanding of [engineers] are universally*

recognized as being no less necessary to a professional engineer than are technical knowledge and skill." (1918, p. 106)

Current engineering jobs request similar requirements for engineering graduates. Surveys that analyzed online descriptions for engineering jobs found communication skills (oral, written, and/or generic) consistently in the top three skills desired for new hires (Durelli et al., 2024; Chaibate et al., 2019; Jaimes-Acero et al., 2023; Lancetti et al., 2023; Zaharim et al., 2009). Engineering industry personnel, executives, and hiring managers have also emphasized the importance of technical communication skills (Ford et al., 2021; Katz, 1993; Karimi & Pina, 2021), even some of whom stated graduates "need to learn basic people skills combined with technical communication skills or they will fail horribly" (Sageev & Romanowski, 2001, p. 690). Specific books and courses have been created to target engineering communication skills (Alley, 2013; Cox et al., 2009; Masoud & Muhtaseb, 2021; Stone, 2015; Yalvac et al., 2007) and engineering students themselves voice technical communication as a critical skill (Bielefeldt, 2018; Carberry et al., 2013; Itani & Srour, 2016). Calls from industry and the emergence of more collaborative work enabled by recent technological developments have made academia refocus on the importance of professional skills. Since 2000, ABET mandates communication as a required outcome for engineering, stating that engineers must graduate with "an ability to communicate effectively with a range of audiences" (ABET, 2025).

5.3.4 Relationships between Spatial Skills and Written Communication Skills

Despite the continued calls extolling the importance of professional and technical communication skills, the design of academic programs is better equipped for technical content knowledge delivery and examination. In a freshman undergraduate geography class taught in both Writing Across Curriculum (WAC) and traditional formats, students' were tasked with journaling information about geographical events in two sections that were handed in weekly; this consisted of the summary of the geographical event followed by a personal opinion of the event (Hooey & Bailey, 2005). The task was more informal and allowed students to focus on "spatial thinking rather than formal paper writing," which resulted in students being able to document "their spatial thinking and analytical abilities" and finding the entries becoming "more insightful through time" (2005, p. 259). Results indicated that over the course of three years there were statistically significant results between the WAC and non-WAC sections; students enrolled in WAC sections earned an average final grade of 79% in comparison to the traditional sections that earned an average grade of 74% (2005, p. 260).

In an undergraduate English course researchers provided visual cues of a hamburger to spatially orient students and discuss document design, and students mentioned it improved conceptual understanding as a subconscious learning experience (Kothalawala & Kothalawala, 2021). A total of 833 kindergarten children were followed longitudinally into first grade in Singapore and undertook visuo-motor and visual-spatial tasks, such as building with blocks and drawing pictures and examined any links between spatial activities, graph-motor copying to "reading and spelling in English" (Mohamed & O'Brien, 2021, p. 880). Of this cohort, there was a significant relation between visual-spatial skill and letter writing, reading, and spelling skills in English. Results indicated that graphomotor abilities are related to later literacy achievement, and that there is a "relationship between visual-spatial integration/graphomotor and reading skills [which] extends this link to spelling outcomes" (2021, p. 894). Further relationships between spatial skills and writing skills were examined by Bourke and Sumner in terms of younger students' ability to correctly produce proper letters for word spelling:

"The findings suggest, that, after controlling for the effects of reading in the first order correlations, as well as phonological WM [working memory], the variation in ability to produce shapes correctly on paper (visual perceptual processing) and the transcription of upper and lower case letters of the alphabet in further analyses, visuo-spatial WM is able to account for a unique proportion of the variance in children's spelling and independent text writing skills" (2014, p. 17).

It is important to note that the research discussed is not explicitly written communication as defined in this research context; however, spatial skills may be helpful in document layout, organization, word-spelling, lexical access of students, and visualizing written text, which are key elements of strong technical communication (Aller, 2002). With the skills defined and other research which show a potential positive correlation between spatial skills and subsets of written communication skills, the following section will introduce the methodology of the research.

5.4 Methodology

The guiding research question of this project asked: what is the relationship between spatial skill level and written communication skills for engineering undergraduate students when describing their first-year design projects? Specifically, what are relationships between these skills and low, medium, high spatial visualizers, men / women, and domestic / international students? To answer these questions, this research used a mixed-method approach for quantitative and qualitative data collection and analysis. The methods used to collect the data are described in the following sections.

5.4.1 Data Collection

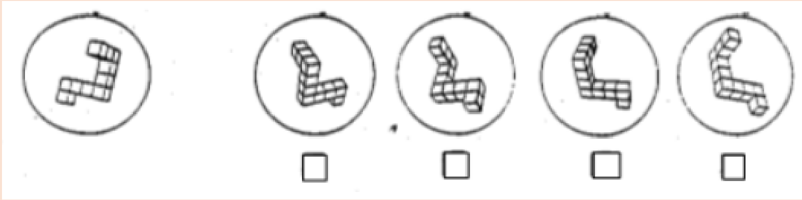
Data was collected from first-year engineering students at a large midwestern R1 institution. The students were enrolled in the second course of a two-course sequence taken by all engineering majors at the university. Students explicitly practiced spatial thinking skills in the first-semester course through two weeks of in-class activities and graded assessments. Their training and practice with written communication came from their experiences prior to college as well as any written communication courses they may have enrolled in in their first semester at the university. Both courses in the first-year engineering sequence involved a semester long team-based robotics project that students must demonstrate during an end of semester event. The project involved students being given a disaster relief scenario and information on how to design a robotic device that can navigate and sort specific materials in the environment. Teams were composed of a coder, designer, builder, and project manager; roles were decided by each team. Throughout the semester, teams built a mock robot out of EV3 lego bricks and demonstrated its operations through various tasks at a final demo.

In this research, students were incentivized with a gift-card at the beginning of the second semester to complete an online proctored Zoom survey over Qualtrics hence referred to as Phase One of this research. Students' who successfully completed all Phase One instruments were invited to participate in Phase Two, an approximately hour-long one-on-one interview with a member(s) of the research team that involved fluency tasks and completion of a written technical communication task focused on their robotic project from the *previous* semester. To ensure all quantitative and qualitative data was available for data analysis only students who completed both phases were analyzed.

5.4.2 Phase One Instruments

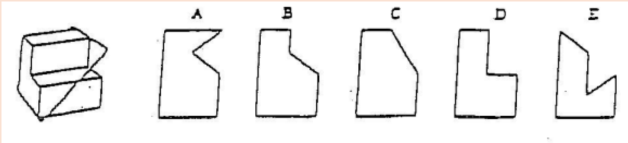
Spatial factors for students were measured with the Mental Rotation Test (MRT) (Vandenburg and Kuse, 1978) and the Mental Cutting Test (MCT) (CEEB, 1939). The MRT is a timed exam where students complete 24 questions in 6 minutes. This was included because mental rotation skills have been related to overall success in engineering (Sorby, 2009) and speeded mental rotation tasks have the largest gender differences in spatial skills (Voyer, 2011). An example problem from the MRT is shown in Figure 18; students are presented with a criterion image on the left side and provided four possibilities of the original figure rotated on the right side. Students must select the two figures on the right side that identify the rotated views of the original figure; they score 1 point if both correct options are selected or 0 points if they fail to identify both.

Figure 18. *Sample problem from MRT (Correct answer is 1 & 3)*



In the MCT, students are shown a criterion figure on the left side that has an imaginary cutting plane passing through it and they are asked to determine the cross-section that would result from the choices given. Students are given a total of 20 minutes to complete 25 questions with a total of 25 points possible, one point per correct cross-section selected. An example of the MCT is provided in Figure 19.

Figure 19. *Sample problem from the MCT (Correct Answer = D)*



A Verbal Analogy instrument was also administered to the students to measure verbal/logic skill. This instrument had a total of 16 items with no time limit and consisted of three words with one missing where students' had to select the relevant word. An example of a verbal analogy question is provided in Figure 20.

Figure 20. *Sample problem from the Verbal Analogy Task (Correct Answer = Saw)*

WOOD : (______) :: BUTTER : KNIFE

a) String b) Paper c) Saw d) Drill

The final Phase One instrument included a self-reported confidence questionnaire and self-reported general demographic information (e.g. gender, parent's education, GPA).

5.4.3 Phase Two Instruments

Students who successfully completed all Phase One tasks were invited to complete a face-to-face recorded interview session with a member of the research team. Students were completed tasks aiming to measure communication skills. The tasks included semantic fluency measurements (production of words that belong to categories) and phonemic categories (words that begin with specific letters). These measures were based on previous research conducted in neuropsychological assessments (Hostetter & Alibali, 2007; Spreen & Strauss, 1991). For the written communication task, students were given as much time as needed until they stated they had finished writing. The written communication task instructions were as follows:

> For the writing portion of this study, reflect back on your robot from [redacted] and please write a document about your robot that describes:
> - What problem were you trying to solve?
> - What task was it supposed to do?
> - What did it look like?
> - How did it operate?
> - What features of your robot solved the problem?
> - How did your robot perform in the demo?

Participants also completed four fluency tasks, two semantic and two phonemic, before and after the written communication task; the order of tasks are shown below in Table 5.

Table 5. *Phase Two Student Communication Tasks*

Task	Description	Approximate Time

Phonemic Fluency Task (letter "s")	Name all of the words you can think of that begin with the letter "s."	60 secs (enforced)
Semantic Fluency Task (animals)	Name all of the animals you can think of.	60 secs (enforced)
Written Communication Task	Describe your [redacted] project on a written document.	~15-20 Minutes (not enforced)
Phonemic Fluency Task (letter "t")	Name all of the words that you can think of that begin with the letter "t."	60 secs (enforced)
Semantic Fluency Task (fruits and vegetables)	Name all of the fruits and vegetables you can think of.	60 secs (enforced)

5.5 Results

All data analysis for Phase One and Phase Two was conducted in RStudio 2026.04.0 Build 526. To provide a more comprehensive analysis of the data, participants who successfully completed all Phase One and Phase Two tasks were analyzed. A total of 90 students completed both tasks, but 4 had to be removed due to technical recording issues, leaving a total of n=86 participants who were included in the analysis. Results from the demographic survey showed 71% (n=61) of final participants identified as Male, 28% (n=24) identified as Female, and 1% (n=1) preferred not to say. For student status, approximately 54% (28M, 18F) self-identified as domestic students, 44% as international students (32M, 6F), and 2% (1M) preferred not to disclose this information. A principal component analysis was applied to individual MRT and MCT scores to generate a single spatial score that was used to categorize students into low, medium, and high spatial visualization ranks; this categorization system was used in similar spatial visualization works to explore trends in spatial skills (Jones & Burnett, 2007; Raju & Sorby, 2024; Sorby, 2009). Verbal analogy scores were calculated out of a max of 16 points, one point correct per question. For the fluency tasks, morphological changes (e.g. twenty-one, twenty-two) and proper nouns were not counted per the standards of previous research (Hostetter & Alibali, 2007). Average counts for the two phonemic and semantic tasks were calculated and are represented by phonemic average and semantic average.

Written reports were graded with a validated rubric generated by a member of the research team with background and expertise in technical writing and verified through multiple rounds of interrater reliability reviews. The full rubric can be viewed in Appendix B. The rubric acknowledged findings that organization, document structure, accuracy, and succinctness contribute to effective communication, as do more traditional emphases on spelling, grammar, and word choice (Aller, 2002). The rubric ranked different elements of the written document on a Likert scale of 1 to 6 (Unacceptable, Marginal, Adequate, Above average, Strong, Exceptional) and were applied by two members of the research team. Inter-rater reliability was calculated on all of the completed rubrics with RStudio to ensure validity for each individual question and on the summation of all questions. Interrater reliability was calculated twice, once for agreement between individual questions in the rubric for each participant, and again for the total score of the rubric across all participants. Weighted Cohen's Kappa and intraclass correlation methods were applied to allow for partial agreements (i.e. 3 vs. 4 is less disagreement than 1 vs. 4). Cohen's Kappa Equal variance resulted in a kappa of 0.408 ($z=0.408$, $p=0$, fair agreement) and squared variance resulted in 0.556 ($z = 0.556$, $p=0$, moderate agreement) when applied to each individual question; a kappa of 0.728 (substantial agreement) for equal variance and a kappa of 0.926 (almost perfect agreement) for squared variance was found for the total scores. Intraclass correlations with a two-way mixed-effects model was calculated for consistency in rating; mixed-effects model are typically applied to a set of fixed-raters rather than randomly selected raters. The results of these intraclass correlations with two-way mixed-effects model is shown below in Table 6.

Table 6. *Intraclass Correlation Coefficients (ICC) scores across rubrics.*

Model	Type	Unit	ICC-Estimate	CI	P-Value
Interrater on individual questions					
Two-way	consistency	single	ICC(C,1) = **0.566**	0.504 – 0.623	p = 5.45e-45
Two-way	consistency	average	ICC(C,2) = **0.723**	0.671 – 0.767	p = 5.45e-45
Interrater on total score					
Two-way	consistency	single	ICC(C,1) = **0.931**	0.896 – 0.954	p = 3.37e-39
Two-way	consistency	average	ICC(C,2) = **0.964**	0.945 – 0.977	p = 3.37e-39

As shown in Table 6, results indicate that the two raters had moderate agreement on each question and significant agreement on the total score for each participant's written document. In other words, the raters agreed that a participant had a weak or strong written document yet were more varied on the exact qualities that determined its strength.

5.5.1 Descriptive Statistics and Parametric Tests

Primary data analyzed included a single component spatial score (composed from MRT / MCT), verbal analogy score, semantic / phonemic fluency counts, and a written communication task score. Applicable data was analyzed and no data significantly violated assumptions of normality except written score; however, as this was a score derived after data collection via a Likert-rubric, this deviation was expected. Demographic information of student status and gender alongside spatial skill were used to categorize participants; demographic information of participants can be seen in Table 7. Table 8 contains the descriptive statistics of participants based on spatial visualization rank. Table 9 contains the correlations between spatial scores, verbal analogy scores, phonemic / semantic fluency averages, and final written report scores.

Table 7. *Demographics of participants (n=85: one participant did not disclose status)*

Spatial Rank	Male		Female	
	Domestic	International	Domestic	International
Low	1	7	4	0
Medium	18	22	14	6
High	9	2	2	0

Table 8. *Descriptive statistics based on spatial rank (n=86)*

Spatial Rank	N	Spatial (out of 100)		Verbal (out of 16)		Semantic Average		Phonemic Average		Written (out of 36)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Low	12	11.89	7.59	6.92	1.78	20.29	5.51	14.25	5.32	15.75	4.75
Medium	60	48.38	13.89	9.42	2.13	21.80	5.53	16.01	4.90	19.92	5.71
High	14	86.2	8.92	11.57	2.50	24.96	3.86	18.46	4.58	23.71	4.75

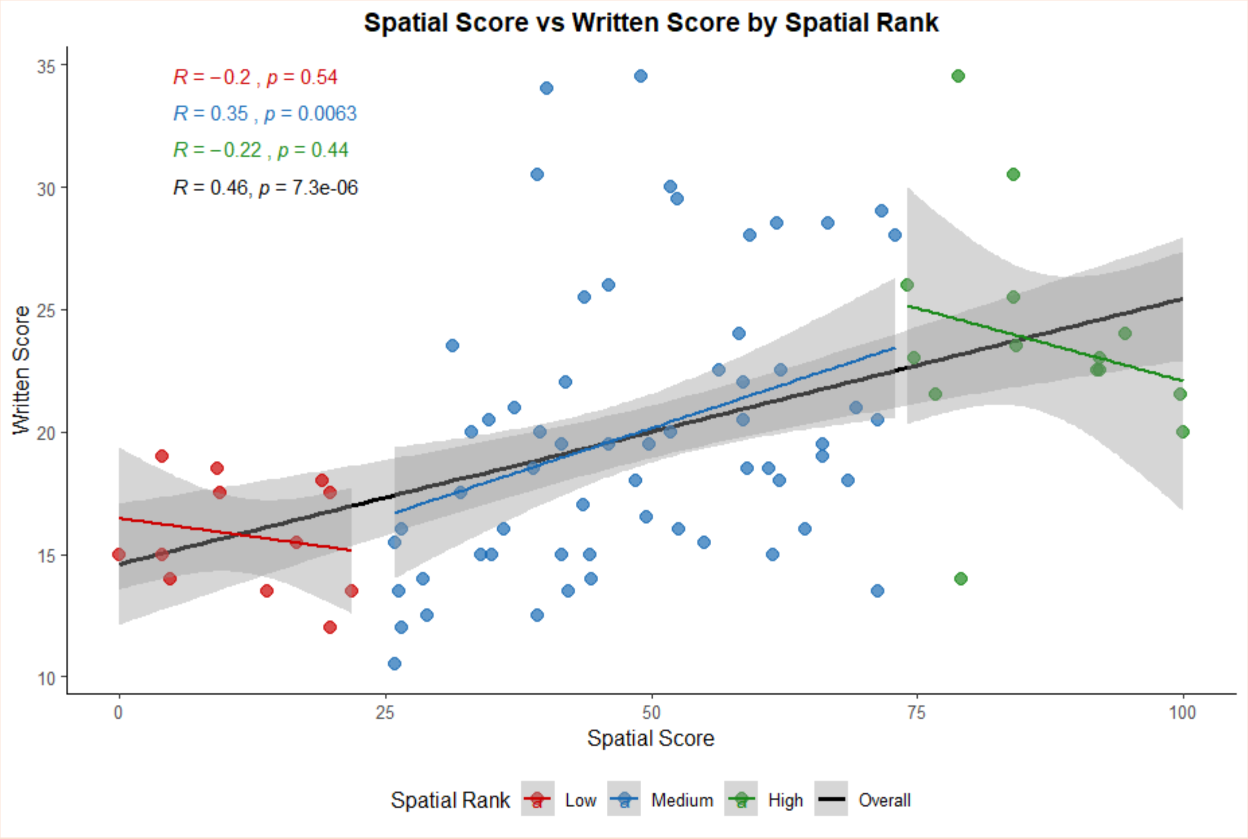
Table 9. *Means, standard deviations, and correlations with confidence intervals (n=86)*

Variable	*M*	*SD*	1	2	3	4
1. Spatial	49.43	24.00				
2. Verbal	9.42	2.49	.58**			
			[.42, .70]			
3. Phonemic	16.16	4.99	.27*	.17		
			[.06, .45]	[-.04, .37]		
4. Semantic	22.10	5.41	.28**	.16	.53**	
			[.07, .46]	[-.05, .36]	[.36, .67]	
5. Written	19.96	5.62	.46**	.47**	.24*	.29**
			[.28, .61]	[.29, .62]	[.03, .43]	[.08, .47]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

Spatial skills were positively and significantly correlated with all communication tasks when examined for the full cohort. Scatter plots of spatial score and written scores reveal that low and high spatial visualizers have a non-significant and negative relationship between spatial and written skills, while medium spatial visualizers have a positive and significant relationship between the two skills. Correlations between spatial scores and written scores by spatial rank can be viewed in Figure 21.

Figure 21. *Correlation plot of spatial score vs written score by spatial rank*



Parametric tests were applied to the data to examine differences in collected scores based on demographic information. Individual multiple regression models were then applied to individual groups (e.g. male participants, international participants), to examine what specific variables in the data help predict written report scores.

As spatial rank was composed of three groups, an analysis of variance (ANOVA) and TukeyHSD was conducted to determine how scores on different communication tasks differ based on spatial skill. Verbal analogy scores were statistically significantly different based on spatial rank ($F(2, 83) = 15.09$, $p < 0.001$), with high spatial visualizers scoring significantly higher than the low spatial visualizers (mean = 4.65, $p < 0.001$), and high spatial visualizers scoring significantly higher than medium spatial visualizers (mean = 2.15, $p = 0.003$). There were no statistically significant differences in semantic fluency and phonemic fluency averages by spatial rank. Written scores were statistically different based on spatial rank ($F(2, 83) = 7.49$, $p < 0.001$), with high spatial visualizers scoring significantly higher than low visualizers (mean = 7.96, $p < 0.001$), and medium spatial visualizers (mean = 3.79, $p = 0.04$). Multiple regression models were not statistically significant for low and high spatial visualizers; however, the regression model for medium spatial visualizers was statistically significant for medium spatial visualizers ($F(4, 55) = 3.561$, $p = 0.012$, R^2=0.21, $R = 0.45$). For medium spatial visualizers, spatial score neared significance for predicting written scores ($b = 0.10$, $p = 0.06$). Tables 10 and 11 provide means and standard deviations for participants based on gender and student status. Tests of equal variances ($H_0: \sigma_1^2 / \sigma_2^2 = 1$) indicate that equal population variances could be assumed when performing t-tests across the subgroups of gender and status for all variables.

Table 10. *Descriptive statistics by gender (n=86)*

Spatial Rank	N	Spatial (out of 100)		Verbal (out of 16)		Semantic Average		Phonemic Average		Written (out of 36)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	27	45.93	21.05	9.26	2.49	22.76	5.31	16.41	5.32	21.26	7.09
Male	59	51.04	25.24	9.49	2.50	21.81	5.48	16.05	4.88	19.36	4.75

No statistically significant differences were found on spatial scores, verbal analogy scores, semantic, and phonemic fluency scores. On average, women did score higher than men on written reports; however, this was also not statistically significant. Regression models were statistically significant for males ($F(4, 54) = 6.9$, $p < 0.001$, $R^2 = 0.34$, $R = 0.58$), with the model explaining 34% of variance in written scores. Verbal analogy scores ($b = 0.57$, $p = 0.049$) were statistically significant, and spatial scores ($b = 0.059$, $p = 0.054$) neared significance in the model. For females, the regression model was statistically significant ($F(4, 22) = 4.46$, $p = 0.009$, $R^2 = 0.45$, $R = 0.67$), with the model explaining about 45% of the variance in written scores, but this stronger power is likely due to smaller sample sizes; verbal analogy score neared significance in the model ($b = 1.00$, $p = 0.06$), but no other variables neared statistical significance.

Table 11. *Descriptive Statistics by Student Status (n=85: one participant did not disclose status)*

Spatial Rank	N	Spatial (out of 100)		Verbal (out of 16)		Semantic Average		Phonemic Average		Written (out of 36)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Domestic	48	55.83	23.91	10.06	2.55	22.91	4.93	16.95	5.04	21.36	5.83
International	37	40.45	21.40	8.62	2.20	20.97	5.91	15.07	4.84	18.05	4.84

Statistically significant differences were found in spatial scores (difference = 15.38, 95% CI [5.43, 25.32], $t(83) = 3.07$, $p = 0.003$; Cohen's $d = 0.67$, 95% CI [0.23, 1.11]), verbal analogy scores (difference = 1.44, 95% CI [0.40, 2.49], $t(83) = 2.74$, $p = 0.008$; Cohen's $d = 0.60$, 95% CI [0.16, 1.04]), and written report scores (difference = 3.31, 95% CI [0.95, 5.67], $t(83) = 2.79$, $p = 0.007$; Cohen's $d = 0.61$, 95% CI [0.17, 1.05]), with domestic participants scoring higher than international participants on these variables. The regression model was statistically significant for domestic students ($F(4, 43) = 4.114$, $p = 0.006$, $R^2 = 0.28$, $R = 0.53$), with verbal analogy score being a statistically significant predictor ($b = 0.74$, $p = 0.048$). For international students the regression model was statistically significant ($F(4, 32) = 2.84$, $p = 0.04$, $R^2=0.26$, $R = 0.51$); however, none of the predictors reached statistical significance.

Overall, each subgroup relies on different cognitive skills to assist when writing about engineering design topics, with some relying on verbal analogy skill while others rely on spatial skill. While high spatial visualizers did score statistically significantly higher in domains of fluency and written reports, it may not be purely due to spatial skill; in other words, someone that is a strong spatial visualizer may not immediately generate better written reports. Rather it may be that a combination of spatial and verbal cognition contributes to how effectively an engineer communicates information via a written document. To explore this theory, a structural equational model was developed and applied to the dataset to examine latent constructs.

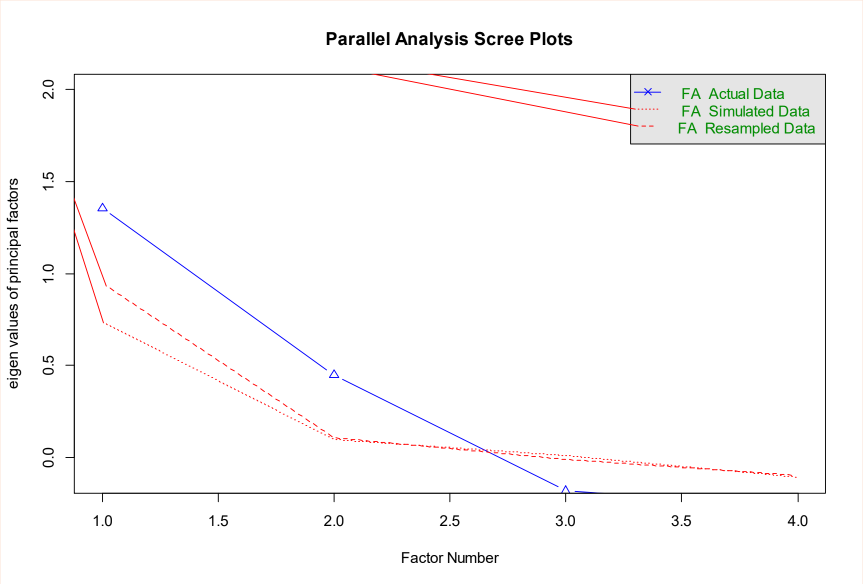
5.5.2 Exploratory Factor Analysis and Structural Model

The aforementioned literature from the mid-1900s stated the importance of spatial visualization ability for engineering; this literature also proposed that verbal ability is the psychological opposite of spatial ability (Smith, 1965). The idea of two separate intelligences that utilize verbal and spatial skills may align with Paivio's Dual Coding Theory (DCT), in which the two stimuli of verbal and non-verbal information help process information (Paivio, 1991). A caveat is that unlike Smith's (1965) statements, DCT does not assume that non-verbal and verbal processing are opposites, rather they are two separate systems that may operate independently or simultaneously to process information (Paivio, 1991). As data collected as part of this research contains a mixture of verbal and non-verbal measurements, an exploratory factor analysis (EFA) was conducted to determine which latent constructs exist in the data and if they are associated with the discussed theories; specifically, how the measured variables of spatial, verbal analogy, semantic, and phonemic fluency load onto latent constructs that predict written scores. EFA standards were based on Brown's recommendations (2015); Kaiser-Meyer-Olkin (MSA = 0.69) was acceptable, and Bartlett's sphericity test was significant (X^2=99.65, p<.001,df=10). Eigen-value scores and parallel analysis scree plots, alongside oblimin rotation factor analysis to allow for correlation amongst factors, indicated a two-factor solution in the data, as shown in Table 12 and Figure 22.

Table 12. *Factor analysis with oblimin rotation*

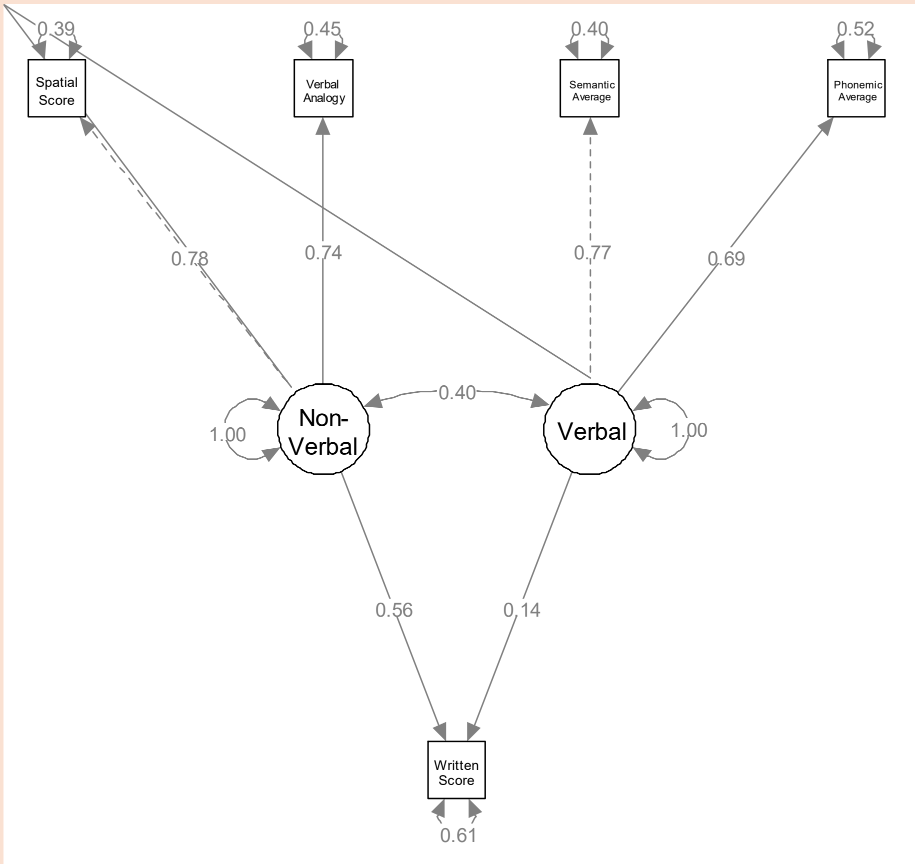
Variable	Factor 1	Factor 2	H2	U2
Verbal Analogy Score	0.78		0.58	0.42
Spatial Score	0.74		0.60	0.40
Semantic Average		0.80	0.63	0.37
Phonemic Average		0.66	0.46	0.54

Figure 22. Parallel analysis scree plot for factors



Factor analysis indicates that two latent constructs exist within the data; H2 values were above 0.50 for most factors except phonemic fluency, which indicates that the factors moderately explain the variance for each of the four items. When applied to DCT, the constructs of non-verbal (Spatial Score, Verbal Analogy Score) and verbal (Semantic Fluency, Phonemic Fluency) cognitive skill can be used to determine a final written score for participants. While it appears contradictory to have verbal analogy scores attributed to the non-verbal factor, the factor analysis indicated these two constructs belong together; furthermore, the task for verbal analogy did have aspects of logic. While it did involve finding correct words, pattern recognition of words may not rely on exclusively verbal cognition. A final confirmatory model equation that predicts written score and the structural equation model is provided below in Figure 23.

Figure 23. *Structural equation model for prediction of written scores (n = 86)*



NonVerbal =~ SpatialScore + VerbalAnalogyScore
Verbal =~ SemanticAvg + PhonemicAvg
WrittenScore ~ NonVerbal + Verbal

Model standards for indices of good fit were based on Brown (2015). RMSEA < .06 indicates good fit, < .08 indicates reasonable fit. CFI and TLI > .95 indicates adequate fit, SRMR <.10 indicate acceptable model fit. The final model's parameters were CFI = 1.0, TLI = 1.04, RMSEA = 0.00, SRMR = 0.026, and $\chi^2(3) = 1.948$, p = .583, which indicates the model fits the data well; this can be assumed as the model was just-identified, or that it was applied to the same data that was used to develop the model. The structural equation model indicates that both non-verbal and verbal skill, latent constructs generated from measured variables in this data, are both positive predictors of written score. The model explains 39% of variance in written scores of engineering students. Table 13 presents the standardized loadings and how well the observed variables are captured by the latent constructs of non-verbal and verbal skill

Table 13. *Observed variables factor loadings*

Factor	Observed Variable	B	SE	Z	B (std.all)	*p*	R^2	Residual
Non-Verbal	Spatial	1.000	~ (ref)	~ (ref)	0.779	~ (ref)	0.61	0.39
Non-Verbal	Verbal	0.098	0.020	4.828	0.741	0.000	0.55	0.45
Verbal	Semantic	1.000	~ (ref)	~ (ref)	0.772	~ (ref)	0.60	0.40
Verbal	Phonemic	0.828	0.295	2.813	0.693	0.005	0.48	0.52

Findings indicate that the observed variables load well onto the theorized latent constructs. Table 14 presents how these latent constructs predict the written score of engineering participants.

Table 14. *Latent Construct Factor Loadings for Written Score Prediction*

Construct	B	SE	z	*p*	B (std.all)
Non-Verbal	0.167	0.043	3.855	**0.000**	0.556
Verbal	0.190	0.176	1.085	0.278	0.142

Results show that the latent construct of non-verbal skill is statistically significant at predicting the written scores of engineering students; verbal skill does positively predict written score, however this was not statistically significant. An important finding is that per Figure 23, the latent constructs of non-verbal and verbal skill covariance indicates a statistically significant moderately positive relationship ($p = 0.019$, $R = 0.396$, $R^2 = 0.15$), which indicates that as an individual has stronger non-verbal skill it may correlate with stronger verbal skill; however, these are not correlated enough that they represent the same underlying cognition, rather they are two separate intelligences that share overlap. The model does leave 61% of the variance in written scores unexplained; this could be attributed to the student's roles, capabilities with typing, environmental, or personal factors. Regardless, these variables and the model do explain a significant portion of final written report scores. Findings reaffirm DCT, where the subsystems of non-verbal and verbal processing are distinct but can operate simultaneously to help process information and help communication; the idea that these two intelligences, spatial and verbal skills, are psychological opposites was not corroborated by this data.

5.6 Discussion of Results

Results indicated that spatial skills were the strongest predictor of written communication scores, with high spatial visualizers scoring statistically significantly higher than non-high spatial visualizers on written reports that described their first-year robotic engineering project. Some literature, which explored broader communication skills, concluded "[t]he ability to describe things properly depends on individual spatial and verbal skills" (Lucking & Pfeiffer, 2012, p. 22)". The results presented in this paper may imply that individuals with high spatial skills may be more likely to communicate spatial information more effectively through written mediums, such as a text document generated on a computer. However, this improved writing skill is likely due to a combination of strong spatial visualization skills and verbal capabilities, or non-verbal and verbal intelligences. Furthermore, the written report was graded not just on how one writes about spatial phenomena, but about broader issues that required the robotic project, performances at demonstrations, and which tasks were to be completed; the positive relation between spatial and verbal skills may imply that spatial skills also assist in writing about abstract or non-spatial phenomena as well. The result that the latent factor of non-verbal construct is more statistically significant and a stronger predictor of written score could be attributed be the nature of the task itself. Prior work by Hooey and Bailey explored how documentation can improve spatial comprehension of topics, which may, in turn, explain why students with strong spatial visualization students are more effective at writing about a spatial event, relationship, or objects (2005). Hooey and Bailey noted that the informal nature of journaling and self-reflection helped improve both spatial and written skills (2005). In this research, students were asked to compose a written document in an interview setting and no grades or traditional academic consequences were associated with the assignment, which may have impacted how students wrote and reviewed their writing.

High spatial visualizers scored higher on the tests of semantic fluency, phonemic fluency, and verbal analogy questions compared to the low visualizers. It could be concluded that these students did exceptionally well on all tests administered and have higher test taking capabilities or general intelligence. In other words, the high spatial skills translate to high general intelligence. Prior research examined this issue by questioning if spatial skills were an indicator of general intelligence or were a separate factor of problem solving in the context of mathematical word problem-solving:

> *"[S]olving the simple math word problems used in this study, both mathematical and spatial abilities are relevant and that of these, spatial ability has a slightly larger effect size. It is worth noting that the verbal ability level required for the items included in the current study would be considerably lower than the verbal ability threshold requirements for university entry. While this limits an in-depth analysis of the relationship between*

spatial and verbal ability, research from the last 50 years suggests that these two abilities are typically not closely related (Wai, Lubinski, & Benbow, 2009). In terms of representing the problems, however, only spatial ability was found to be relevant marking it out as separate and distinct from the other two abilities in this thought process." (Duffy et al., 2019, p. 45).

Spatial skills uniquely contributed to the representation of word problems more than students' verbal ability, determined by verbal standardized test scores, and acts as a specific cognitive function rather than just the general intelligence used in word problem solving (2018). While these word problems were noted as simple, it may relate to these findings of written communication skills. Spatial skills may not just be indicative of overall intelligence but rather operate as a mediating factor that impacts elements of reading and writing ability. Other research examined how visual-spatial ability influenced academic success in 5th and 6th grade Chinese grade schoolers, and found that:

"[T]here were two indirect paths from children's visual–spatial ability to academic achievement. One pathway showed that visual–spatial ability indirectly influenced academic achievement via arithmetic ability (visual–spatial ability → arithmetic ability → academic achievement). The other pathway suggested that arithmetic ability and reading ability played a chain mediating role between visual–spatial ability and academic achievement (visual–spatial ability → arithmetic ability → reading ability → academic achievement)." (Liu et al., 2021, p. 7)

This may suggest that visual-spatial skills may not directly impact written and verbal communication skills; however, they may improve these skills through the mediation of mathematical comprehension or other cognitive functions. It is important to note that the reading ability represented by Liu et al's research (2021) was for the Chinese language, which may rely more on spatial comprehension. The "writing [of] Chinese characters or hieroglyphics involves increased activation of the right hemisphere, particularly in visuospatial processing areas, due to the intricate and non-linear nature of the script" (Marano et al., 2025, p. 2), whereas alphabetical languages like English rely on phonological processing areas of the left hemisphere of the brain (2025). The "cognitive demands of writing hieroglyphic characters may lead to enhanced visuospatial memory and motor coordination compared with alphabet-based writing, highlighting significant differences in neural processing between these two systems" (2025) meaning that Chinese students may have larger impacts on their reading ability from their visual-spatial ability due to the processing of symbols required based on the Chinese language. Furthermore, these writing skills may relate to penmanship, or the readability of written letters by hand, which may not immediately translate to effective written communication done through typing. However, alphabetical languages could still benefit from elements of visual-spatial processing.

Another study found that high spatial visualizers had a significant and moderately positive correlation with phonemic fluency tasks (Hostetter & Alibali, 2007). This research hypothesized that phonemic fluency tasks in the English language, and potentially by extension other alphabetical languages, could share the cognitive processes as spatial skills:

> *"[S]uccess with the task is thought to rely on frontal lobe abilities such as task switching, strategic search, and effortful planning…[the] same frontal lobe processes [which] are presumably necessary for taking a holistic image and breaking it down into component parts for speaking, as speakers must efficiently organize the image in a way that coincides with the linear demands of speech and quickly switch their attention between different components that need to be mentioned." (2007, p. 77)*

While the phonemic fluency task involved in the above study measured only lexical skills and not technical written communication, participants may have had to use similar strategic searches to find different words with the same letter or words that belonged to similar categories. This skill could be useful when breaking down a holistic image into component parts when writing. To this end, the fluency tasks, a small but important aspect of overall communication skills, may share executive control with general spatial communication skills (Hostetter & Alibali, 2007; [redacted] et al., 2024). This executive control could help with aspects of written media such as document layout, sentence structure, the ability to access similar lexicons for information, and overall flow.

Another aspect that may impact writing skills is the medium itself. Neurological research has examined brain function differences between typing and writing by hand and which regions of the brains are activated by each mode.

> *"there is a unique correspondence between the letter and the movement that produces it, demanding a deeper level of attentional processing. Typing, on the other hand, also involves spatial learning, as individuals must construct a mental map of the keyboard to accurately locate and press each key. Unlike handwriting, the finger movement required to reach and press a key is simpler and more intuitive, lacking any graphomotor component. It has no direct relationship to the shape of the letter." (Marano et al., 2025, p. 16)*

It may be theorized that individuals with stronger spatial skills would have stronger mental models of a keyboard, which may help with typing; however, memorization of specific locations of keys does not seem likely to improve a person's skill to construct effective written documents. These neurological activations go beyond just memorization of a keyboard. For instance, “[w]hile typing requires less fine motor control, its dependence on working memory and executive functions is pronounced, reflecting the task’s reliance on higher-order cognitive processes” (2025, p. 6). Furthermore, “[t]he results suggest that while handwriting primarily activates the motor cortex and visuospatial integration areas, typing predominantly engages linguistic processing and working memory circuits” (Marano et al., 2025, p. 9). These linguistic processing can also relate to high spatial visualizers demonstrating stronger phonemic fluency due to an enhanced ability to strategically search for words. However, as it was found that typing engages fewer neural circuits which resulted in more passive cognitive engagement (2025), this could explain why some engineers have a writing style that may be not what industry expects (Aller, 2002; Britton, 1965; Winsor, 1992).

Other results from this research include a lack of significant differences in written scores based on student status, or domestic and international students. As all written reports were created in English, one may assume that the domestic students would have had an advantage. Prior work by the authors found that domestic and international students had similar semantic and phonemic fluency skills, with no statistically significant differences between the groups ([redacted] et al., 2024). This could be attributed to the research setting, or that English as Second Language courses and curricula have done an effective job of readying international engineering students. However, because this research could not access standardized test scores for international students it cannot be definitively answered. Further results found no statistically significant differences in spatial scores based on gender, which is a unique result in the context of prior work that found marked differences by gender (e.g., Casey et al., 2011; Newcombe & Shipley, 2015; Wai et al., 2009). This could be attributed to the spatial visualization training undertaken in the first semester by all students and reinforces that spatial visualization skills are malleable, and that students who may have weaker skills can be trained and have marked improvements.

This research attempted to explore why industry reports that recent engineering graduates are lacking in communication skills. Results indicate that spatial skills are significant predictors of written communication skills and do not negatively impact other linguistic skills of an individual; in fact, spatial skills may enhance elements of written communication when combined with an individual's verbal skillset. These results appear positive in that the technical skills being taught to engineering students in academia are not negatively impacting their capability to communicate through a written medium. This is crucial as the ability to write effectively and clearly has been listed as important for new employers (Hirudayaraj, 2021, p. 26), and dependent on the industry, new engineering graduates had writing proficiency that exceeded assumed level of important or weren't far behind expectations (2021, p. 28). Other research into communication skills for construction engineers found that business and professional communication (BPC) courses focus heavily on writing skills; when the authors asked construction engineers to rank communication skills they found:

> *[A] large difference…between oral communication skills (n=383) and written communication skills (n =84) [in ranking], especially given that their importance from employers' perspectives has previously been ranked as equal or nearly equal to each other…[w]riting skills are of course vital, and employers find writing errors to be bothersome...[p]erhaps the communication element attached to writing is what creates a disparity between the frequencies of oral and written communication skills…writing a report may not have been mentioned in job ads because employers viewed it as a writing task but not a communication task (2024, p. 327-328).*

The current research's results that spatial visualization skills are positively connected to aspects of communication and writing skills may explain why industry places writing skills underneath oral communication. Engineering graduates may have effective writing skills due to technical communication courses embedded in the curriculum, or that the skillsets that are beneficial to engineers, like spatial skills, enhance aspects of writing communication and verbal cognition. These findings suggest a positive outlook for new engineering graduates, where the skills that assist in technical content knowledge gain for engineers have meaningful gains in other verbal domains. However, the issue persists that industry continues to indicate that engineering graduates are lacking in communication skills (Coffelt, 2024; Hirudayaraj, 2021).

A fundamental issue when addressing the gap between engineering communication skills and industry expectations is the extreme breadth of concepts umbrellaed under *communication skills*. Research found that elements of humility, curiosity, eagerness to learn, social awareness, being well-rounded (e.g. extra-curricular activities), being enthusiastic, taking initiative, and other intrapersonal traits were all stated as critical by industry (2021). This was to the extent that some employers stated, "[a] successful new hire will not be the most technically proficient, instead it will be the one best able to learn and communicate" (2021, p. 24). Technical communication courses in engineering must teach concepts of prose, language, structure, proper presentation styles, applications to engineering domains, and potentially more topics. It is difficult to then add the training of specific personality traits if that could even be possible within an academic context. Furthermore, engineering majors have vastly different experiences; while this research had all first-year engineering majors participate in a team-based project, computer engineering / science majors and architectural majors may not participate in as many team-based projects as construction / mechanical engineering majors. The concept that a team-based project for all engineering majors will teach these personality traits is not consistent with literature, where experiences of engineering students vary based on representation and gender (Jiménez et al., 2020; Sellers & Villanueva-Alarcón, 2023). Hidden curriculums in engineering were found, and these curriculums reinforce traits of individualism and survival of the fittest mentalities (Sellers & Villanueva-Alarcón, 2023). These mindsets are the polar opposite to the outgoing and benevolent character traits industry expects of the newly graduated engineering majors. Future work must have academia, accreditation institutions, and industry work in tandem to address these elements of personality traits and communication styles of engineering students. Academia will need to address elements of the hidden curriculums that reinforce personality traits antithetical to industry expectations, and if industry does state that technical competency is no longer a determining factor, academia may be able to eliminate requirements for more advanced technical courses in favor of experiential learning to reinforce personality traits and learning styles. Accreditation bodies will have to work alongside these efforts and ensure that the expectations of industry for graduates are realistic and aligned with modern trends. Finally, industry will need to be more deliberate in the explicit aspects of communication they find lacking, and work with academia and accreditation institutions to insure a more cohesive ecosystem for engineering graduates to learn, mature, and grow. This will allow engineering students to be prepped not just for their immediate industrial contexts and application of their technical knowledge, but to be effective and altruistic members of a more globalized and interconnected society.

5.7 Limitations and Future Work

The reports created by student participants were written on a laptop and they were given explicit instructions in the form of a bullet list regarding what points to discuss in their document. This situation may not reflect writing assignments in traditional academic or industrial contexts, where an engineer may be asked to write about the progress being made on a project. In these situations, it would be up to the engineer to determine the genre and the information to include. As there was no explicit time limit enforced, participants were also able to take more time than originally expected (15-20 minutes) and utilize any spell-checking aspects of Microsoft Word. However, the laptop was not connected to the internet so no elements of online research or generative writing tools could be accessed.

Participants were at the beginning of their second semester of a two-course sequence; the robot project from the prior semester was likely still familiar and fresh in their mind, which was likely beneficial when asked to discuss specific information about it. Conversely, the engineering design project was completed by teams consisting of 3 to 4 members, with explicit roles and responsibilities determined by members of the group. Typical team roles involved coding, project management, report writing, or the actual construction of the robot. Research participants were not asked about their role on the project; however, their knowledge and recollection of the project would be informed by their roles, which may skew some results (e.g. the builder may have a more intricate recollection of robot operations than the project manager). Other information such as prior communication courses or standardized test grades (ACT / SAT) were not collected as part of the research, so the communication skills of the participants was solely determined by the research data. Participants were interviewed in one-on-one sessions in which video recording equipment was set up. When administering the phonemic and semantic fluency tasks, participants were recorded with no prior explanation. Furthermore, participants were not informed that morphological changes (twenty-one, twenty-two) would not count towards overall word count, which could skew some results in the data. Any undue difficulties due to this format may have impacted phonemic and semantic fluency counts and final written report scores.

Further analysis of the data will include two other components of overall technical communication skill: graphical communication (sketching / imaging) and oral communication. These other two communication areas will provide further insight into the role that spatial skills play in overall effective communication skills, a critical component of an engineer's skillset and a precursor of success in academia and industry. After this additional analysis, a more holistic picture of how spatial skills interacts with oral, written, and graphical communication will be presented to the broader scientific community.

5.8 Conclusions

This research article conducted a unique examination of a recurrent phenomenon in engineering, where recent engineering graduates enter industry with strong technical content knowledge but are reported to be lacking in communication skills; this occurs despite dedicated efforts via specific courses and cross-departmental initiatives to improve communication skills. Through two phases of testing, first-year engineering students in the second semester of a two-semester introductory engineering course completed multiple spatial, verbal, and written measurements. Participants were categorized through a principal component analysis into low, medium, and high spatial visualizers. Participants completed a written report that asked them to detail their robotic project from the previous semester; each report was graded with a validated rubric generated by members of the research team. Results indicated that high spatial visualizers created stronger written reports that communicate a previous project and spatial phenomena. Further structural analysis of data revealed non-verbal and verbal latent constructs; of these, non-verbal skills were statistically significant positive predictors of final written report scores, while verbal skills were positive predictors but were weaker and not statistically significant. Notably the two constructs of non-verbal and verbal skills were significantly positively correlated, which indicates that while these two skillsets are distinct, they share overlap and may be used in tandem to enhance communication of engineering topics.

Analysis of the literature that focused on modern industry's comments revealed that the writing communication of recent engineering graduates is acceptable or can be improved, and industry's remarks of a lack communication skills could be due to interpersonal and intrapersonal skills. Suggestions for improvements outside the immediate context of academic courses are made. Engineering undergraduates likely have the proper cognitive baseline to be effective at written communication. The persistent gap of communication skills is likely not attributable to the skillsets of technical knowledge that engineering majors obtain and maintain throughout their degree, rather it may be the specific personality traits that are developed or reinforced in undergraduate engineers due to engineering curricula.

Prior statements have stated that institutions "over-value[d] the verbal type of ability at the expense of its psychological opposite–spatial ability" (Smith, 1965, p. 5), and that "research from the last 50 years suggests that these two abilities [spatial and verbal] are typically not closely related" (Duffy et al., 2019, p. 45). Examination of these two domains with preconceptions that they are opposite may make it difficult to see shared elements of cognitive processing, or if there are potential pathways that can show how spatial skills help in indirect ways to improve the brain functions that written, graphical, and verbal ability utilize. The link between spatial skills and written communication skills may not be direct, but that does not imply that there are no mediating pathways and other cognitive processes the two could potentially share. The idea that engineers are poor writers but have strong technical skillsets, which suggests negative relationships, not only seems a superficial stereotype but is here shown to not be the case.

5.9 Acknowledgements

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Chapter 6. Journal Article 3: Relationships between spatial visualization, oral communication, and gesture production amongst first-year engineering students.

European Journal of Engineering Education (Submitted)

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6.1 Abstract

Industry continues to state the importance of communication skills among recent engineering graduates, specifically listing oral or verbal communication within the top three skills for new hires. Despite industrial statements and efforts from academia to improve communication skills, the gap between recent engineering graduates' communication skills and industry expectations persists. Conversely, engineering students often graduate with stronger overall technical knowledge and spatial skills through engineering curricula. This research explores relationships between the two skillsets, oral communication and spatial skills, to see if trends between these two skillsets can help illustrate why recent graduates may not be meeting communication expectations. Methods were influenced by gesture and linguistic research which has examined how spatial skills and verbal (specifically oral) communication interact with the amount and types of gestures produced.

A total of 81 engineering participants who were in their second-semester of their first-year engineering program completed two phases of data collection; the first phase involved an online survey that distributed spatial visualization tasks, verbal analogy task, and collected demographic information; the second phase involved a recorded in-person interview where participants explained an engineering design project they completed in the prior semester, alongside completing various communication tasks. A principal component analysis was applied to collected spatial visualization scores to categorize participants into low, medium, and high spatial visualizers. Furthermore, averages of phonemic / semantic fluency, final oral report scores, and amounts and types of gestures produced during the interview were calculated. . Analysis revealed that high spatial visualizers outperform low spatial visualizers on various measures of verbal skill; however, oral report scores were not statistically different for the two groups. Domestic participants outperformed international participants on multiple measures;

however, international participants gestured more during their oral presentation. No notable differences between men and women were found. A final structural model found two latent constructs of spatial cognition and verbal fluency within the data, which had a statistically significant moderately positive correlation between each other. Results imply that spatial skills may share deeper cognitive connections to oral communication than previously assumed in engineering education. Reviews of industry comments reveal that engineers' poor communication skills may lie elsewhere, potentially within new graduates' intrapersonal traits and temperament. Results reinforce the need for spatial skills in engineering education, as they have pronounced benefits in both technical content comprehension and engineering success, and may share overlap with the cognitive domains of communication that were previously assumed separate.

6.2 Introduction

6.2.1 Spatial Skills in Engineering

Spatial skills have been defined in various ways, with one definition being an intelligence comprised of two components: one component, *spatial orientation*, which involves mental representations and operations on visual stimuli, and *spatial visualization*, which is an individuals' ability to picture spatially arrayed elements from various perspectives (Bednarz & Lee, 2011). Spatial skills have also been defined as "[t]he ability to make use of simulated mental imagery to solve problems…recalling images in the mind's eye" (Reid, 2022, p. 29), and a person's capability of imagining in their mind visual stimuli and applying manipulations or transformations to that stimuli (Raju & Sorby, 2024).

Since the mid-1900s spatial skills were noted as critical to the success of an engineer (Smith, 1964; Super & Bachrach, 1957). An abundance of research has since empirically validated spatial skills as an important indicator of an individual's decision to major in STEM disciplines and their later success in those fields (Kell & Lubinski, 2013; Lane & Sorby, 2022; Ramey & Uttal, 2017; Shea et al., 2001; Uttal & Cohen, 2012; Yoon & Mann, 2017). Spatial skills have been found to have marked gender and socio-economic differences (Casey et al., 2011; Wai et al., 2009); however, because spatial skills are trainable through interventions (Ramey & Uttal, 2017; Uttal et al., 2013), these differences can be mitigated which could lead to improved representation for more groups in engineering. Spatial skills have also been reported as an important component in mathematical word-problem solving (Duffy et al, 2024; Reid, 2021), engineering design problem solving (Raju & Sorby, 2024), creative design performance (Chang, 2014; Chang et al., 2016; Olkun, 2003), and chemical engineering problem solving (Loney et al., 2019). Recent research has also revealed that spatial skills are important in STEM domains that may not typically be associated with traditional engineering contexts, such as computer science achievement and success in programming exercises (Bockmon et al., 2020; Endres et al., 2021; Fincher et al., 2005; Fisher et al., 2006; Ly et al., 2021; Parkinson & Cutts, 2022).

6.2.2 Technical and Oral Communication in Engineering

Oral communication is often umbrellaed under the larger term of technical communication, a term that summarizes various elements of communication an engineer performs as part of their work. A more globalized economy and infrastructure produced a shift that pushed for stronger professional skills, where reports stated that the modern engineer "[has] to work in teams [and] communicate with multiple audiences…more effectively in the future" (National Academy of Engineering, 2004, p. 43). More recently this focus was re-emphasized by the Accreditation Board for Engineering and Technology (ABET) which stated in the third criterion for student outcomes that graduates must have "an ability to communicate effectively with a range of audiences" (2025). The focus on improved communication for engineering graduates is also seen in modern industry demands.

Surveys that analyzed online descriptions for engineering jobs found communication skills (oral, written, and/or generic) in the top three skills desired for new hires (Chaibate et al., 2020; Jaimes-Acero et al., 2023; Lancetti et al., 2023; Zaharim et al., 2009). This is consistent with sentiments from engineering industry personnel, executives, and hiring managers who have emphasized the importance of technical communication skills (Ford et al., 2021; Katz, 1993; Karimi & Pina, 2021), with some stating graduates "need to learn basic people skills combined with technical communication skills or they will fail horribly" (Sageev & Romanowski, 2001, p. 690). Further reviews of hiring applications have found that communication "is one of the most commonly used of all skills, with several studies showing that engineers working in industry spend over half of their working hours on some form of communication, including writing, oral presentations, or other oral discussions" (Fleming et al., 2024, p. 4). Furthermore, the oral communication required in industry is not just formal presentations but speaking with non-technical and technical audiences in various fields in a multitude of situations (2024). This demand for technical communication skills has resulted in myriad methods being implemented in higher education to improve communication skills for engineering students; some are described in the following.

Specific books have targeted communication and presentation within engineering contexts (Alley, 2013; Stone, 2015). Academic institutions have made significant efforts aimed at addressing these communication gaps through writing workshops with constructive feedback loops (Badran et al., 2022; Berthouex, 1996; Boyd & Hassett, 2000; Cox et al., 2009; Masoud & Muhtaseb, 2021), self-reflective written assignments (Selwyn & Renaud-Assemat, 2020), and embedded grammatical modules as part of engineering courses (Issa et al., 2022). Other efforts have implemented the flipped-classroom model to target professional and teamwork skill development (Baytiyeh, 2017; Boelt et al., 2022), examined the impact of co-curricular activities on oral presentation skill (Garrett et al., 2022), and attempted to recreate authentic industry experiences for students (Laewpet & Sukamolson, 2011). Institutions have created cross-departmental initiatives that involve engineering faculty, humanities faculty, linguistic faculty, and industry practitioners to determine the best practices and scalable strategies for future technical communication education (Conrad et al., 2015; Gallagher et al., 2020; Lappalainen, 2009; Yoritomo et al., 2018).

One difficulty is that efforts to improve engineer's technical communication focus on various elements of communication, such as writing, presentations, graphical design, and oral communication, typically done in one course, which may not provide enough time or opportunities for overall development. Introduction of further courses in an already saturated curriculum is difficult, so this issue may be something that persists. In summary, technical communication is important for all engineers, particularly oral / verbal communication that must be adaptable to various contexts.

6.2.3 Gesture Production and Oral Communication

As technical communication research in engineering education must focus on the teaching and examination of written, oral, and graphical techniques, the focus on complex aspects of communication such as gesture have been sparsely analyzed. Research into gesture outside of engineering has explored different theories on the origin and meaning behind gestures. Some of this research utilizes the theory of working memory, which refers to "a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" (Baddeley, 1992, p. 1).

In the Lexical Gesture Process Model, a speaker's working memory begins the process of generating a propositional representation, or a pre-verbal message, which are sometimes reflected in lexical gestures to help explain the words accompanying a message when a concept is being explained. The authors of this model suggest that "gestures are a product of the same conceptual processes that ultimately result in speech, but the two production systems [visual imagery and speech-based subsystems] diverge very early on" (Krauss et al., 2000, p. 17). These authors further posited that gestures should not be assumed to automatically generate meaning for speech, particularly because speakers make gestures even when they cannot be seen (2000). This has also been found in work related to learning, where a mismatch in gesture and speech indicates a child is ready to learn a problem (Alibali & Goldin-Meadow, 1993, p. 477).

The Interface Model theory by Kita & Ozyurek explains that gesture production occurs simultaneously through the language of the speaker and non-verbalized spatial information about the subject discussed (2003). The spatio-motoric processes that are simultaneously occurring with speech production generate gestures, which in turn chunks information to be verbalized later. This can help organize the verbal messages for the speaker (2003). The Growth Point Theory proposes that the start of a sentence involves the combination of "linguistic and imagistic information together to initiate the dynamic cognitive processes that organize thinking for speech and results in co-speech gesture" (Clough & Duff, 2020, p. 2).

6.2.4 Potential Relationships between Spatial Skills, Oral Communication, and Gesture Production

Gestural theories may disagree on the exact details on when language and imagistic information for the speaker begin to diverge or merge, but what is common is that both verbal and spatial imagery interact with gesture; researchers found that “[t]he ability to describe things properly depends on individual spatial and verbal skills (Hostetter and Alibali 2011 as cited in Lucking & Pfeiffer, 2012). Information processing through two separate systems, verbal and non-verbal, can also be seen in elements of Dual Coding Theory (DCT) (Paivio, 1991), which has been used in prior research in engineering education. Engineering design problem-solving found spatial visualization as a critical component of successfully completing problems during think-aloud sessions through the lens of the DCT (Raju et al., 2025). Results showed that high spatial visualizers produced more sophisticated and higher-quality solutions to problems regardless of year, while final-year and first-year low spatial visualizers produced similar quality results (2025). DCT claims two primary systems are involved when an individual processes information: these two are linguistic and the non-linguistic world, or verbal and non-verbal information, and these two systems are functionally independent of one another (Paivio, 1991). This means the verbal and nonverbal systems can be active individually or at the same time, and both systems help interconnect information in unique ways; verbal words may transform into phrases or sentences with further verbal information added, and nonverbal information may be transformed with mental transformations in spatial dimensions, such as size, shape, sound, movement, or color (1991). While not explicitly stated in the prior research examined, the concept of DCT aligns with some of the examined gesture theories, primarily that gestures occur through the usage of both linguistic and nonverbal information, which typically originate from different cognitive systems but may work independently or simultaneously. This posits one potential relationship between the domains of spatial skills in the context of engineering education and oral communication and gesture research.

Prior research in gesture has linked spatial skills to gesture production ability (Alibali & Goldin-Meadow, 1993; Alibali, 2005; Lucking & Pfeiffer, 2012; Wakefield et al., 2019). Gestures are also related to verbal ability, in which the combination of gesture and verbal speech generate new meaning (Alibali & Goldin-Meadow, 1993). Gesture production was examined in two groups of participants, one which had events described only verbally and another with events described both verbally and with visual information. The results indicated "that speakers do gesture more when they are describing events that they have witnessed visually than when describing events they have only heard about" (Hostetter & Skirving, 2011, p. 220). Hostetter and Alibali have explored the three areas of verbal skills, spatial skills, and gesture production by measuring the phonemic and semantic fluency abilities in relation to gesture production and found participants with low phonemic fluency, but high spatial skills produced the most gestures (2007).

It is tempting to see these relationships and assume the correlations are consistent, however Hostetter and Alibali state that a potential reason that some of the relationships between spatial skills, verbal skills, and gesture are ambiguous could be the "expectation that the relationship…is linear" (2011, p. 75). A further complexity is that the verbal skills examined in these areas of gesture research may not be what is expected in engineering industry, where engineers must convey complex technical information through language and must maintain elements of self-perceived abilities, environmental factors, and elements of genre and audience; these verbal skills may not be what engineering education means when teaching oral communication, however as these aspects of verbal communication are still important, research into the specific skills may reveal underlying issues and provide novel solutions to address industry's comments.

6.3 Methodology

Based on the previous analysis of literature, the following research questions for this study were generated:

- *What is the relationship between spatial skill levels, oral communication scores, and gesture production for engineering undergraduate students when describing their first-year design projects?*
  - *Is the relationship similar for high / low visualizers, women / men, domestic / international students?*
  - *Are there interactions between spatial skills, forms of fluency, and gesture production when engineers describe their engineering design projects?*

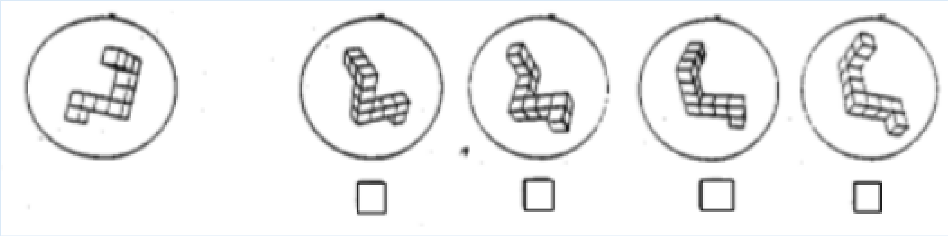
6.3.1 Data Collection

Data was collected from first-year engineering students at a large midwestern R1 institution in the United States. The students were enrolled in the second course of a two-course sequence taken by all engineering majors at the university. Students explicitly practiced spatial thinking skills in the first-semester course through two weeks of in-class activities and graded assessments. Their training and practice with communication came from their experiences prior to college as well as any communication courses they may have enrolled in in their first semester at the university. Both course sequences involve a semester long team-based robotics project that students must demonstrate at an end of semester event. Students were incentivized with a gift-card at the beginning of the second semester to complete an online proctored Zoom survey over Qualtrics, hence referred to as Phase One. Students' who successfully completed all Phase One instruments were invited to participate in Phase Two, an approximately hour long one-on-one interview with a member of the research team that involved technical communication tasks and discussions of their robotic project from the previous semester. To ensure all quantitative and qualitative data was available for data analysis only data for students who completed both phases were analyzed.

6.3.2 Phase One Instruments

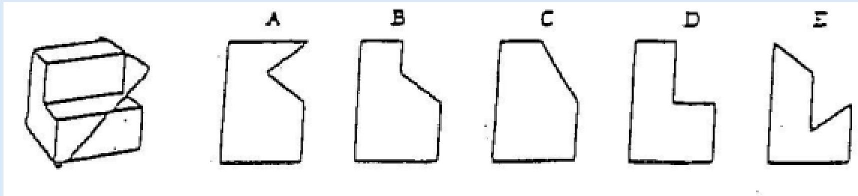
Spatial skills for students were measured with the Mental Rotation Test (MRT) (Vandenburg and Kuse 1978, 599) and the Mental Cutting Test (MCT) (CEEB, 1939). The MRT is a timed exam where students complete 24 questions in 6 minutes. This was included as mental rotation skills have been related to overall success in engineering (Sorby, 2009) and speeded mental rotation tasks have the largest gender differences in spatial skills (Voyer, 2011). As shown in Figure 24, students are presented with an original image on the left side and provided four options of the original figure rotated on the right side. Students must select the two figures on the right side that identify the rotated views of the original figure and score 1 point for both correct options and 0 points if they fail to identify both.

Figure 24. *Sample problem from MRT (Correct answer is 1 & 3)*



In the MCT, students are shown a figure with that has a cutting plane through it and are asked to select the resulting cross-section from the choices given. Students are given a total of 20 minutes to complete 25 questions with a total of 25 points possible, 1 point per each correct cross-section selected. An example of the MCT is provided in Figure 25.

Figure 25. *Sample problem from the MCT (Correct Answer = D)*



A Verbal Analogy instrument was also administered to the students to measure verbal skill. This instrument had a total of 16 items with no time limit and consisted of three words with one missing; students had to determine the relevant word from four choices given. An example question from this instrument is shown in Figure 26.

Figure 26. *Sample Problem from the Verbal Analogy Task (Correct Answer = Saw)*

WOOD : (_______) :: BUTTER : KNIFE

a) String b) Paper c) Saw d) Drill

Two final instruments completed by the participants included a self-reported confidence questionnaire and self-reported general demographic information (e.g. gender, student status).

6.3.3 Phase Two Instruments

Students who successfully completed all Phase One tasks were invited to complete another set of instruments in a face-to-face recorded interview session with a member of the research team. Students were provided with tasks to measure technical communication skills, which included semantic fluency measurements (production of words that belong to categories) and phonemic fluency measurements (words that begin with specific letters). These measures were based on previous research conducted in neuropsychological assessments (Hostetter & Alibali, 2007; Strauss & Spreen, 1991). Participants also responded to a set of questions read aloud by a member of the research team who asked them to describe their robotic project completed in the previous semester:

- *What problem were you trying to solve?*
- *What task was it supposed to do?*

- *What did it look like?*
- *How did it operate?*
- *What features of your robot solved the problem?*
- *How did your robot perform in the demo?*

Note that for the majority of participants, this oral portion of the interview was given after they had completed a written document where they responded to the same set of questions. The set of tasks analyzed in this research and estimated time are provided in Table 15 below.

Table 15. *Phase two student tasks*

Task	Description	Approximate Time
Phonemic Fluency Task (letter “s”)	Name all of the words that you can think of that begin with the letter “s”.	60 secs (enforced)
Semantic Fluency Task (animals)	Name all of the animals you can think of.	60 secs (enforced)
Phonemic Fluency Task (letter “t”)	Name all of the words that you can think of that begin with the letter “t”.	60 secs (enforced)
Semantic Fluency Task (fruits and vegetables)	Name all of the fruits and vegetables you can think of.	60 secs (enforced)
Oral Communication Task	Describe your robotic project orally (described above).	~5-10 Minutes

For all four fluency tasks, each 60 second session had transcripts generated and valid counts for words were totaled; note that for the phonemic fluency tasks, morphological changes of words were not counted past the first word (e.g. twenty-one, twenty-two, twenty-three) and proper nouns were not included in analysis per prior conventions (Speen & Strauss, 1991, as cited in Hostetter & Alibali, 2007, p. 83).

To grade participants responses on their oral communication task, a member of the research team with an expert background in technical communication in engineering education generated a rubric over multiple iterations. The rubric contained 7 Likert Options on a 6-point scale (1: Unacceptable, 2: Marginal, 3: Adequate, 4: Above Average, 5: Strong, 6: Exceptional) for a final score of 42 possible points. The questions covered whether the participant answered the prompts provided by the interviewer alongside the participant's flow, accuracy, organization, the effectiveness of verbally communicating information, and if physical features and operations could be discerned via verbal and gestural information; the rubric was applied twice, once with only audio and then with audio and video, the full rubric is provided in Appendix A. This rubric was applied by two separate raters to a subset of $n = 22$ oral project tasks. Squared weighted kappa was applied to allow for partial agreements (Q1: 0.947, $p < 0.01$; Q2: 0.74, $p < 0.01$; Q3: 0.839, $p < 0.01$; Q4: 0.898, $p < 0.01$; Q5: 0.807, $p < 0.01$; Q6: 0.903, $p < 0.01$; Q7: 0.85, $p < 0.01$), which resulted in statistically significant moderate to substantial agreement for each question. Squared weighted kappa for the final score of this subset resulted in $k = 0.634$, $p = 0.002$ for audio only rubrics, and $k = 0.613$, $p = 0.003$ for audio and video rubrics; the lower kappa scores are due to smaller sample size. Intraclass correlation (model: twoway, type: agreement) were also applied to total final scores, which resulted in $ICC(A,1) = 0.987$, $p < 0.001$ for audio only reports, and $ICC(A,1) = 0.994$, $p < 0.001$ for audio and video reports.. These results indicate that raters had statistically significant and strong agreement on both forms of oral report rubrics.

All participants' videos were analyzed and coded for gestures generated per 100 words based on the thematic coding scheme used by Hostetter and Alibali (2007). The coding scheme counts representational gestures (gestures that imply semantic meaning) and beat gestures

(gestures that imply no clear semantic meaning). An example of a representational gesture is "if a participant moved her right index finger around in a circle several times while saying 'the mouse swung around the bar,' this motion was counted as one representational gesture" (2007, p. 85). Simple and rhythmic motion that occur with specific words and phrases with no specific semantic depiction will be counted as beat gestures. An example of this can be an individual having their left hand make a small circular motion while attempting to remember a word.

6.4 Results

All data was analyzed in RStudio 2026.04.0 Build 526. A total of n = 90 participants completed both phases of the research; five were removed due to missing data or video recording failure, and a further four were removed as extreme outliers where the oral report videos were extremely shorts (under a minute) or were extremely long (over 10 minutes); the average oral report was around 4 to 5 minutes. Keeping these outliers in the overall dataset would drastically change averages for gestures per 100 word, word counts, and times for different spatial ranks based on the oral project video analysis (extremely brief or long responses).

6.4.1 Descriptive Statistics

A total of 81 participants were analyzed; applicable data was analyzed and no data significantly violated assumptions of normality. A principal component analysis was applied to all participants' MRT and MCT scores, which resulted in a single spatial score that categorized participants into low, medium, and high spatial visualizers. Descriptive statistics based on spatial rank and demographics are provided in Table 16.

Table 16. *Descriptive statistics of participants (N = 81; one participant did not disclose status)*

Spatial Rank	**Men**		**Women**	
	Domestic	International	Domestic	International

Low	0	6	4	0
Medium	18	19	14	6
High	9	2	2	0

The primary goal of this research was to examine potential relationships between spatial skills and different forms of communication. The following section looks at trends within each of these groups, specifically the low / high visualizers, men / women, and domestic / international students, which is followed by analysis of overall group data to examine how spatial skills for engineering students relate to scores on oral communication tasks and measures of verbal fluency.

6.4.2 Spatial skills and communication scores

The following section examines the differences between groups in the data, which involve low / high spatial visualizers, men / women, and domestic / international students. Each section is stylized similarly for each group.

6.4.2.1 Low and high visualizer students.

Mean Scores (SD) for both low and high spatial visualizers on their spatial scores and communication tasks are provided in Table 17. As the gestures per 100 words were used for gesture coding, GPW and RPW represent gestures per 100 words and representational gestures per 100 words respectively. Beat gestures can be calculated based off the subtraction of total gestures from representational gestures. Tests of equal variances (H_0: $\sigma_1^2 / \sigma_2^2 = 1$) indicated that equal population variances could be assumed when performing t-tests across the subgroups of spatial rank, gender, and status for all variables.

Table 17. *Means (SD) of low and high spatial visualizers on measurements*

Spatial Rank	Spatial Score	Oral Score	Verbal Analogy Score	Phonemic Avg	Semantic Avg	Oral GPW	Oral RPW
Low (n=10)	13.39 (7.45)	20.2 (5.22)	7 (1.83)	15.15 (4.53)	21 (4.52)	7.7 (2.05)	4.75 (2.18)
High (n=14)	86.2 (8.92)	23.86 (4.9)	11.57 (2.5)	18.46 (4.58)	24.96 (3.86)	5.42 (3)	4.16 (2.42)

Two Sample t-tests were run on all above variables except spatial score as these participants were already separated based on that variable. High visualizers scored statistically significantly more on verbal analogy tasks *(High = 11.57, Low = 7.00, difference = 4.57, 95% CI [2.64, 6.50], t(22) = 4.91, p < .001; Cohen's d = 2.03, 95% CI [1.01, 3.02])* and had higher semantic fluency averages *(High = 24.96, Low = 21.00, difference = 3.96, 95% CI [0.41, 7.52], t(22) = 2.31, p = 0.031; Cohen's d = 0.96, 95% CI [0.09, 1.81)* than low visualizers. Low visualizers produced statistically significantly more total gestures generated per 100 words *(High = 5.42, Low = 7.70, difference = -2.28, 95% CI [-4.56, -2.85e-03], t(22) = -2.08, p = 0.050; Cohen's d = -0.86, 95% CI [-1.70, -9.73e-04])* and beat gestures generated per 100 words *(High = 1.26, Low = 2.95, difference = -1.69, 95% CI [-3.02, -0.35], t(22) = -2.62, p = 0.015; Cohen's d = -1.09, 95% CI [-1.95, -0.20])* than high visualizers. The proportion of representational gestures was higher in the high spatial visualizer group (~77%) than the low spatial visualizer group (~62%), however this difference was not statistically significantly different (p=0.061, CI [-0.284, 0.0046]).

Multiple linear regression models were applied to low and high spatial visualizers oral scores to determine which variables presented in Table 17 significantly predict their final oral report scores; gestures were not included as final oral rubric scores did not change greatly based on gestures produced. Neither model was statistically significant (likely due to sample size). For low visualizers, 38.3% of variance in their final oral report score can were predicted by spatial skill, verbal analogy skill, and phonemic / semantic fluency. For high visualizers, 16% of variance in their final oral report score were predicted by the four variables. No individual variable statistically significantly predicted oral report score in both groups. These results indicate that the four observed scores somewhat predicted oral report scores for low and high spatial visualizers; however, low spatial visualizers may rely on the combination of spatial cognitions ,verbal analogy skill, and fluencies slightly more than high visualizers. High visualizes may draw on other intelligences not measured by any of the spatial or verbal measurements in this research to communicate oral information. However, it should be noted that the smaller sample size makes these conclusions hypothetical.

6.4.2.2 Male and female students.

Two Sample t-tests were run on the variables presented in Table 18 below to examine differences in scores based on self-reported gender.

Table 18. *Means (SD) of men and women participants on measurements*

Gender	**Spatial Score**	**Oral Score**	**Verbal Analogy Score**	**Phonemic Avg**	**Semantic Avg**	**Oral GPW**	**Oral RPW**
Men (n=54)	53.84 (24.18)	21.04 (5.53)	9.67 (2.48)	16.12 (4.64)	21.94 (5.43)	6.62 (3.2)	4.64 (2.45)

Woman (n=27)	45.93 (21.05)	22.89 (5.89)	9.26 (2.49)	16.41 (5.32)	22.76 (5.31)	7.81 (2.67)	5.73 (2.21)

Compared to trends of sex-based differences in spatial scores (Casey et al., 2011; Newcombe & Shipley, 2015; Wai et al., 2009), there were no statistically significant differences in spatial score based on self-reported gender. This data suggests a small difference between women and men in spatial scores, with women scoring below men, however this was not statistically significant *(Women = 45.93, Men = 53.84, difference = -7.92, 95% CI [-18.80, 2.97], t(79) = -1.45, p = 0.152; Cohen's d = -0.34, 95% CI [-0.81, 0.12])*. While women on average scored higher than men on oral reports, this was also not statistically significant *(Women = 22.89, Men = 21.04, difference = 1.85, 95% CI [-0.80, 4.50], t(79) = 1.39, p = 0.168; Cohen's d = 0.33, 95% CI [-0.14, 0.79])*. No other scores or gestures produced were statistically significantly different between women and men. Men and women also produced a similar proportion of representational gestures, ~70% and ~73% respectively ($X^2 = 0.65$, $p = 0.422$, CI[-0.108, 0.045]).

Similar to low and high visualizers, multiple linear regression models were applied to the four variables (spatial score, verbal analogy score, phonemic / semantic fluency) to examine which variables may contribute to final oral report scores based on gender. For men, spatial scores were statistically significantly predictive of oral score (b = 0.46, p = 0.008), while the other three variables of linguistic skill did not predict oral score. This may imply that when men are describing engineering design topics they may rely on more spatial information to inform their oral communication. For women, spatial score was negatively correlated with oral score, while verbal analogy and semantic fluency were stronger predictors of oral score. For women their semantic fluency average was neared statistical significance (b = 0.41, p = 0.056), which may indicate that while women did score similar to men on spatial tasks, they opt to rely on linguistic fluency to communicate engineering information.

6.4.2.3 Domestic and international students

A final set of Two Sample T-tests and multiple linear regression models with the variables presented in Table 19 below were conducted to examine differences between domestic and international students

Table 19. *Means (SD) of domestic and international participants on measurements*

Status	Spatial Score	Oral Score	Verbal Analogy Score	Phonemic Avg	Semantic Avg	Oral GPW	Oral RPW
Domestic (n=47)	56.93 (22.91)	23.04 (5.41)	10.17 (2.46)	16.97 (5.09)	22.87 (4.98)	6.77 (2.89)	4.95 (2.29)
International (n=33)	42.33 (21.51)	19.7 (5.65)	8.67 (2.27)	15.06 (4.35)	21.18 (5.87)	7.59 (3.09)	5.22 (2.49)

Results indicate statistically significant differences between domestic and international students on spatial scores *(Domestic = 56.93, International = 42.33, difference = 14.60, 95% CI [4.50, 24.70], t(78) = 2.88, p = 0.005; Cohen's d = 0.65, 95% CI [0.19, 1.11]),* oral scores *(Domestic = 23.04, International = 19.70, difference = 3.35, 95% CI [0.85, 5.84], t(78) = 2.67, p = 0.009; Cohen's d = 0.61, 95% CI [0.15, 1.06])*, and verbal analogy scores *(Domestic = 10.17, International = 8.67, difference = 1.50, 95% CI [0.42, 2.58], t(78) = 2.77, p = 0.007; Cohen's d = 0.63, 95% CI [0.17, 1.08]),* with domestic students scoring higher on all three tasks. There were no statistically significant differences in gestures produced between the two groups, however international participants gestured more on average,. No significant differences were found between the proportions of representational gestures produced by domestic students (~73%) and international students (~68%), ($X^2 = 1.367$, p=0.2423 CI[-0.03, 0.12]).

A final set of multiple linear regression models were created using the four variables to determine which variables predict oral report scores for domestic and international students. For domestic students none of the four variables were significant predictors of oral score, with spatial score being negatively correlated with oral scores in comparison to semantic fluency. This may imply that native English speakers rely more on fluency to communicate engineering information rather than spatial skill. For international participants, spatial score was statistically significantly predictive of oral score (b=0.469, p=0.019) in comparison to other skills observed. This may be due to less reliance on English language and having to compensate information and communication through spatial means as forms of fluency may not be present.

6.4.3 Spatial skills and communication scores for all participants.

For all participants (n=81), spatial scores were statistically significantly and positively correlated with oral scores. The correlation plot and box plot presented in Figures 27 and 28 below reveal that spatial skill and oral report scores were statistically significantly correlated ($R = 0.22$, $p = 0.05$) for the entire cohort analyzed. While each spatial rank group (low, medium, high) did not have a statistically significant relationship between spatial score and oral report score, each group did have a near-zero to slightly positive relationship between the two skill sets. This may imply that, based on someone's spatial visualization skill, they have improved oral communication reports when they discuss engineering topics or a design project. As someone's spatial visualization skill increase so does their skill in explaining spatial information about engineering topics; this trend can be seen with how the correlations between spatial skill and oral skill get stronger as spatial rank improves (as shown in Figure 28 below).

Figure 27. *Correlation plot for spatial scores vs oral scores based on spatial rank (n=81)*

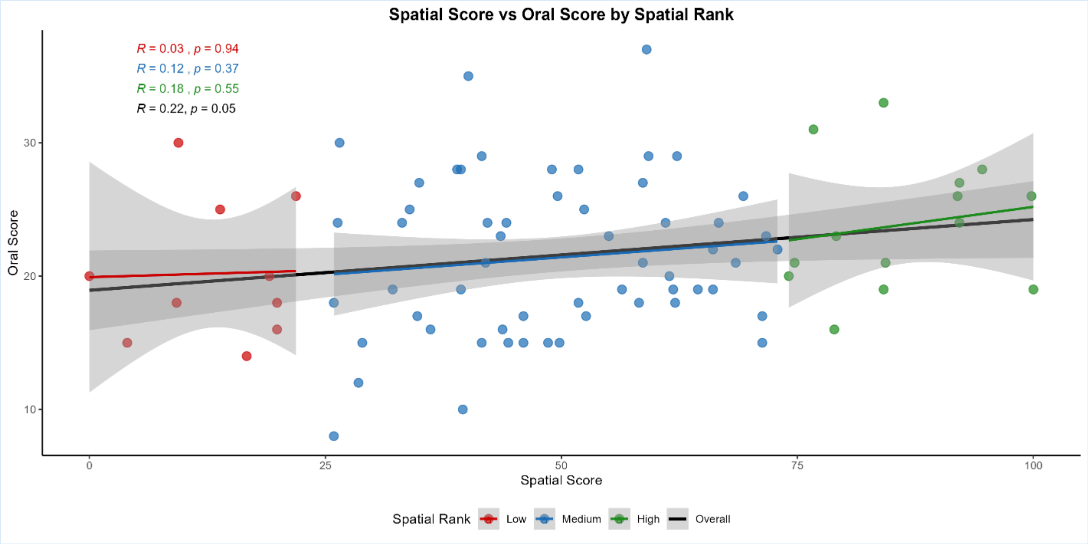
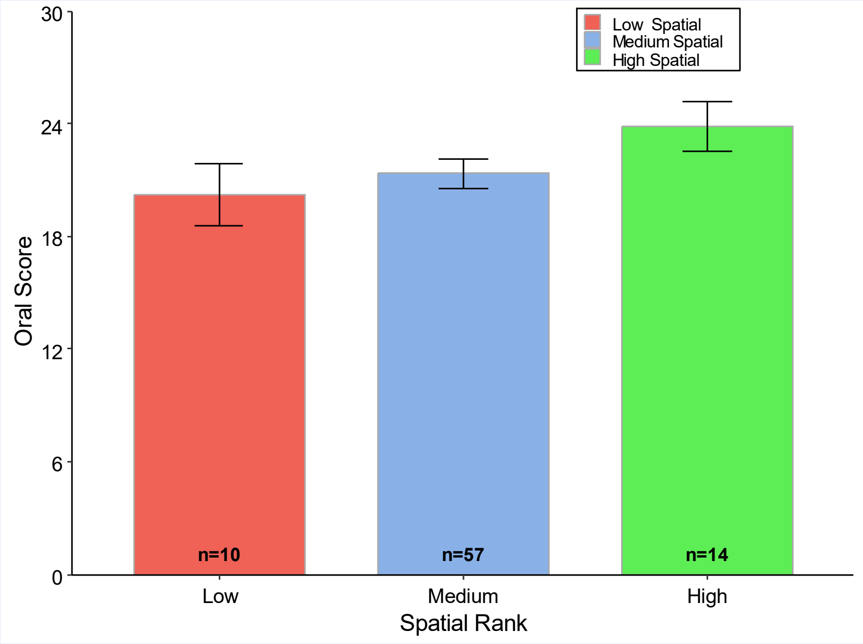


Figure 28. *Box plots for Spatial Scores vs Oral Scores based on spatial rank (n=81)*



A correlation matrix for all participants was generated and is presented in Table 20 below.

Table 20. *Correlation matrix for all variables examined (n=81)*

Variable	M	SD	1	2	3	4	5	6	7
1. Spatial Score	51.20	23.36							
2. Oral Score	21.65	5.68	.22* [.00, .42]						
3. Verbal Analogy Score	9.53	2.48	.55** [.38, .69]	.17 [-.06, .37]					
4. Phonemic Average	16.22	4.85	.25* [.03, .44]	.16 [-.06, .37]	.15 [-.07, .36]				
5. Semantic Average	22.22	5.37	.26* [.04, .45]	.30** [.09, .49]	.17 [-.05, .37]	.51** [.33, .66]			
6. Gestures Per 100 Words	7.02	3.07	-.21 [-.41, .01]	.05 [-.17, .26]	-.09 [-.31, .13]	-.16 [-.36, .06]	-.05 [-.27, .17]		
7. Rep. Gestures Per 100 Words	5.00	2.42	-.08 [-.29, .14]	.11 [-.12, .32]	.00 [-.22, .22]	-.11 [-.32, .11]	-.07 [-.29, .15]	.69** [.55, .79]	
8. Beat Gestures Per 100 Words	2.02	1.41	-.31** [-.50, -.10]	-.08 [-.29, .14]	-.21 [-.41, .01]	-.15 [-.36, .07]	.01 [-.21, .23]	.39** [.19, .56]	.23* [.02, .43]

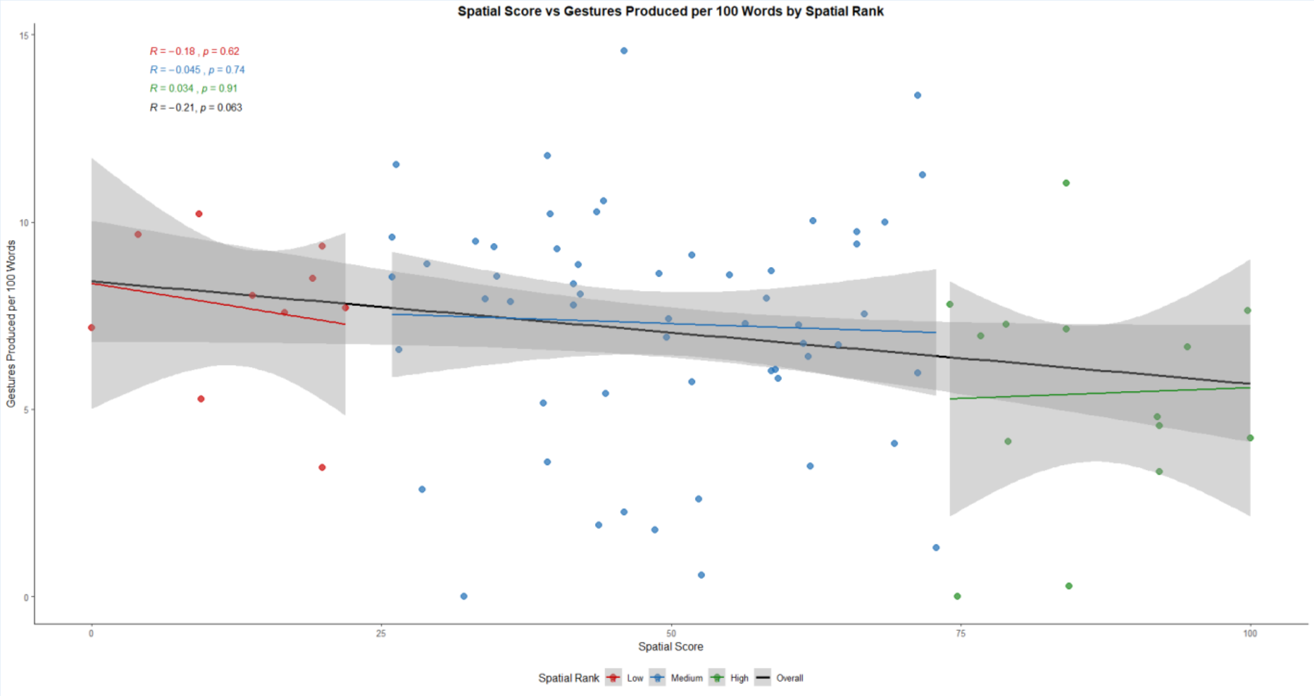
*Note: * p < .05, ** p < .01, *** p < .001*

For all participants, spatial scores were positively and statistically significantly correlated with oral score, verbal analogy scores, and both forms of fluency. Gestures were negatively correlated amongst all participants, particularly beat gestures which were statistically significant and negatively correlated, however this is likely due to an overall lower amount of beat gestures produced by all participants, perhaps due to the spatial nature of the oral communication task or interview environment.

6.4.4 Spatial skills and gesture production for all participants

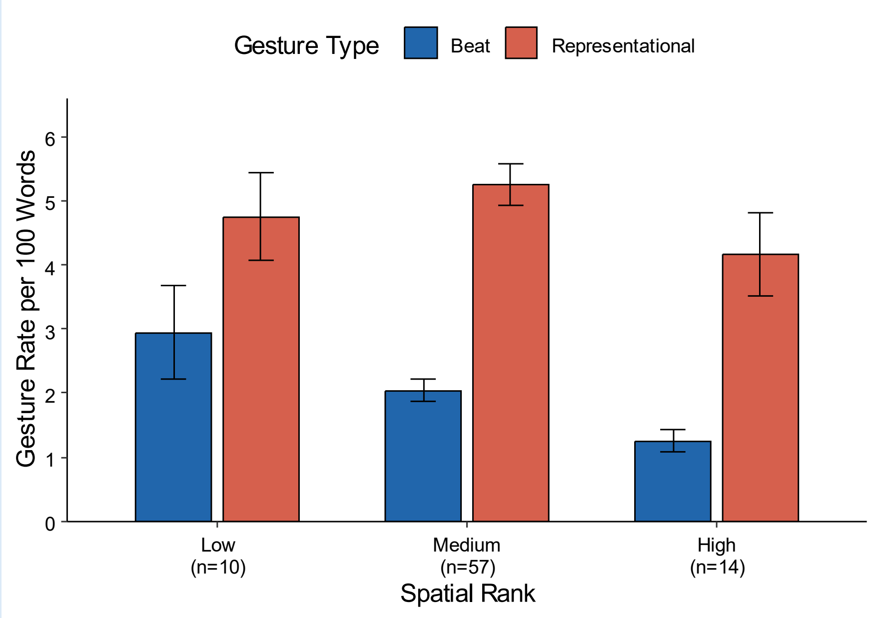
A correlation plot between spatial scores and gestures produced per 100 words was generated and is presented in Figure 29 below.

Figure 29. *Spatial scores by oral report gestures produced per 100 words (n=81)*



Results indicate a non-statistically significant and moderately negative relationship between gestures produced and spatial scores. Based on spatial rank, this correlation may be less negative, but none of these were statistically significant. Figure 30 presented below illustrates the amount and types of gestures produced based on spatial rank.

Figure 30. *Spatial rank by oral report beat and representational gestures produced per 100 words.*



Representational gestures were produced more than beat gestures across all spatial ranks; High spatial visualizers produced the least amount of gestures, yet scored stronger on oral communication reports, which could imply that spatial visualization skills help retrieve, manipulate, and present verbal communication about engineering topics, which allows an in dividual to not have to rely on gestures to help externalize and explain information.

Adopting approaches used in the work of Hostetter and Alibali (2007), participants had valid words spoken across fluency tasks averaged and used to categorize participants into low, medium, and high phonemic or semantic fluency ranks. Participants were placed in low phonemic fluency (<13 words across phonemic fluency tasks), medium phonemic fluency (>= 13 words and < 18 words in phonemic fluency task), and high phonemic fluency (>=18 words). This was also used for semantic fluency, with the categories of low semantic fluency (< 20 words), medium semantic fluency (>= 20 words and < 24 words), and high semantic fluency (>= 24 words). The following figures (Figures 31-36) report both oral scores, total gestures produced, and total representational gestures produced as a function of participants spatial rank and different types of fluency ranks to examine trends in how these different forms of cognition may interact together. These results and analysis should be taken with caution, as due to smaller sample sizes and non-significant results specific conclusions cannot be drawn. However, per the exploratory nature of this research, these findings can help inform future directions for similar research.

6.4.5 Spatial skills, oral communication, and phonemic fluency

Phonemic fluency is often used as a measure to examine how effectively an individual can "transfer a cluster of ideas and concepts into an appropriate chain of linguistic units without perseverating on one or advancing prematurely" (2007, p. 91). Phonemic fluency can often help an individual to explain their concepts, particularly when they transfer information from what concept to another; while phonemic fluency may not immediately represent stronger oral communication skill, stronger phonemic fluency can help measure how effectively an individual can retrieve information they plan to provide to others. Figure 31 and Table 21 present oral report scores and based on spatial visualization and phonemic fluency rank.

Figure 31. *Oral scores by spatial and phonemic fluency ranks.*

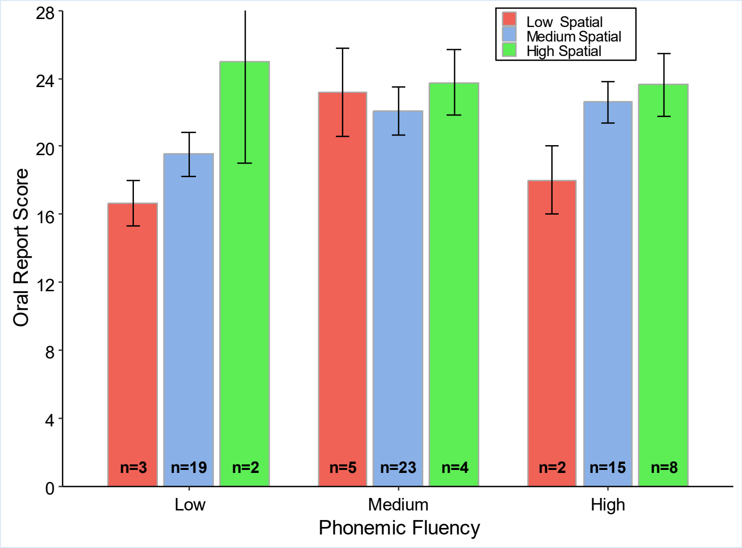


Table 21. *Means (SD) for oral scores by spatial and phonemic fluency ranks.*

Phonemic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Low	3	16.7 (2.31)	5	23.2 (5.81)	2	18 (2.83)
Medium	19	19.5 (5.51)	23	22.1 (6.71)	15	22.6 (4.61)
High	2	25 (8.49)	4	23.8 (3.86)	8	23.6 (5.24)

Results indicate that individuals with medium phonemic fluency scored similarly on oral report scores regardless of spatial rank. This could imply that spatial visualization skill does not play a large role in helping an individual orally communicate; furthermore, the majority of individuals in the cohort fell into the medium phonemic fluency category (n=32). An interesting trend is that on both extremes of phonemic fluency (low / high), spatial visualization skill does appear to improve final oral report score. If an individual has lower phonemic fluency, they may rely on spatial visualization skills to help improve their oral communication to explain concepts to another individual, as they may be able to visualize mentally what they are trying to communicate. Conversely, if an individual has both high spatial visualization skill and high phonemic fluency, they can use the combination of these two skills to further enhance their oral explanations. This specific result could imply that phonemic fluency, being related to the skill to explain concepts to an individual and how effectively someone can mentally transfer ideas within one's mind, may be enhanced further by spatial visualization skills. The actual skill of clustering words that start with a specific letter may be a somewhat spatial task in someone's mind; an individual could apply their spatial visualization skills to actually imagine the project they design, but then to access words, letters, or a verbal aspect of communication in their mind.

An analysis was applied to the total gestures produced by phonemic and spatial rank for this cohort, as shown in Figure 32 and Table 22 below.

Figure 32. *Oral report gesture rate per 100 words by spatial and phonemic fluency ranks*

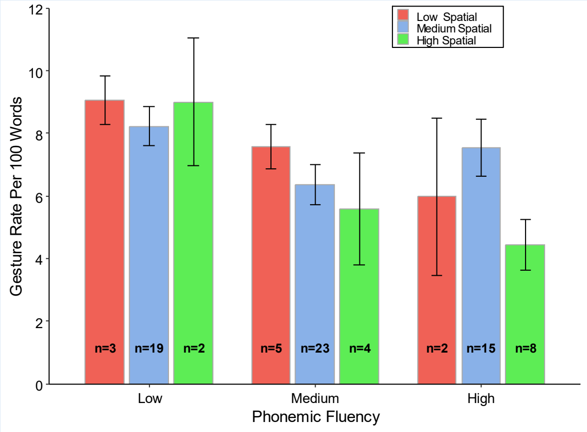


Table 22. *Means (SD) for oral report gesture rate per 100 words.*

Phonemic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Low	3	9.05 (1.34)	5	7.58 (1.59)	2	5.97 (3.57)
Medium	19	8.23 (2.73)	23	6.36 (3.06)	15	7.54 (3.54)
High	2	9 (2.89)	4	5.59 (3.58)	8	4.44 (2.28)

For the majority of groups, it appears that as phonemic fluency increases, the overall gesture amount decreases, except for medium spatial visualizers with high phonemic fluency; this may be due to the larger sample size of participants in that group, which may introduce variations in how many gestures were produced. Likewise, for low and high spatial visualizers, there was a consistent trend that as their phonemic fluency improved the amount of gestures decreased. This could imply that as someone can say information more clearly, or speak about a project in detail, they rely less on externalization of information for another individual; this skill can be enhanced by spatial visualization skills too, as if an individual has stronger mental images of the concept they wish to explain, they also will not need to externalize information as much.

An analysis of representational gestures (gestures that imply semantic meaning) was conducted based on spatial and phonemic fluency rank. Representational gesture counts and scores can be seen in Figure 35 and Table 23 below.

Figure 33. *Oral report representational gesture rate per 100 words by spatial and phonemic fluency ranks*

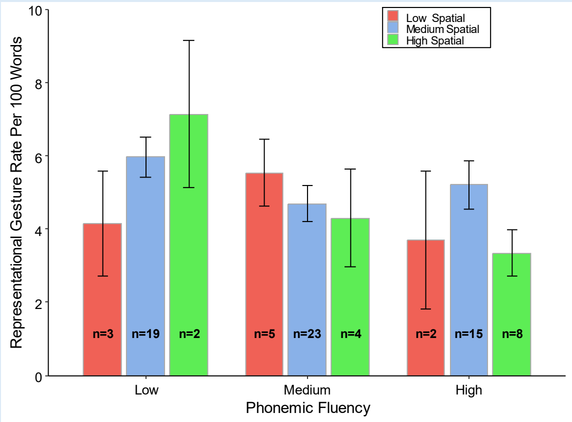


Table 23. *Means (SD) for oral report representational gesture rate per 100 words.*

Phonemic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)

Low	3	4.15 (2.51)	5	5.54 (2.04)	2	3.7 (2.66)
Medium	19	5.96 (2.4)	23	4.69 (2.35)	15	5.21 (2.57)
High	2	7.14 (2.84)	4	4.3 (2.69)	8	3.35 (1.81)

Results indicate that while individuals with low phonemic fluency produced similar amounts of *total* gestures regardless of spatial rank, individuals with low phonemic fluency and high spatial skill produced more *representational* gestures than low and medium spatial visualizers. This could imply that individuals that struggle to access verbal information to explain concepts would gesture more to help their oral communication; these gestures can be further affected by spatial skill, where gestures are more meaningful if done by an individual with stronger spatial skill. A consistent trend exists in the medium phonemic fluency rank, where when spatial skill increases the amount of representational gestures decrease, which is the same trend as total gestures produced. Individuals with stronger spatial skills may rely less on externalization of information via gestures, as they could rely on stronger mental imagery. For the high phonemic fluency ranks, low and high visualizers produced similar amounts of representational gestures, while medium spatial visualizers produced the most, however this could be due to the larger sample size in that population; when low and high spatial visualizers gesture to assist in speech production, high spatial visualizers do so more meaningfully.

6.4.6 Spatial skills, oral communication, and semantic fluency

Semantic fluency is associated with lexical access, or how effectively an individual can retrieve information associated with a word and similar categories; this may be particularly useful for engineers that need to change information based on current audiences or genres. Similar to phonemic fluency, individuals were categorized into low, medium, and high semantic fluency scorers and oral scores, total gestures, and representational gestures were examined throughout groups. Interestingly no high spatial visualizers were categorized into the low semantic fluency category. Trends and scores of oral scores and semantic fluency across spatial rank can be seen in Figure 34 and Table 24 below.

Figure 34. *Oral scores by spatial and semantic fluency ranks.*

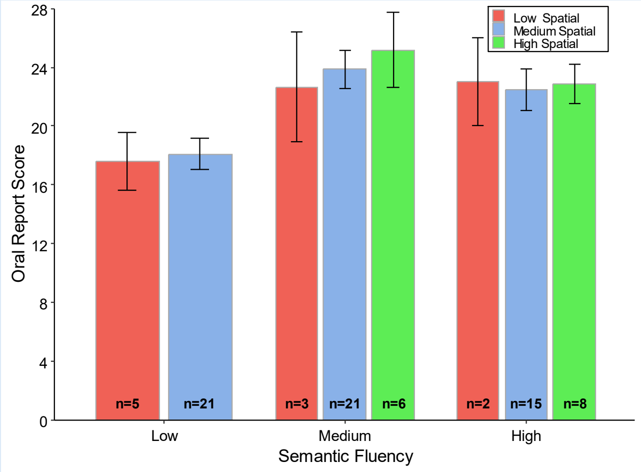


Table 24. *Means (SD) for oral scores by spatial and semantic fluency ranks.*

Semantic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Low	5	17.6 (4.39)	3	22.7 (6.43)	2	23 (4.24)
Medium	21	18.1 (4.81)	21	23.9 (5.86)	15	22.5 (5.42)
High	N/A	N/A	6	25.2 (6.27)	8	22.0 (3.72)

High spatial visualizers were split between medium and high semantic fluency ranks in this data; notably the high spatial visualizers in the medium semantic fluency rank scored more than other categories, where high spatial visualizers with high semantic fluency scored less than medium and low spatial visualizers with high semantic fluency. For low and high semantic fluency averages, individuals scored similarly on oral reports, which may imply that spatial visualization skills do not impact oral report skill as significantly as semantic fluency. Figure 35 and Table 25 present how gestures per 100 words interact with spatial and semantic fluency ranks.

Figure 35. *Oral report gesture rate per 100 words by spatial and semantic fluency ranks.*

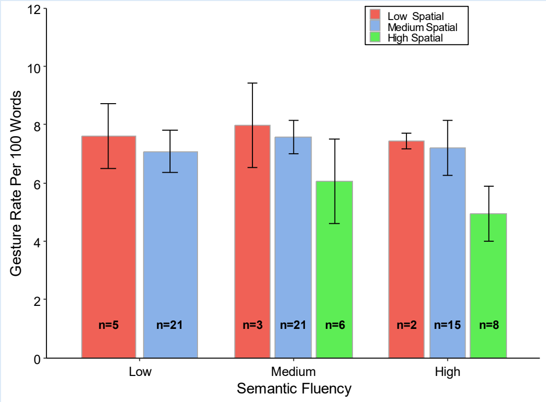


Table 25. *Means (SD) for gesture rate per 100 words by spatial and semantic fluency ranks.*

Semantic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Low	5	7.62 (2.49)	3	7.99 (2.51)	2	7.45 (0.38)
Medium	21	7.08 (3.31)	21	7.57 (2.64)	15	7.21 (3.7)
High	N/A	N/A	6	6.05 (3.58)	8	4.94 (2.64)

High spatial visualizers gestured the least across all semantic fluency groups, and gestured were produced less as semantic fluency improved; this may imply that as fluency and verbal skill improve, less reliance on outside illustration of information is required as they can verbalize it more easily, or access categories of information which does not rely on visual stimulation.

A final analysis of representational gestures and their interactions with spatial skill and semantic fluency can be seen in Figure 36 and Table 26.

Figure 36. *Oral report representational gestures per 100 words by spatial and semantic fluency ranks*

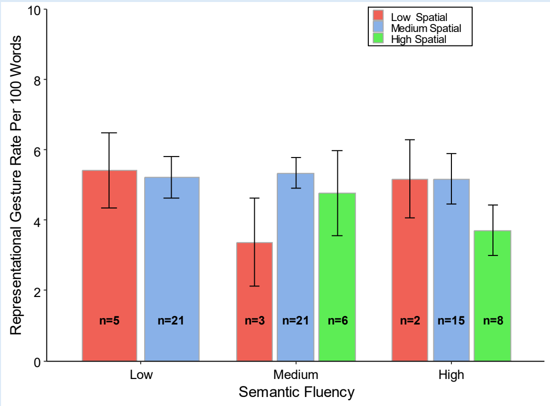


Table 26. *Means (SD) for oral scores by spatial and semantic fluency ranks.*

Semantic Rank	Low		Medium		High	
Spatial Rank	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Low	5	5.42 (2.38)	3	3.37 (2.16)	2	5.17 (1.58)
Medium	21	5.22 (2.72)	21	5.34 (2.01)	15	5.17 (2.75)
High	N/A	N/A	6	4.76 (2.97)	8	3.71 (2)

While most of the representational gesture trends remain the same as phonemic fluency, individuals with low spatial skills and medium semantic fluency produced less representational gestures, which may imply they generated beat gestures while struggling to find the correct words they wanted to produce.

To finalize how all these different aspects of cognition may impact final report scores, a factor analysis and subsequent structural equational model that aimed to predict the final oral scores of participants was created.

6.4.7 Factor analysis and structural equational model of oral communication and spatial skills

The aforementioned theories from both gesture and engineering design problem-solving research have posited that communication of information typically involves two independent systems of verbal and non-verbal (e.g. spatial) information; an individual may rely on one or the other to process and communicate a message or rely on both at the same time (Hostetter & Alibali, 2007; Paivio, 1991; Raju et al., 2025). While gesture may be associated more with non-verbal comprehension, or with communicating spatial information that can't easily be put into words, it could also act as an individual construct that interacts with verbal and non-verbal systems. Prior research has found that individuals produce gestures when not seen, and that gestures may not always be meaningful, it may imply that gesture is not specifically just a by-product of speech, but rather its own construct (Krauss et al., 2000).

An exploratory factor analysis was conducted to determine if latent constructs exist and how they may predict oral scores for participants, followed by a confirmation of the model to examine how accurately these factors predict the oral scores of participants. The measures of spatial scores, verbal analogy scores, semantic and phonemic fluency scores, and representational and beat gestures produced were used in the model. The sample size was smaller but appropriate for 5-10 cases per parameter (Brown, 2015, p. 380), Kaiser-Meyer-Olkin (MSA = 0.59) was slightly below acceptable range (Kaiser, 1974) and Bartlett's test of sphericity was statistically significant (X^2=74.60, p<.001,df=15). Both eigen-value scores and parallel plot analysis suggested a three factor model with oblimin rotation due to assumed correlations between data (Brown, 2015). The final three factor model explained 51% of the variance in the data, with the remaining 49% unexplained by the model. Figure 39 and Table 27 display the data that validate a potential 3 factor but certain 2 factor structure.

Figure 37. *Parallel analysis plot for factor analysis*

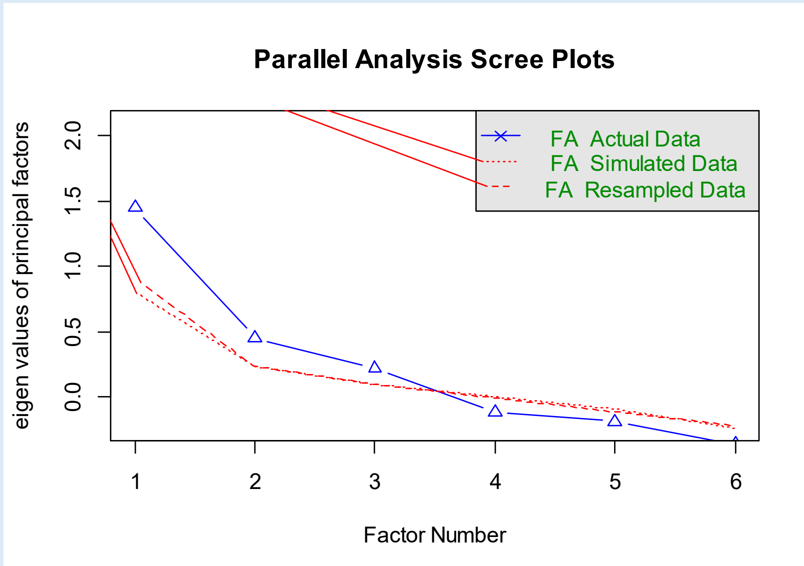


Table 27. *Factor loadings and Cronbach alpha for EFA*

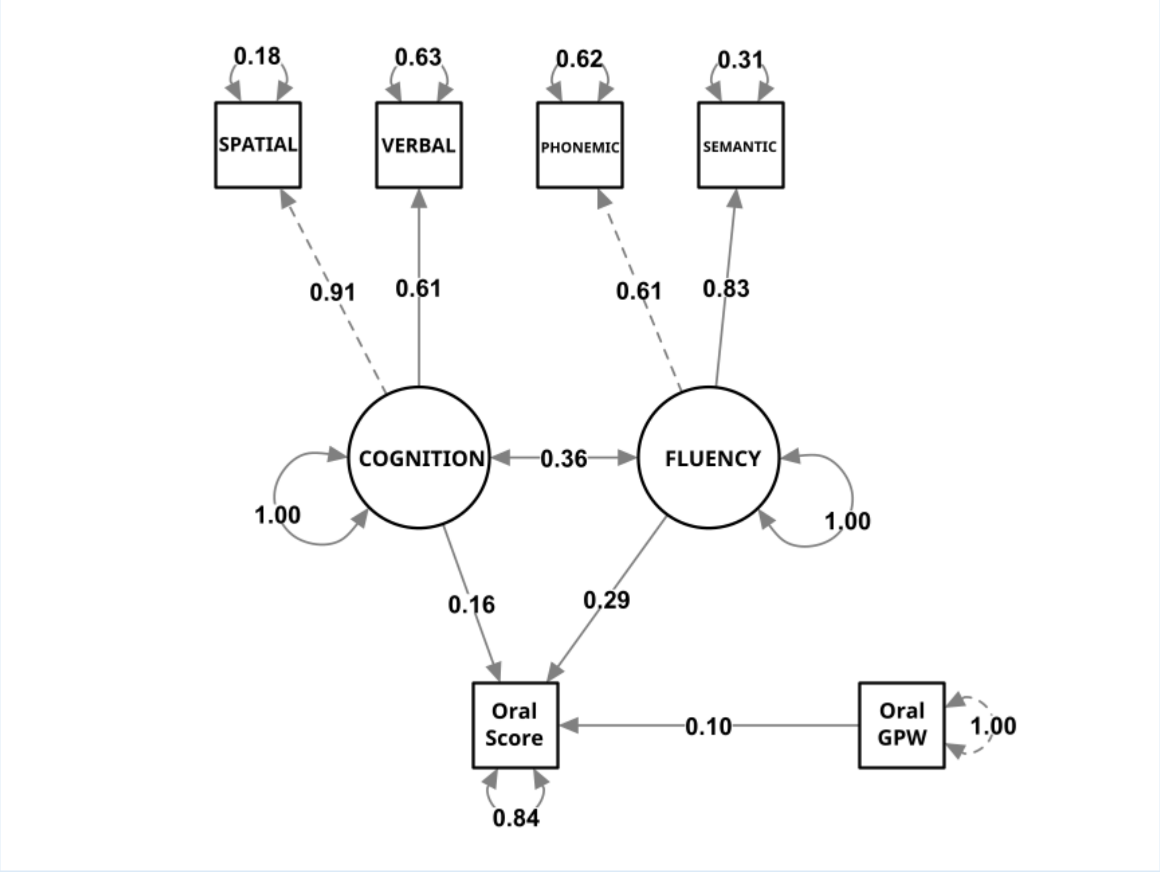
Variable	Factor 1	Factor 2	Factor 3	H2	U2	Std. Cronbach Alpha	Total Cronbach Alpha
Semantic Fluency	0.87			0.76	0.24	0.71	0.34
Phonemic Fluency	0.59			0.39	0.61		
Verbal Analogy		0.84		0.67	0.33	0.68	
Spatial Score		0.59		0.52	0.48		
Oral Project Beat Gestures			0.77	0.61	0.39	0.38	
Oral Project Rep. Gestures			0.35	0.12	0.88		

Fluency variables loaded onto a single factor, verbal analogy and spatial score loaded onto a single factor, and both gesture types loaded onto a single factor. However, the gesture variables were negatively correlated with the first principal component, so this factor was removed and instead the overall gesture rate was used in a final exploratory structural model. The model failed to meet convergence with all three factors, so the following equation was used:

Cognition =~ Spatial Score + Verbal Analogy Score
Fluency =~ Phonemic Fluency Average + Semantic Fluency Average
Oral Score ~ Cognition + Fluency + Oral Project Gestures Per 100 Words (GPW)

Standards for the indices of fit for the CFA were based on recommendations from Brown, 2015; RMSEA < .06 indicates good fit, < .08 indicates reasonable fit. CFI and TLI > .95 indicates adequate fit, SRMR <.10 indicate acceptable model fit. The generated model resulted in a CFI = 1.00, TLI = 1.042, RMSEA = 0.0, and SRMR = 0.066. Chi-square analysis indicated $\chi 2(7) = 5.79$, p-value = .565, which indicates acceptable fit. The full model is displayed in Figure 40. Figure 40 can be divided into two sections; how the two hypothesized latent factors map to observed data, and then how those two latent factors and gesture production predict final oral scores.

Figure 38. *Structural equational model: cognition and fluency prediction of oral scores (n=81).*



Spatial scores, as the reference indicator for cognition, showed that 82% of the variance in participants spatial scores can be associated with the underlying theoretical construct of cognition, while the remainder of variations in spatial scores were explained by other factors not observed by this model. Verbal analogy score was statistically and moderately loaded onto cognition ($R = 0.61$, $p = 0.018$, $R^2 = 0.37$), with the remaining 63% variance in verbal analogy scores came from other factors. Phonemic fluency, the reference indicator for fluency, moderately loaded onto the underlying fluency construct, with 37% of variance in phonemic fluency explained by this construct, while the remainder of variance in scores belong elsewhere; semantic fluency was strongly and statistically significantly loaded onto fluency ($R = 0.83$, $R^2 = 0.69$, $p = 0.007$). These results affirm the prior exploratory factor analysis that these theoretical constructs exist, and the variables properly map to them. The theoretical constructs of cognition and fluency were statistically significantly correlated (b = 22.48, $p = 0.047$, R = 0.36, R^2=0.13) which indicates that while they are distinct constructs, there appears to be an overlap where an individual with higher cognition may have higher fluency; however, the variance and low correlation does not reinforce that it is a consistent trend.

The second portion of the model examines how well the theoretical constructs with gesture production predict the final oral score of the participants. Of the three constructs predicting oral score, fluency was the only statistically significant predictor (b = 0.293, p= 0.041), while cognition (b = 0.159, p = 0.267) and gesture rate per 100 words (b =0.104, p = 0.314) were not statistically significant. Together these variables explained 16% of the variance in oral scores, which implies final oral scores come from a multitude of other factors not captured by this research design. Full loadings can be seen in Table 28 below.

Table 28. *Factor and observed variables loadings*

Factor	Variable	SE	z	p	R	R^2	Residual
Cognition	Spatial	~ (ref)	~ (ref)	~ (ref)	0.91	0.82	0.18
Cognition	Verbal	0.030	2.359	0.018	0.61	0.37	0.63
Fluency	Phonemic	~ (ref)	~ (ref)	~ (ref)	0.61	0.37	0.63
Fluency	Semantic	0.560	2.692	0.007	0.83	0.69	0.31

6.5 Discussion of Results

In relation to gesture research, the results presented here reaffirm some findings in prior research about the role of gesture and how it occurs in speech about spatial topics.

6.5.1 Spatial skills and gesture production

The higher rate of representational gestures in comparison to beat gestures across all spatial ranks align with previous findings which stated that "representational gestures tended to occur with visuo-spatial and motoric speech content; beat gestures, in contrast, tended to occur with more abstract speech content" (Alibali, 2005, p. 311). An element of the oral communication task was to describe movement of the robot, which could explain differences in gesture production. Further research that linked spatial visualization skill to verbal fluency (phonemic / semantic) and gesture production found that "individuals with low verbal fluency and high spatial visualization skill gestured more than any other group" (Hostetter & Alibali, 2007, p. 90). In the low phonemic fluency group, regardless of spatial rank, more total gestures were produced, however the high spatial visualizers in that group produced the most representational gestures. When ranked by spatial rank and semantic fluency skill, there were no notable trends on which participants appeared to gesture more or less, similar to findings that "semantic fluency is not a strong predictor of gesture rates [which] suggests that representational gestures are not typically the result of difficulty with accessing particular lexical forms" (Hostetter & Alibali, 2007, p. 91)

In the same research, results found that high spatial visualizers produced more gestures per 100 words than average and low spatial visualizers (Hostetter & Alibali, 2007, p. 88). The present analysis contradicts these findings, as total and representational gesture rates were reduced as spatial rank improves. Recent research examined the frequency of gestures made when narrating a cartoon and solving a social dilemma in association with cognitive abilities (predicted through mental rotation tasks), empathy, and personality traits (Canarslan & Chu, 2025). It was found that representational gesture production may vary based both on the individual's spatial skill and the information that is being communicated:

[I]t's plausible that individuals with lower cognitive abilities may employ representational gestures to ease their own speech production, whereas those with stronger cognitive abilities may use them to enhance listener comprehension… we observed significant negative relationships between cognitive abilities and the frequency of representational gestures. This discrepancy might arise because representational gestures primarily serve cognitive functions rather than communicative functions when speakers discuss abstract topics…the positive correlation between spatial transformation and representational gesture frequency may arise from participants with stronger spatial transformation skills generating more representational gestures…to visually demonstrate physical actions to listeners. [R]epresentational gestures have the most significant communication benefits in motor topics, compared with spatial or abstract topics. (Canarslan & Chu, 2025, p. 93 - 94)

The oral communication task in this research involved a mixture of questions that may involve multiple aspects of motoric, spatial, and abstract information. For instance, the first question asked about a larger problem they had to solve (the design problem), while others focused on the looks, operations, and features of the robot they created to solve the problem. Furthermore, this research examined engineers who experienced spatial visualization training through their coursework, which may have improved the base of all participant's spatial skill levels.

6.5.2 Spatial skills and oral communication skills

The primary focus of this research was to examine if spatial skills, an important skill for engineers to succeed, is impacting their skill in oral communication. Industry states recent graduates do not have the communication skills expected (Donnell et al., 2016; Hirudayaraj et al., 2021); if spatial skills are negatively impacting aspects of communication, and engineering curricula may reinforce spatial skills specifically or naturally throughout the degree, that reinforcement may be suppressing the communication skills industry desires.

While gesture is a critical aspect of communication, it may not be the primary factor regarding why perceived communication skills among new engineers are lacking, however gesture does provide "a special window on underlying spatial cognition" (Alibali, 2005, p. 313), particularly with how it relates spatial skills and to aspects of verbal and fluency skills. To further examine oral communication trends, three subgroups were specifically analyzed in this research, low / high visualizers, men / women, and domestic / international participants.

Earlier work in this area found statistically significant differences in male domestic / international participants on the first phase tests of Mental Rotation Task (MRT), Mental Cutting Task (MCT), and the verbal analogy task (Lynch et al., 2023). Notably no significant differences were found here in fluency skills (phonemic / semantic) or gesture production; however, oral scores were statistically significant different with domestic participants scoring higher. Furthermore, international students did gesture more often during oral reports when compared to domestic students. Further regression models showed that none of the four predictors (spatial, verbal analogy, phonemic, semantic) were statistically significant for domestic students oral scores; however, for international students spatial score was a statistically significant predictor of their oral score ($b = 0.469$, $p = 0.019$). This could imply that while international students score lower on spatial tasks, they rely more heavily on spatial skills when they orally communicate engineering related information. All phases of the research were conducted in English; the fluency tasks asked a single question and were timed, whereas the oral task portion had multiple questions and prompts. This may have introduced further variability for comprehension for international participants.

There were no gender-based differences in spatial skills between women and men in this data. Prior research has shown that there are typically marked gender differences between men and women in spatial skill (e.g., Wai et al., 2009). The lack of gender differences here may be because participants had explicitly practiced spatial visualization skills in the semester prior, reinforcing previous findings that spatial skills are malleable and can be trained to reduce differences in skill levels (Ramey & Uttal, 2017). In this analysis, there were no significant gender differences in any of the verbal analogy or fluency tasks. Male children have been reported to engage in object rotation activities and gesture during learning activities, which has been viewed as why they may outperform female children in spatial tasks (Wakefield et al., 2019), but it is likely that early differences in gesture production have either leveled out or are not as impactful to adults (Hostetter, 2011).

High spatial visualizers scored significantly higher than low visualizers on verbal analogy and semantic fluency scores. It appears high spatial visualizers had stronger spatial imagery as well as improved subsets of verbal skills, such as the ability to access similar word categories and make connections across those categories. Low spatial visualizers gestured more in total, which was statistically significantly more than high spatial visualizers. Low visualizers also produced more beat gestures. This may reinforce previous findings in gesture research where individuals with lower cognitive skill gesture to help with their speech production (Canarslan & Chu, 2025, p. 93 - 94). Notably, while high spatial visualizers did score higher on average on the oral communication task, these differences were not statistically significant.

Results reveal a trend where spatial skills seem to impact elements of verbal skills. This may explain why there were no statistically significant differences for men and women on any of the spatial or verbal tasks; because their spatial skills were somewhat similar, so were their verbal and fluency skills. The hypothesis that spatial skills could transfer somewhat to aspects of communication skill is reinforced by the final structural model, where the latent construct of cognition and fluency had a statistically significant and weak positive connection. However, as demonstrated by the low / high spatial visualizer groups with no statistically significant differences in oral scores, spatial and verbal skills, while stronger, may not immediately transfer to an effective oral communication skill. Research in other domains has examined if there is some positive correlation, or potential relationship between spatial skills and technical communication skills.

Research in biology and mental models by Alfred et al. have reinforced that traditionally non-spatial and spatial information processing may be more coupled than previously assumed (2020). Mental models are defined as cognitive frameworks that help spatially organize information and representations of scenarios either through personal experiences or information given about the situation. These mental models were hypothesized to not "have distinct models for every type of content… [rather] it is likely there is a fractionate system that includes a common framework utilized by all problem types" (Alfred et al., 2020, p. 1). Alfred et al. focused on transitive reasoning, or the comparison of magnitudes of items; spatial reasoning was found to be used in various mental activities that compared "literal spatial distance (near and far from an individual), temporal distance (near and far in time from the present moment), and social distance (close friend or stranger to an individual) [which] shared common spatial magnitude processing in the right inferior parietal lobule" (2020, p. 7). Alfred et al.'s work further supported the value of spatial processing by finding that "despite the fact that the content varied from spatial to non-spatial, nearly all participants reported using spatial strategies to organize the structure of the information from these problems" (2020, p. 5). Spatial encoding strategies used across various topic types may also explain why representational gestures are produced for motoric processes, whereas spatial and abstract topics do not need to rely as much on those forms of communication. Research in mental models is complex, and it is likely that spatial strategies are not the only form relied on, as '[i]ndividuals distinguish between relations that elicit visual images, such as *dirtier than*, those that elicit spatial relations, such as *in front of*, and those that are abstract, such as *smarter than"* (Johnson-Laird, 2010, p. 18244). Regardless, these findings help illustrate that spatial processing and organization can be beneficial for non-spatial tasks and understanding.

Research by Cortes et al. examined five public high-schools where some students took a course over a semester where they would create and examine spatial representations (maps) of geographical datasets through geographic information systems (2022). Cortes et al. attempted to examine the Mental Model Theory, and proposed the following hypothesis:

> [The] [m]ental model theory (MMT) posits that ostensibly verbal information is processed by co-opted neural resources that evolved to support visuospatial operations in primates. If this is correct, then fostering spatial processing could yield transfer to improved performance beyond the spatial domain. MMT specifically posits that the spatial process of "scanning", inspecting spatial representations of information for key features, supports mental model–based reasoning (e.g., scanning spatial representations of verbal reasoning premises to determine whether they align to validate a logical conclusion)…curricula designed to foster spatial cognition, especially curricula that

develop spatial scanning ability, might yield transfer to cognitive abilities supported by mental modeling beyond the spatial domain, especially verbal reasoning (2022, p. 1).

A total n=346 students were sampled, and propensity scoring-based matching was used to reduce selection bias and match students based on background traits (GPA, demographics); 77 students enrolled in the geospatial course, and 105 control students were enrolled in different STEM courses in the same high-schools (2022). Participants took four tests in the summer before and the summer after the school year, a subset of 32 geospatial and 31 control students completed the tasks in fMRI machines (2022).

Three tasks were associated with spatial skills; the MRT, the embedded figure task (scanning complex figures to find simpler figures), and a self-reported spatial strategies questionnaire (2022). The fourth task was a modified “syllogistic deductive verbal reasoning task” (2022, p. 3), where “participants read two premises and determined whether a subsequent conclusion was valid on the basis of the premise” (2022, p. 3). Participants had 8 seconds to indicate if the conclusion was true or false (yes / no) via key press on a screen and completed 60 trials; 20 trails involved spatial reasoning (above / below), 20 trials involved nonspatial reasoning (better / worse), and the last 20 trials involved matching; the matching trials were included as a control condition for fMRI analysis, and these trials ask if a statement has been repeated. An example reasoning task asks if “the ape is better than the cat, the dog is worse than the cat, the ape is better than the dog” (2022, p. 3), and example matching task would ask if “the ape is better than the cat, the dog is worse than the cat, the ape is better than the cat” (2022).

Cortes et al. found the “more students improved on spatial scanning and mental rotation, abilities that are specifically theorized to support mental modeling, the more they improved on verbal reasoning” (2022, p. 8). Cortes et al.’s results from the fMRI machines provided “evidence for mental modeling as a basis of human reasoning…by experimentally intervening to improve spatial ability as a means of improving verbal ability” (2022, p. 8). These results supported Cortes et al.’s hypothesis that spatial training helps “[improve] spatial scanning, spatial habits of mind…and verbal reasoning [which] represent spatial curriculum driven gains both within and beyond the spatial domain” (2022, p. 8).

Results from Cortes et al.’s research, and the findings in this research that revealed a slightly positive correlation between cognition and verbal skill, could help explain why fields typically considered non-visual, like computer science, are seeing positive impacts through spatial skills training on programming success and performance (Bockmon et al., 2020; Endres et al., 2021; Fincher et al., 2005; Fisher et al., 2006; Ly et al., 2021; Parkinson & Cutts, 2022). It may be that the lack of communication skills in new engineering students reported by industry is not due to their reliance on spatial visualization skills, but rather due to other elements that impact communication. Some potential aspects that impact communication could be intra / interpersonal traits or cultural and environmental shifts experienced by the students, however there was no data collected part of this research to explore these hypotheses.

6.6 Limitations and Future Work

Participants were at the beginning of their second semester of a two-course sequence; the robot project from the prior semester was likely still familiar and fresh in their mind, which was likely beneficial when participants were asked to discuss specific information about their robot. Conversely, the engineering design project was completed by teams consisting of 3 to 4 members, with explicit roles and responsibilities determined by members of the group. Typical team roles involved coding, project management, report writing, or the actual construction of the robot. Research participants were not asked about their role on the project; however, their knowledge and recollection of the project likely was informed by their role, which may skew some results (e.g. the builder may have a more intricate recollection of robot operations than the project manager). Other information such as prior communication courses or standardized test grades (ACT / SAT) were not collected as part of the research, so the communication skills of the participants was solely determined through the research data.

Participants who completed both research phases were interviewed by members of the research team who may have been in their previous course as a professor or graduate assistant. Furthermore, participants were interviewed in a setting where cameras were set up to record. Any undue anxiety or stress caused by these factors may have impacted scores. Future research in this area should utilize trained outside interviewers to prompt participants, or engineering faculty / students who were not associated in prior courses. Prior gesture research recorded individuals with a hidden camera and then asked if the footage could be used, as an obvious recording setup may impact how comfortable individuals would be with gesture; these approaches could also shift final communication score outcomes.

Two additional gesture-eliciting tasks were asked of participants, one about the pathway the participant took from their home to their high school, and the other that asked how they would wrap a present. Future work will examine participant responses to these and quantify gesture production for examination of further trends between spatial skills and gesture production. Future work should also utilize different types of oral communication tasks for engineering majors, such as social dilemma tasks used in previous gesture research (Canarslan & Chu, 2025), which may provide further insights into communication skills but might also provide insight into the personality traits of empathy and social awareness for engineering students.

Participants completed multiple communication tasks as part of the interview that are not discussed in this paper. A written communication component was completed by participants that asked similar questions to the oral communication task. Having exposure to questions and being able to think through information via written documentation may have impacted oral communication scores; Future research could modify how the oral task is distributed to acquire different results that could support or disprove this hypothesis.

Other work could use industrial professionals that asks these questions to recreate authentic industrial experiences. The participants were first-year engineering students in the second semester of their engineering major. Their communication skills may shift as they go through their degree; future work should recreate these approaches with senior engineering students who will be entering industry after their final year or with engineering students over their programs to provide longitudinal information. The analysis of engineering participants at different stages of their degree would provide further details on how spatial skills and forms of fluency shift throughout their degree and provide further evidence if the examined correlations remain consistent or morph as someone progresses through engineering.

6.7 Conclusions

This research attempted a unique examination of oral communication skills of undergraduate engineering students. Through two phases of testing and adoption of research techniques from gesture research, which has previously analyzed spatial skills and verbal communication skills, results indicate that high spatial visualizers scored higher on oral communication tasks and aspects of their communication skill (phonemic / semantic fluency) than low and medium spatial visualizers. Furthermore, high spatial visualizers did not produce as many gestures to communicate spatial phenomena and their engineering project, which reinforces the idea that strong spatial visualizers have stronger mental representations of information and do not need to externalize it to improve their communication. Unique findings within groups revealed that domestic and international participants had statistically significant differences in some communication tasks and spatial visualization scores; conversely, there were no gender differences found in this analysis on communication tasks and spatial visualization scores, which reinforces the usefulness of training spatial visualization skills to help remedy gender, demographic, and socio-economic differences.

Based on previous theoretical concepts of information processing based on the Dual-Coding-Theory (Paivio, 1991) and the origins of gestures, a factor analysis and structural equational model revealed two primary cognitions in the data, referred to as non-verbal and verbal intelligences. Final analysis indicated a slightly positive and statistically significant relationship between these two latent constructs. This illustrates that these two cognitions, while distinct, do positively impact each other, and likely an individual goes through a sequential or simultaneous process when using either or when orally communicating information. For instance, an individual may recall their robotic project through non-verbal means (spatial phenomena), which then helps illustrate the information they should externalize through verbal means; this can occur in either direction, or someone may do both simultaneously. The results from this research indicate that spatial visualization skills appear to be connected to improved oral communication skill, and that non-verbal and verbal cognitions of engineers are slightly linked.

Early work that advocated for spatial skills noted that spatial aptitude was often ignored by educational institutions in favor of general intelligences; where institutions “over-value[d] the verbal type of ability at the expense of its psychological opposite–spatial ability” (Smith, 1965,

p. 5). Prior research discussed and this current research aim to reduce the normalized notion that engineers are ineffective communicators. This work aims to contribute a statistically validated basis to help reduce these stereotypes of engineers by revealing that the type of intelligence valued and commonly held by engineers are more coupled with intelligences beneficial to aspects of communication. To aide in these shifts necessary to improve communication in engineering students, it is important to not deem non-verbal and verbal intelligences opposite, rather these intelligences should be viewed as two important skills born out of the same cognitive processes and that may exist in a more symbiotic relationship than previously assumed.

6.8 Acknowledgements

This project was funded in whole or in part by the National Science Foundation. Conclusions and opinions expressed are those of the authors themselves and do not necessarily reflect those of the National Science Foundation. NSF#2235687**.** Informed consent was obtained from all participants examined in this study; this study was approved by University of Cincinnati's IRB committee HRP-503.

Chapter 7. Final Conclusions and Recommendations

The goal of this exploratory research was to examine how spatial visualization skills, an empirically validated and critical skill for engineering students, interacts with their technical communication skills. Complaints persist from industry that new engineering graduates are not effective at communication despite dedicated efforts through engineering curricula to target and improve these skills; a hypothesized reason was that engineering curricula reinforces technical content knowledge throughout the degree; spatial visualization skills, often associated with technical knowledge, may have negatively impacted cognitive processes that help with communication, which could explain why these issues continue despite the attempts of academia to improve communication.

7.1 Summary of Findings

This research was conducted at the University of Cincinnati, a large midwestern R1 institution in the United States. Participants were first-year engineering students that were in their second semester of a two semester first year engineering course taken by all engineers in the college. Participants had specifically practiced spatial visualization skills in the semester prior and completed a team-based robotic project which included an end of semester demonstration. This project was provided to students at the start of their first-semester course and was based on real-life disaster relief scenarios seen in industry; the goal was to implement a full design project and create a robot that could assist in a disaster relief situation. The robot would be created with EV3 lego-brick parts and demonstrated at the end of the semester in a final demonstration. Students were assigned to teams of 3 to 4 students with specific individual roles among team members of a coding, building, and/or project management.

In the middle of their second semester, participants were invited to complete two phases of testing, which collected self-perceived communication skills, demographic information, spatial visualization scores, and verbal analogy scores; finally, participants completed an approximately hour-long interview which consisted of a battery of communication tasks which asked them to describe the project and how their robot performed at the demonstration the prior semester. Results of this interview were decomposed into the three skills of written communication, oral communication, and sketching communication.

7.1.1 Spatial tasks and verbal analogy task results

Results from phase one identified statistically significant differences in test scores between male domestic and male international students on mental rotation tasks (MRT), mental cutting tasks (MCT), and verbal analogy tasks. Interestingly, no gender-based differences were observed based on the spatial visualization tasks; this could be explained by the fact that all participants had explicit spatial visualization training in the previous semester. Average student scores on the two spatial visualization tests (MRT / MCT) were compared with students' self-perceived communication ability. Statistically significant differences were found on the average scores of the MCT between students who somewhat agreed and strongly agreed that they are confident in their ability to generate appropriate words or phrases about non-technical ideas. Interestingly, it was found that students who reported lower self-perceived communication abilities often had higher average scores on the spatial tests.

7.1.2 Sketching communication results

Due to limitations in the study design, there were few sketches produced by the participants; spatial skills were not notably predictive of aspects of sketches or the sketch quality. Low spatial visualizers generated schematic sketches that explained movement and overall task design, while high spatial visualizers focused on individual detail views of the robot itself. Both low and high spatial visualizers generated orthographic sketches; however, there was no consistent trend of quality for these sketches; some low visualizers generated better sketches than high visualizers and vice-versa.

Low spatial visualizers often had weaker written documents, and they may rely on sketching to externalize information and examine it through visual mediums to assist with their writing. High spatial visualizers, who often had stronger written documents, may rely on their mental visualization capabilities while they are writing. This could explain why specific detail views were drawn by high spatial visualizers rather than the overall task or robot; high spatial visualizers did not need to externalize information to assist with writing.

These trends were not consistent, and it is likely that the decision to sketch and the subsequent sketch quality are due to personal and environmental factors of the student. Results indicate that sketching communication is often underutilized by current engineering students. Participants opted to rely on the written documentation to explain all information and not rely on sketching to explain or reinforce information. Future work should mandate a sketch to be generated in similar contexts to see how spatial skills interact with sketching skill, and also how the two skillsets interact with oral and written communication.

7.1.3 Oral and written communication results

For written communication, spatial visualization skills were positively and significantly correlated with written report scores, which reveal that spatial skills are important when describing engineering team-based design projects through written and textual mediums. Notably spatial skills were more predictive than elements of fluency. While fluency is not the only factor that impacts written communication, recollection of spatial phenomena through mediums of text may rely on spatial cognition more than other verbal skills.

For oral communication reports, semantic and phonemic fluency were more predictive indicators. However, spatial visualization skills were positively correlated with verbal analogy scores and phonemic / semantic fluency. These findings indicate that spatial visualization skills are not opposite forms of communication and are likely to interact with these different intelligences to different degrees based upon the form of communication.

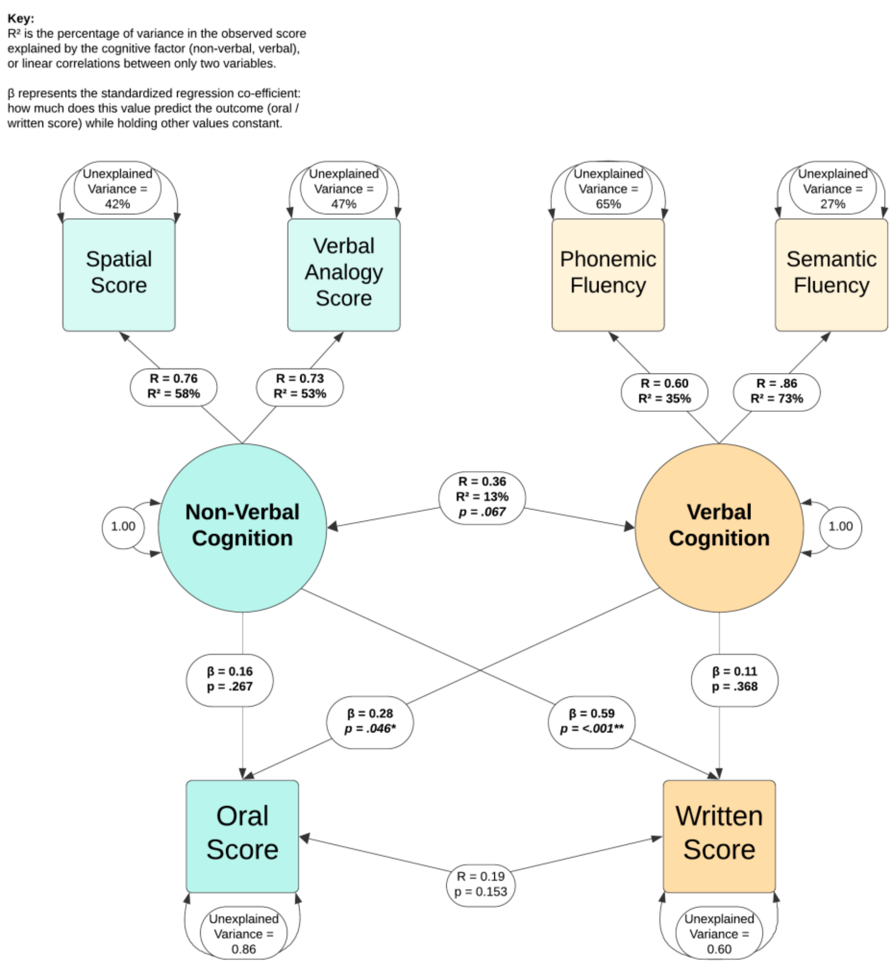
7.2 Contribution to literature

Findings across the three journal articles summarized that the oral and written communication scores of engineering students likely come from a combination of spatial visualization skills and other aspects of communication, such as vocabulary/fluency. To summarize contributions to the broader scientific community, the following section provides the final structural equation model based on this hypothesis, an update to the theoretical framework from Chapter 1 to base future work on, and suggestions to academic and industrial communities on unique ways to improve communication skills of engineering students.

7.2.1 Non-verbal and verbal cognition structural equation model

Per the factor analysis and structural equational modeling generated in the written and oral communication journal articles, a final structural equation model that predicts oral and written scores through non-verbal (spatial / verbal analogy) and verbal (semantic / phonemic fluency) was generated. The aforementioned design issues for sketches resulted in sketch scores being removed from the final model. Furthermore, as gesture production was specifically associated with oral report scores, it was not included with the final structural equation model, rather non-verbal and verbal cognition were applied to determine final written and oral report scores. The final model was acceptable by measures of Brown's (2015) standards. Chi-squared (p = 0.842), TFI = 1.099, CFI = 1.00, RMSEA = 0.000, SRMR = 0.026, are all within acceptable to good measures for the model. Figure 39 below shows the final model with the two latent constructs of non-verbal (NnV) and verbal (Vrb) cognitions alongside how they predict oral (OrS) and written (WrS) communication scores. An alternative model of this output that is directly from the lavaan package is provided in Appendix H; the model presented in Figure 39 has been updated for ease of reading (also visible in Appendix I).

Figure 39. *Final structural equation model for prediction of oral and written communication scores (n = 81)*



This model can be broken into two portions; the top portion where the four observed variables predict theorized latent constructs (factor loadings), and the bottom portion where the cognitions of non-verbal and verbal predict final communication report scores (construct predictions). Factor loadings indicate that all four observed variables load well onto each theorized construct. As spatial score and phonemic fluency average were standardized to set the latent factor scales, they are missing values in the final loadings. All loadings can be viewed in Table 29.

Table 29. *Factor and observed variables loadings*

Factor	**Observed Variable**	**SE**	**z**	**p**	**R**	**R^2**	**Residual**
Non-Verbal	Spatial Score	~ (ref)	~ (ref)	~ (ref)	0.76	0.58	0.42
Non-Verbal	Verbal Analogy Score	0.022	4.566	**< .001**	0.73	0.54	0.46
Verbal	Phonemic Fluency	~ (ref)	~ (ref)	~ (ref)	0.60	0.36	0.64
Verbal	Semantic Fluency	0.560	2.692	**0.007**	0.86	0.74	0.26

Overall, the four observed variables load statistically significantly onto the respective latent constructs. Both spatial score and verbal analogy score loaded onto non-verbal cognition; 42% of variance in spatial scores and 46% of variance in verbal analogy scores were not explained by non-verbal cognition, which indicates a portion of the final scores can be attributed to other factors outside of non-verbal cognition. Likewise, 64% of variance in phonemic fluency and 26% of variance in semantic fluency were not explained by verbal cognition.

Structural paths and regressions indicate that non-verbal cognition showed a weakly positive and non-significant relationship with oral score, while verbal cognition had a moderately positive and statistically significant relationship with oral score. These two cognitions combined explained ~14% of variance in final oral scores, indicating that the majority of oral communication scores were not captured by this model. Non-verbal cognition had a strong, positive, and statistically significant relationship with written scores, while verbal cognition had a weak and non-statistically significant positive relationship. The combination of these two cognitions explained about 40% of variance in final written report scores. Table 30 below provides the full breakdown of regression paths between the two cognitions and prediction of report scores. Final results indicate that written report scores were more strongly explained by the model, while oral report scores are likely predicted through a combination of other factors that were not captured in the final research design. Oral scores and written scores were slightly correlated, but it was non-significant ($R = .19$, $p = .153$).

Table 30. *Regression parameters for oral and written communication scores*

Communication	Cognition	Std.Err	p-value	Significance	R	R^2	Residual
Oral Score	Non-Verbal	.046	.267	No	.16	.14	0.86
Oral Score	Verbal	.279	.046	**Yes**	**.28**	**.14**	**0.86**
Written Score	Non-Verbal	.049	<.001	**Yes**	**.59**	**.40**	**0.60**
Written Score	Verbal	.245	.368	No	.11	.40	0.60

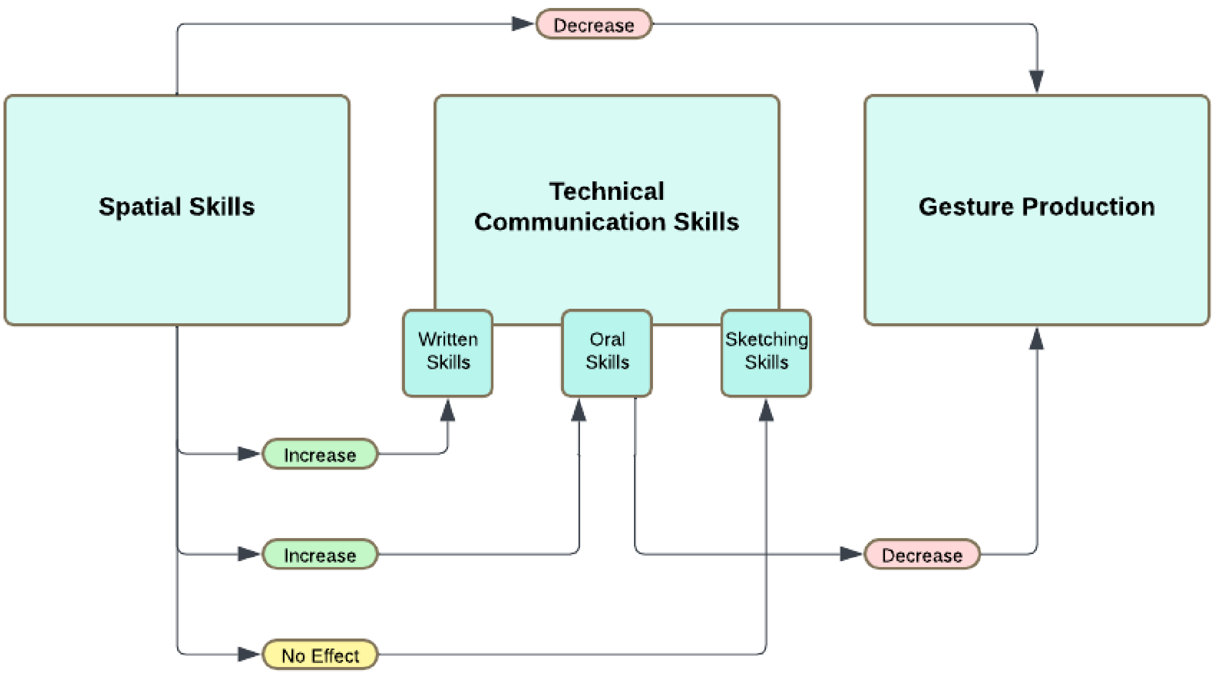
Note: R^2 in this table is the variance explained by the full regression equation (i.e., variation in Oral Score or Written score explained by all predictors together (Non-Verbal + Verbal).

Regardless of the form of communication, both non-verbal and verbal intelligences play a role in predicting how effective that communication occurs. A notable finding are the positive and nearly statistically significant ($R = 0.36$, $R^2 = 0.13$, $p = .067$) correlation between the latent constructs of non-verbal and verbal cognition. While each individual cognition helps predict a different form of communication, it appears that an enhancement of one cognition may help the other; these are two separate cognitive constructs but this result indicates they are not opposites nor are they completely unrelated; these findings reaffirm the hypothesis presented by Cortes et al. in regard to the mental model theory, where verbal information utilizes the similar cognitive processes as visuospatial operations (2022, p. 1). Furthermore, these two separate intelligences that can operate independently or simultaneously reinforce the Dual-Coding-Theory (Paivio, 1991), where non-verbal and verbal information can be processed independently by the two systems, either sequentially or at the same time. It is likely counterproductive to assume that non-verbal and verbal cognition are opposites, rather they perform in a more symbiotic manner to varying degrees based on the information being process and the form of communication occurring. It could be beneficial to reinforce that these two intelligences are potentially related, so individuals who may align more strongly on non-verbal information or processing, like engineers, are aware that their non-verbal skills could help their communication. These findings reinforce that spatial visualization skills can be beneficial across multiple aspects of communication for engineering students, regardless of if an individual is cognizant they are using those skills.

7.2.2 Theoretical model of spatial skills, technical communication skills, and gesture production.

The start of this research adopted approaches from various domains and attempted to apply them to a hypothesized model to help inform relationships between these different skillsets as presented in Chapter 2. The hypothesized model of interactions between spatial skills, technical communication skills, and gesture production was updated to reflect final findings and is shown in Figure 40.

Figure 40. *Final theoretical model of interactions spatial skills, technical communication skills, and gesture production*



As stated in other areas of gestural research, a potential issue is the assumption that relationships between different skillsets would be linear. It is likely a complex interaction amongst many forms of cognition that inform communication skill. To further complicate how these skillsets may interact, communication may also be impacted by environmental and personal factors. These can range from hierarchical structures in place during talks, such as who the two individuals communicating are (boss or worker), the time of day, if an individual is sick, and inter / intra personality traits. Regardless of these factors, the findings from this research indicate that spatial skills, a critical skill associated with the technical content knowledge of an engineering student, are not negatively impacting other intelligences that interact with communication. Similar research in these areas could adopt this theoretical model and help contribute further data to examine if these trends remain consistent or shift based on cohort and environmental factors.

Due to the shared cognitive process between non-verbal and verbal communication, the focus and training on spatial visualization skills goes beyond improvements to technical content knowledge and performance. These skills can be beneficial in multiple domains for an engineer, targeting both professional and technical skills. These results reaffirm the importance of spatial visualization skills for engineers, and they should continue to be taught as an integral part of an engineer's skillset.

7.3 Recommendations

Academia can only operate so far within its limits and must adhere to a rather strict curriculum and well-defined, pursuable degrees, particularly when dictated to by national accreditation organizations such as ABET. These requirements may not allow the time necessary to promote the types of personality traits and professional skills that industry states are lacking in current graduates. Future approaches should adopt more project-based and potentially student-led lecture components, to help expose students to similar industrial contexts throughout the curriculum rather than in a specific course or year. An abundance of effort and research has been done to improve technical communication for engineers through curriculum additions, cross-departmental efforts, and unique internship / co-op experiences. These efforts should persist. Elements of course work, workshops, and modified curricula should continue to be part of an engineering degree. However, as industry remarked that they would prefer someone with less technical knowledge but greater professional skills, which indicates they are confident they can learn (Hirudayaraj, 2021), these sentiments may provide the opportunity to reduce workloads in an already bloated curriculum and further streamline precisely what engineers should be learning. However, this can only be done if there is consistent, clear, and deliberate communication between academic institutions, accreditation boards, and industries.

Early work that advocated for spatial skills noted that spatial aptitude was often ignored by educational institutions in favor of general intelligences; where institutions "over-value[d] the verbal type of ability at the expense of its psychological opposite–spatial ability" (Smith, 1965, p. 5). This work and other research discussed aim to reduce the normalized notion that engineers are simply "bad communicators" and only want to work by themselves for themselves. While this goal must involve outside institutions and cultural shifting, this work provides a potential basis to start this shift by revealing that the type of intelligence valued and held by engineers are more coupled with intelligences beneficial to aspects of communication than previously assumed. To aid in these shifts necessary to improve communication in engineering students, it is important to not deem these two as opposite intelligences, rather they should be viewed as two important skills born out of the same cognitive processes and that may exist in a more symbiotic relationship than previously assumed.

7.4 Limitations

Participants were at the beginning of their second semester of a two-course sequence; the robot project from the prior semester was likely still familiar and fresh in their mind, which was likely beneficial when asked to discuss specific information. Conversely, the engineering design project was completed by teams consisting of 3 to 4 members, with explicit roles and responsibilities determined by members of the group. Typical team roles involved coding, project management, report writing, or the actual construction of the robot. Research participants were not asked about their role on the project; however, their knowledge and recollection of the project would be informed by their roles, which may skew some results (e.g. the builder may have a more intricate recollection of robot operations than the project manager).

Participants who completed both phases were interviewed by members of the research team who may have been in their previous course as a professor or graduate assistant. Furthermore, participants were interviewed in a setting where cameras were set up to record; any undue anxiety or stress caused by this may impact scores.

A written communication component was completed that asked similar questions to the oral communication task. Having exposure to the questions and being able to think through information via written documentation may have had an impact on oral communication and how effective they were in discussions. Future recreations of this research may modify how the oral task is distributed to acquire more holistic results; these distributions should be discussed with industrial professionals to recreate authentic industrial experiences. The participants were first-year engineering students in the second semester of their engineering major. Their communication skills may shift as they go through their degree; future work should recreate these approaches with senior engineers who will be entering industry after their last year or follow engineers over their degree to provide longitudinal information. The analysis of engineering participants at different stages of their degree would provide further details of how spatial skills and forms of fluency shift throughout their program and provide further evidence if the examined correlations remain consistent or morph as someone progresses through engineering.

7.5 Future Work

7.5.1 Suggestions for engineering academia and industry

Current findings are positive as skillsets promoted by academic institutions for engineering students are not negatively impacting aspects of cognition that assist communication, in fact, they may be useful in improving those same cognitions. However, the issue remains that literature continues to be produced where engineering industry personnel state that the expectations of communication skills of recent graduates are lacking. Around 500 engineering companies and organizations rated the importance and proficiency of various skills of recent entry-level engineers (Hirudayaraj, 2021, p. 9-11). Results indicated that employers have strong expectations for new graduates to be reliable and to be proficient in technical tasks, alongside having adaptable attitudinal skills. Furthermore, “the greatest difference between expectations and perceptions of proficiency across the set of soft skills [were] communication skills, personality traits, and interpersonal skills” (Hirudayaraj, 2021, p. 27).

Employers were more focused on the professional-skills of engineering graduates as a final factor for hiring, to the extent that a candidate with less technical proficiency but stronger professional skills would be the preferred hire; this was true regardless of the university attended and the degree or program completed by the engineer; “[t]he final choice is all about the attitude… [i]t is the proficiency in soft [professional] skills that allow engineers to become successful technical, programmatic and functional leaders in organizations” (Hirudayaraj, 2021, p. 23-24). Industry personnel appear to rank a new engineering graduate who is confident in their capability to learn new information and seek out help over an individual who may know more technical content but has difficulty asking questions.

The lack of confidence of some newer engineering graduates may stem from being trained in a system where there is a single correct or incorrect answer, where course policies punish incorrect answers, and where an individual may not feel comfortable to explore and make mistakes. Industrial contexts are often not as binary as academic ones. In industry there are usually a gradient of solutions, found through multiple iterations of work and conversations across different audiences and teams, and with unique benefits and drawbacks for each solution. There may be a negative feedback loop that new co-op, interns, or engineering graduates are prone to enter which results in a lack of experiences that potentially could improve their communication.

Prior research that explored industry's sentiments on new engineering undergraduates' skills found that professional skills and inter / intra personality traits were just as important if not more so than technical content knowledge (Coffelt, 2024; Hirudayaraj, 2021). There are multiple factors that impact skill at communication, some of which include personal experiences, how someone feels that day, environmental factors, societal, or even global trends.

There have been multiple efforts to attempt to induce these "real-life" experiences within the engineering curriculum that can have cascading impacts on both technical and professional skills. Some of these have included flipped-classroom models, co-curricular activities between different departments, and recreation of authentic industry experiences (Baytiyeh, 2017; Boelt et al., 2022; Garrett et al., 2022; Kaewpet & Sukamolson, 2011). However, these may not be integrated throughout the entire curriculum, and there may be a few semesters or years where an undergraduate must take an abundance of technical content courses that are not conducive to the previously described experiences. Furthermore, these experiences may not always be beneficial and may reinforce negative aspects of engineering culture. Findings by Seron et al. revealed that men tend to weather difficulties and failures in earlier courses, whereas women seek out support through peers or groups (2016). Men may be more likely enjoy the synergistic project-based learning, but women might experience more gendered stereotyping and are often being reduced to organizational roles (2016, p. 206). Furthermore, internships and "real-world" exposures that men and women experience as part of their engineering degrees may have different impacts. Some men describe growing competence and feeling fulfilled as they contributed to "true" engineering projects, whereas women may discover an isolationist and sexist culture, one that does not focus on socially conscious agendas (2016). Women may be particularly negatively impacted by the lack of focus on social issues, as contribution to progressive institutions and doing work that was socially impactful often motivated women to pursue engineering (2016, p. 206 – 207). Other research has found that curriculum difficulty and rigor, coupled with institutional norms and belief structures that are often seen as inflexible, contributed to the development of a survival of the fittest mindset in engineering students, which forced them to compare their own skills and worth to other students (Sellers & Alarcon, 2023, p. 194-195).

Engineering faculty beliefs and motivations in regard to the social responsibilities of engineers may also reinforce these negative aspects, as engineering professors "associate the responsibility of engineers with an individual behavior that respects professional laws and regulations, more than with the behaviors in which engineers act together with other agents to solve community problems" (Jimenez et al., 2020, p. 87). Earlier work found that older, professional industry engineers ranked strongly on extraversion, emotional stability, and conscientiousness (Van der Molen et al., 2007). However, this focused on professionals, and findings indicated that this population scored lower on agreeableness, which may relate to the survival of the fittest elements found in other research (Sellers & Alarcon, 2023).

The engineering education curriculum has made tremendous efforts to improve communication and personality development of engineering students; however, the rigidity and culture of engineering may force students to buy into the culture of meritocracy in their engineering degree that could have later impacts on their effectiveness at functioning in industry. The culture of current engineering schools may not be conducive to the empathetic, motivated, selfless engineer industry wants, particularly as they had their formative years in an environment termed “survival of the fittest” (Sellers & Alarcon, 2023, p. 194-195). Academic institutions should continue to make efforts to not foster environments that create harmful stereotypes which reinforce beliefs of individualism and self-preservation. Academic cultures should attempt to remove foundations and curricular structures that create experiences which excise the important traits of empathy, teamwork, and curiosity in undergraduate engineers; traits that are critical to their later success in industry. It could be hypothesized that engineering students may already have effective oral or written communication skills, or the cognitions to help develop those skills; however, the personality and willingness to utilize these skills in the way industrial contexts requires may be potentially not prioritized by engineering education.

7.5.2 Suggestions for future research in spatial skills, technical communication skills, and gesture production

Attempts to replicate similar research that explores spatial and technical communication skills should utilize trained outside interviewers to prompt participants, or engineering faculty / students that were not associated in prior courses. Prior gesture research recorded individuals with a hidden camera then asked if the footage could be used, as an obvious recording setup may impact how comfortable individuals would be with gesture; these approaches would likely shift final communication score outcomes.

Two other gesture eliciting tasks were distributed to participants, one that asked how a participant took a pathway to their high school, and the other that asked how they would wrap a present. Gestures per 100 words for both tasks have been calculated and could be applied to an analysis in a similar fashion as this research; this could help provide further data on how engineers explain different types of information. Prior gesture research found that "representational gestures have the most significant communication benefits in motor topics, compared with spatial or abstract topics" *(Canarslan & Chu, 2025, p. 93 - 94)*. While pathway and present wrapping are likely spatial topics, these could be further subdivided into more abstract (present) or motoric (pathway) topics. As prior work theorized a fractionate system with a common framework for abstract, spatial, and nonspatial information (Alfred et al., 2020; Cortes et al., 2022), data on how an engineer's spatial visualization skills impact their comprehension and communication of these different forms of information would be useful; this can relate to industrial contexts, where an engineer would likely communication about spatial phenomena, but also about prices, time limits, and relationships, which could fall into spatial, abstract, and nonspatial categorizations.

Future work should also examine different types of communication tasks for engineering majors, such as social dilemma tasks that have been used in gesture research (Canarslan & Chu, 2025). Findings by Canarslan and Chu found that "in situations where representational gestures serve a communicative purpose, individuals with higher empathy levels tend to generate more representational gestures to enhance the quality of communication with their listeners" (2025, p. 95). Additional tasks that elicit empathy or conflict could provide further insights into communication skills and potential personality traits of engineering majors. This type of work could extend beyond gestural tasks, where empathy and conflict could attempted to be elicited through the forms of communication examined in this research (sketching, oral, written). For instance, how does an undergraduate engineer generate an email to their boss, friend, or colleague; how does an undergraduate engineer create a short story, or explain a concept or idea they personally enjoy? More work and research will need to be done to effectively develop a research study of that scope, but it could be worthwhile to examine communication alongside personality traits; traits found not just through self-reported information but through tasks to elicit inter / intrapersonal traits industry continues to extoll as critical for engineers.

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Appendix A: Oral Communication Task Rubric

Oral Task Rubric, version 3 (02/25/25)
Student Identification #: _________________ Interviewer: ______________
Evaluator: ___________
no-video video Prompting: Minimal Moderate Frequent

Use the scale of 1-6 in each of the areas described below by circling the number that best reflects the student's response. Numerical scoring is required; comments are especially helpful to clarify the numeric score. Add any bullet points or questions needed to improve the rubric.

1. Overall design project and goals identified

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Some "big picture" of robot design project is provided (e.g., natural disaster, garbage on beach, etc.)
- Any pedagogical value mentioned (e.g., help students learn about…, etc.)
- ***"Adequate"*** if some context / background / robot purpose / big picture is given.

Comments:

2. Robot's specific design requirements and tasks to perform are identified

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Specific design requirements are acknowledged:
  - Must not use wheels for movement.
  - Must operate autonomously, not remote controlled
  - Robot is made of LEGOS
  - LabView is used to control
  - What else?
- Specific tasks robot must perform are identified:
  - Must follow straight and curved solid black line
  - Must follow straight and curved dotted black line
  - Must follow straight and curved segmented black line
  - Must navigate closed-loop path using one of the line types above
  - Must be able to navigate uneven terrain
  - Must be able to pick up a container
  - Must be able to determine container contents
  - Must be able to walk while holding container
  - Must place container at designated location

1 or 2 if only minimal info is provided, or if only design OR required tasks is addressed.

Comments:

3. Robot's *appearance* and *physical features* described

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Robot's overall appearance – size / dimensions / materials – is well described.
- Specific attachments / appendages and their purposes are explained.
- The listener can envision what the robot looks like.
- Robot's basic operation and control mechanisms are clear.

Comments:

4. Robot's *operation* and overall *performance* or success during testing / demo explained

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Student's control of robot is described.
- Listener can understand the robot's processes described in relation to achievement of task.
- Summarizes robot's performance / success in achieving assigned goals.
- Provides explanation of constraints that kept robot from fully achieving goals.
- Suggests specific upgrades or changes to improve future performance. ***(5 or 6)***

Comments:

5. Was sufficient detail provided?

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Description of project purpose, robot, activities, and results is thorough and specific.
- Listener can fully envision the robot and activities performed.
- No gaps in explanation that confuse listener are present.
-

Comments:

6. Organization, flow, and accuracy

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Organization is clear and effective; explanation develops logically.
- Phrasing is tight and specific *vs.* rambling or vague.
- Information seems accurate and correct.
- Transitional words and phrases may help.

Comments:

7. Oral communication effectiveness

1	2	3	4	5	6
Unacceptable	Marginal	Adequate	Above average	Strong	Exceptional

- Speaker is audible, generally easy to understand.
- Speaker did not require frequent promptings.

Comments:

Appendix B: Written Communication Task Rubric

Written Communication Task Rubric

Student Identification #: ____ Evaluator Name: _________________

Task: Written Task

Use the scale of 1-6 in each of the areas described below by circling the number that best reflects the student's response. Add specific comments to support and clarify the numeric score.

1. Overall design project, and robot's purpose and goals are identified and described

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**

- The "big picture" of the robot design project is shown.
- Problems and robot's specific goals to be accomplished are identified.
- Precise tasks for the robot to perform are clearly described.
- Reader has a sense of the overall project purpose and student's approach to solving goals.

Comments:

2. Robot's appearance and operation are described

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**

- Overall appearance – size / dimensions / materials – is described.
- Specific robot attachments / appendages and their purposes are explained.
- The reader can envision what the robot looks like.
- Basic operation and control mechanisms are clearly explained.
- Student's intended interaction / control of robot is described.
- If a drawing or graphic is included, check here: ____ and answer question #8.

Comments:

3. How, *technically,* did robot solve the problem / required tasks during testing / demo?

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**

- Student's and robot's technical performance of required tasks is described.
- How robot functioned to complete various tasks is clear.
- The features of the robot involved in solving the problem are adequately described.
- Reader can understand the processes described in relation to achievement (or not) of tasks.

Comments:

4. Communication effectiveness: Organization, logical development, document structure

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**

- Organization is clear and effective; explanation develops logically; no confusing gaps.
- Phrasing supports logical development (introductory / closing info; topic sentences; transitional phrases; etc.)

• Layout of the response document helps with reader's understanding overall. • *In comments, indicate the document structure (narrative, large blocks of text, lists, etc.)*
Comments:

5. Communication effectiveness: Writing style, clarity, accuracy, concision, syntax

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**
• Information seems accurate and correct. • Phrasing is tight and specific *vs.* wordy and vague. • Information is concisely presented, without redundancy or overlaps. • Word choice and usage are appropriate and clear.					
Comments:					

6. Communication effectiveness: Mechanics, grammar, word usage, etc.

1	2	3	4	5	6
Unacceptable	**Marginal**	**Adequate**	**Above average**	**Strong**	**Exceptional**
• Standard and correct English usage support reader's understanding of the response. • No or minimal misspellings or punctuation errors. • Word choices, tense, agreement, etc. are correct.					
Comments:					

Appendix C: Sketching Communication Task Rubric

Student Identification #: ________________ Evaluator: _____________________

For the following questions, please review the sketch of the student and respond to the prompts using the Likert scale (1-5). For each question, please provide comments on why you chose the score and any other information in the white box below each bullet list.

1. Overall robotic sketch

1	2	3	4	5
Not Applicable	Unacceptable	Marginal	Average	Above Average
• From a single sketch can the operation of the robot be determined? • Is the general form of robot comprehendible? • Can you derive a clear purpose of the robot from the full sketch alone (not detail views)				

2. Detail views of the robotic sketch

1	2	3	4	5
Not Applicable	Unacceptable	Marginal	Average	Above Average
• Are there multiple sketches that highlight specific details of the overall robot and operations / tasks it had to complete? • Are there multiple perspectives of the detail views (side / front / bottom) and are they consistent with the overall robotic form? • Do the detail views add or remove from overall understanding of the sketch?				

3. Callouts, annotations, and labels of sketch

1	2	3	4	5
Not Applicable	Unacceptable	Marginal	Average	Above Average
• Are there specific figure labels, titles, and callouts to clarify information about the robot? • Do callouts reference other detail views / overall sketch? • Is motion, direction, function shown with arrows or other annotations? • Are the callouts and text information necessary to clarify key elements of the sketch?				

4. Sketch perspectives, forms, and angles

1	2	3	4	5
Not Applicable	Unacceptable	Marginal	Average	Above Average
• Is the sketch in 2D, 2.5D, or 3D form? • If the sketch has detail views, are they consistent in the form and can they be spatially connected? (e.g., are the leg amounts consistent / in the same location) • Do detail views, callouts, and the full robotic sketch logically fit together? • Are there multiple angles shown in the sketch?				

5. Overall sketch and written report communication effectiveness

1	2	3	4	5
Not Applicable	Unacceptable	Marginal	Average	Above Average
• After only reviewing the sketch, is the written report necessary to explain features / operations of the robot that the sketch does not show? • How much did the written report help or detract from your comprehension of the sketch? Did the two elements align or were there mismatches? • Is the sketch a critical component of explaining the operations of the robot? • Is the sketch too cluttered / simple, or is spacing effective? • For these, a lower score indicates that either the sketch, the written report, or both were not aligned, did not help explain operations; a higher score indicates that they were both effective tools to communicate information. • Try to grade this question based on the combination of the two artifacts rather than separating them out.				

Appendix D: Written and Oral Communication Task Instructions

Writing Instructions

For the writing portion of this study, reflect back on your robot from ENED1100 and please write a document that describes:

- What problem were you trying to solve?
- What task was it supposed to do?
- What did it look like?
- How did it operate?
- What features of your robot solved the problem?
- How did your robot perform in the demo?

If you need to include a figure in your document, please use the blank sheets of paper provided and hand-sketch the figure. Do not spend a great deal of time trying to make a computer-generated sketch either in Word or elsewhere.
Your document should be 2 pages maximum.

Speaking Instructions

The next section of this study involves a speaking test. Think back to your ENED1100 project and explain the following

- What problem were you trying to solve?
- What task was it supposed to do?
- What did it look like?
- How did it operate?
- What features of your robot solved the problem?
- How did your robot perform in the demo?

Appendix E: Interviewer Instructions for Phase Two

Writing Task First Order

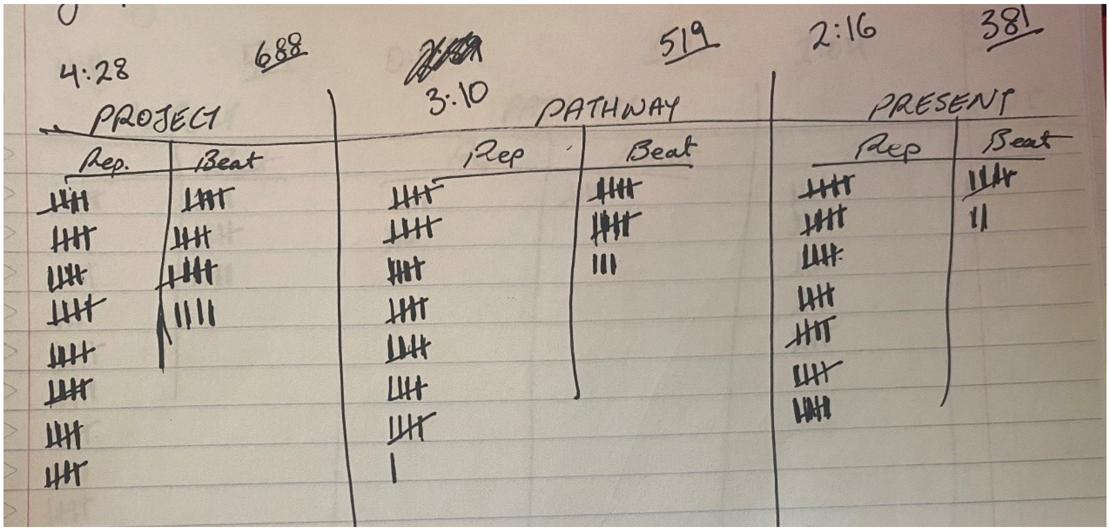
This document is to be used for the Spatial Skills interviews when doing the writing task first and the oral task second

Before Starting Tasks

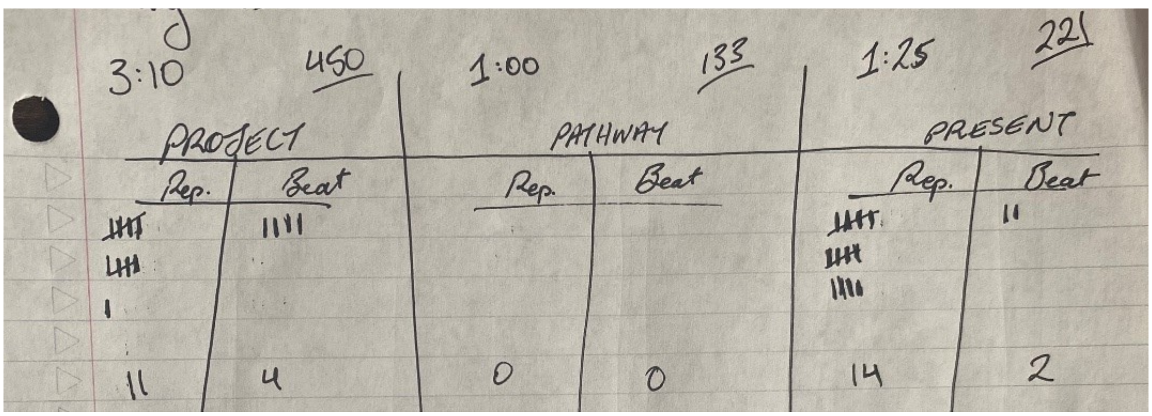
1. Consent Form – participant and interviewer sign
2. Pre-save a Word document with their 6+2
3. Get the participant's Mnumber on the Calendly printout for giftcards
4. Start cameras to ensure participant is within the field of view of both cameras
5. On video, have the participant state their name and 6+2

Task	**Approximate time**
1. Phenomic Fluency Task (Name all the words that begin with letter "s"—they have 60 seconds to complete the task)	2 minutes
2. Semantic Fluency Task (Name all the animals you can think of within 60 seconds)	2 minutes
3. Communications Task 1 – Writing	5-10 minutes
4. Phenomic Fluency Task (Name all the words that begin with the letter "t"—they have 60 seconds to complete this task)	2 minutes
5. Semantic Fluency Task (Name all the fruits **and** vegetables you can think of in 60 seconds)	2 minutes
6. Describe the path you normally took when going from your home to your high school. Include street names, landmarks, and distances if you can.	2 minutes
7. Communications Task 2 - Oral	5-10 minutes
8. Present Wrapping Task	4 minutes

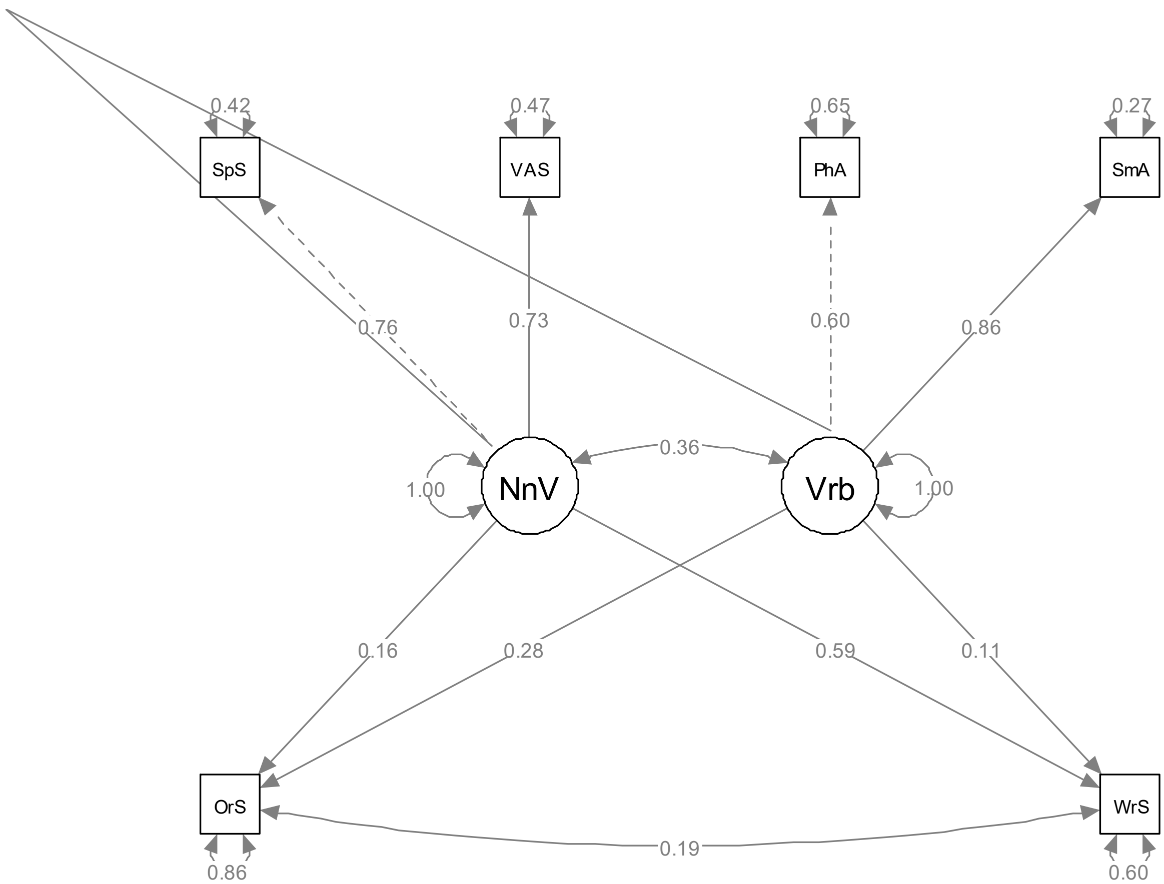
Appendix F: Gesture Production Rate Tally Example 1



Appendix G: Gesture Production Rate Tally Example 2



Appendix H: Full SEM – Original Lavaan Model



Appendix I: Full SEM – Updated Model with Color Codes

Key:
R^2 is the percentage of variance in the observed score explained by the cognitive factor (non-verbal, verbal), or linear correlations between only two variables.

β represents the standardized regression co-efficient: how much does this value predict the outcome (oral / written score) while holding other values constant.