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Spatial Skills and Design Problem Scoping Behaviors in Undergraduate Engineering Students

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Abstract

Context

Engineering design skills are essential for engineering students to succeed in their careers. Engineering design is a skill that is in high demand in the current job market and should be prioritized in education.

Purpose

While design has been acknowledged as a cognitive skill in research, there exists limited literature addressing the cognitive foundations of design thinking. Hence, engineering educators must understand the engineering design process, as well as the different ways students approach design problem-solving and the potential reason behind these differences. To understand how people solve design problems, we need to consider how their minds work and the strategies they use. Spatial ability stands out as a cognitive factor that is crucial for designers and holds significance in well-established theories and models of intelligence. However, to date, research exploring the impact of spatial ability on design thinking and its influence on problem-scoping behaviors remains limited. This paper examines how engineering students' spatial skills influence how they define the scope of open-ended design problems. The central research question that guides this paper is "How do design problem-scoping behaviors differ for engineering students based on their spatial scores?".

Methods

The researchers used a mixed methods research approach to answer their research question, collecting qualitative and quantitative data in two phases. One hundred twenty-seven undergraduate engineering students completed four tests that measure spatial reasoning skills in the quantitative phase and 101 students returned to finish the three design tasks in the second phase. This paper will examine the performance of students with low spatial and high spatial skills on one of the completed design tasks.

Outcomes

From the study, it was clear that spatial skills have an impact on the design-scoping behaviors of the undergraduate engineering students. It was inferred that high spatial skill visualizers emphasized the technical details of the design problem whereas low spatial skill visualizers emphasized the context of the design problem during their problem-scoping behavior. A Mann-Whitney test revealed there was a statistically significant difference in detail- and context-focused segments between the high and low spatial visualizer groups.

Conclusion

This research study confirms that a relationship exists between spatial and design skills. The study also found that undergraduate engineering students with different levels of spatial skills had different approaches to scoping design problems.

Keywords— *Spatial visualization skills, engineering design, design skills, problem-scoping behaviors, undergraduate engineering students*

I. INTRODUCTION

DESIGN is an important attribute of professional engineering practice. It is an important part of engineering education curriculum and a competency skill that is essential for student success in their chosen field. In our everyday lives, we see the benefits of engineering design, but we also experience the catastrophic consequences of engineers failing to consider the long-term effects of their design projects. As engineers it is important for us to develop the solutions of any design problem by taking into account of factors such as societal, cultural, and environmental. As engineering operates within real-world contexts, possessing the capacity to contemplate extensive ramifications, spanning technical, social, economic, political, cultural, and environmental facets, stands out as a crucial element in achieving success as an engineer (Cross, 1995; Nelson & Stoltermann, 2003; Cross, 2006).

Several reports, research studies, and accreditation criteria for engineering programs have indicated the need for consideration of non-technical contexts in the future of engineering practice (ABET Engineering Accreditation Commission, 2021; National Academy of Engineering, 2004; Lau, 2004). For instance, the Accreditation Board for Engineering and Technology (ABET) has included design as one of the outcomes of engineering programs.

Specifically, ABET says that undergraduates must attain:

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"an ability to apply engineering design to produce solutions that meet specified needs with consideration of public health, safety, and welfare, as well as global, cultural, social, environmental, and economic factors."

ABET-accredited programs prepare graduates to be creative and innovative problem-solvers so that they can work with incomplete information, apply imagination to generate novel and unexpected solutions, as well as use drawings and other visual representations to communicate their ideas effectively (ABET Engineering Accreditation Commission, 2021). Engineering design is a cognitively demanding process that requires engineers to think about all the different parts of a system and how they work together (Lammi, 2013).

Research studies have identified design as a high-level cognitive skill that involves the production of successful iterative internal and external representations of an artifact to analyze and improve the design (Aurigemma et al., 2013; Kim & Maher, 2008; Lazar, 2018; Dorst, 2011). Still, the cognitive basis of the design thinking process is a relatively understudied area of research. While there is a growing body of research literature on the topic, there is still a lack of consensus on the specific cognitive processes involved in design thinking. Research studies have broken down the design process into "steps" such as defining the problem, researching solutions, coming up with ideas, building a prototype, choosing the best solution, implementing it, reframing the solution, learning from the experience, and so on (Ambrose & Harris, 2009; IDEO Education, 2012; Brown, 2009; Kueh & Thom, 2018). However, we still need to conduct additional research to fully understand the cognitive basis of design thinking. Spatial visualization skill is one of the key cognitive elements that is necessary for a designer (Williams & Sutton, 2011; Suh & Cho, 2020).

A. *Spatial Skills and Engineering Design*

Spatial skills are very important for engineering students, and there is more and more research showing that improving these skills can lead to significant benefits and help engineers to function more effectively in their respective fields of work (Serdar & deVries, 2015; Sorby & Baartmans, 2000; Duffy, et al., 2020). Many research studies have shown that students with strong spatial ability are more likely to be successful in STEM (Sorby et al., 2014; Sorby et al., 2018; Wai et al., 2009; Uttal et al., 2013). Spatial ability also helps individuals improve their capacity to imagine representations and mentally manipulate and transform these representations in different ways (Xue et al., 2017; Pylyshyn, 2003; Shepard & Metzler, 1971). Research studies have established spatial ability's crucial role in supporting and enhancing cognitive functions such as advanced thinking, abstract reasoning, and creative processes (Sorby et al., 2013; Ishikawa & Newcombe, 2021). These abilities are considered fundamental for navigating and interacting with our surrounding environment.

Engineers are known for their problem-solving skills. Research studies have shown that spatial skills are closely related to the ability to solve problems in mathematics and chemical engineering (Duffy, 2017; Loney, et al., 2019). There is a large body of research that shows the importance of spatial ability in engineering graphics. Engineers rely on their spatial visualization skills to effectively convey their design concepts (Sorby et al., 2013) and design projects of individuals with high spatial skills tended to show strengths in better design approach (Suh & Cho, 2020). Despite the importance of both spatial thiking and design thinking in engineering, there is still relatively little research on how the two relate to each other (Sutton & Williams, 2007; Sutton & Williams, 2010). Thus, this study aims to investigate the relationship between spatial skills and the engineering design scoping behaviors of undergraduate engineering students.

II. METHODOLOGY

In the present study, a sequential mixed methods research methodology was used to answer the central research question. This methodology consisted of two distinct data-collection and analysis strands as shown in Fig. 1. Firstly, the quantitative phase involved the collection and analysis of numeric data. Following this, the qualitative strand was implemented, involving the collection and analysis of textual data in a consecutive manner (Creswell & Clark, 2017). Sequential mixed methods research design methodology aims to purposefully select participants for the qualitative phase based on the quantitative data, rather than using random sampling. By doing so, we can leverage qualitative contextual data to enhance the interpretation of the findings (Subedi, 2016). We then put all of the data together and look at it closely to better understand the scientific findings and how they relate to our research questions (Creswell & Clark, 2017).

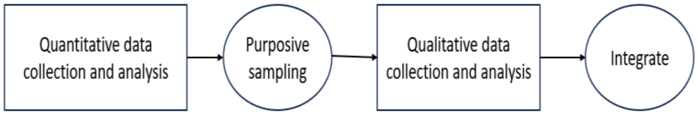

Fig. 1. Procedural diagram of the Mixed Methods Design –Sequential

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This research aims to examine the relationship between the spatial skills and engineering design problem-scoping behaviors of undergraduate engineering students. This work is informed by answering the mixed methods research question: "How do design problem scoping behaviors differ for engineering students based on their spatial scores?".

A. Study Setting

The study was conducted at a public in the College of Engineering at the University of Cincinnati. Engineering students in the first and final years of their programs were recruited through emails and flyers that were posted around the college. In the initial phase, participants took four well established spatial ability tests online via Qualtrics while being proctored by the researchers. In the second phase, individual participants came back to complete three design tasks, while thinking aloud about their thoughts and processes. The Institutional Review Board (IRB) at the University of Cincinnati approved this study.

B. Quantitative Strand - Data Collection

A total of 127 undergraduate engineering students participated in the quantitative phase of the study. They took four well-established spatial ability tests online, proctored by a research assistant. The tests were the Paper Folding Test (PFT) (Ekstrom & Harman, 1976), the Mental Cutting Test (MCT) (College Entrance Examination Board, 1939), the Spatial Orientation Test (SOT) (Kozhevnikov & Hegarty, 2001) and the Mental Rotation Test (MRT) (Shepard & Metzler, 1971). A verbal analogy test was also included to control for general intelligence. Once the tests were graded, a principal component analysis was conducted to separate students into high and low spatial visualizers (data from medium-level visualizers were not included in this analysis).

C. Qualitative Strand - Data Collection

Thirty-one participants (15 high and 16 low spatial) were purposively chosen to participate in the phase 2 concurrent verbal protocol phase (Atman & Bursic, 2013). In this phase of the research, each participant was given three design problems to solve. For this study, the emphasis will be solely on one of these three problems, which involves listing factors for designing a retaining wall system. The problem statement for the third design task was:

> "*Over a typical summer the Midwest experiences massive flooding of the Mississippi River. What factors would you take into account in designing a retaining wall system for the Mississippi?*".

The qualitative phase of the study was conducted individually for each of the participants in a neutral and restful environment within the college premises. The room was chosen for its lack of distractions, which helped to ensure that the participants were able to focus on the task at hand. All of the participant's sessions were video- and audio-recorded, with the participants' permission, to facilitate the analysis of the data.

As each student completed the Midwest flood listing design task, their zoom session was recorded. The recording of each student was then analyzed using the following steps:

a) transcription – the students verbal protocol was transcribed from the video recording.
b) segmentation – the transcribed verbal text was divided into units that could be coded using a pre-defined two-dimensional coding scheme (Atman et al., 2008)
c) coding – the coding scheme shown in Table I (Raju et al., 2022, adapted from Atman et al. (2008)), was used to code each segment for physical location and frame of reference.

To ensure consistency in coding, two coders coded each part of the lists generated by each participant individually. The coders then compared their coding to make sure that they agreed with at least 90% of the codes assigned for each participant. After resolving any disagreements, the coders calculated their interrater reliability, which was a Cohen's Kappa of 0.965. This high value means that the two coders agreed very strongly on how they assessed the participants' design problem scoping behaviors.

D. Coding

In previous research studies, researchers used a two-dimensional coding scheme to describe how broadly participants scoped design problems (Adams et al., 2003; Bogusch et al., 2000; Rhone et al., 2001; Rhone et al., 2003; Raju et al., 2022). In this study, we use the same coding scheme where each of the responses was coded for frame of reference and physical location of the design problem. Researchers used physical location codes to record the physical area of focus that the participant focused on. There were four codes: *wall*, *water, bank*, and *surroundings*. The codes were ordered to show how participants' focus moved from the details of the wall to the context of the problem. The w*all* and *water* represent parts of the problem that are close to the retaining wall. These are considered detail issues because they are typical of bounded engineering problems that focus on core engineering science issues.

The frame of reference codes represents how participants thought about the design problem on a broader scale. They are divided into four categories: *technical*, *logistical, natural,* and *social*. These categories of codes are also arranged to show how participants' thinking moved from the *details* of the problem to the *context* of the problem. *Technical* and *logistical* factors are about the details of the problem, while *natural* and *social* factors are about the context of the problem. Table I shows a summary of the two-dimensional coding system and the four codes.

TABLE I
CODING DIMENSIONS AND ITS DESCRIPTION (Adams et al.,2003)

Physical Location	**Description**
Wall	The wall itself, what affects it, other options for having a wall, where to put it.
Water	River's length, aquatic fauna, flood (but not effects on flood on other locations), pressure problems (without mention of the wall).
Bank	Earth immediately adjacent to river, earth below the river (riverbed), wall's interface, river's edge, river's width.
Surroundings	Everything far from water, residential units, items along water, particular impacts of the flood to bank.
Frame of Reference	**Description**
Technical	Engineering or technical terminology such as design problems, choices about construction of the wall
Logistical	Expenses, financing, process of construction, maintainability issues, resources needed.
Natural	Water's level (volume), destruction, effects of flood, geography, animals, flora, climate, and climate projections.
Social	People, people's safety, views, cities, living areas, policies

III. RESULTS

A. *Quantitative Phase*

In the quantitative phase, spatial tests were graded in Excel after importing the data from Qualtrics by the research assistant. There were 127 undergraduate engineering students (42 Female and 85 Male) who participated in the study. Internal consistency reliability for each of the four spatial tests was calculated. The KR-20 score was found to be above 0.80 for each of the spatial tests expect SOT (KR20=0.65), which is generally considered to represent a reasonable level of internal consistency reliability (El-Uri & Malas, 2013). Considering the transition of paper pencil test to online, it was expected to have some impact. We performed principal component analysis to group the research participants into low, and high groups (Jolliffe & Cadima, 2016). We used the first principal component to divide the participants into three groups: those with low and medium spatial skills and those with high spatial skills. We only focused on the high and low spatial groups in this study. Table I shows the summary of the spatial scores of high and low spatial visualizers who participated in this phase. The average score and standard deviation for each spatial group was determined with a maximum score of 81.

TABLE II
SPATIAL SCORES – AVERAGE AND STANDARD DEVIATION

Spatial Scores	
Low Spatial Visualizer (n=16)	
Avg. Score	23.63
Std. Dev	5.39
High Spatial Visualizer (n=15)	
Avg. Score	61.2
Std. Dev	5.80

B. *Qualitative Phase*

As shown in Figure 2 (a), undergraduate engineering students generated an average of 12.22 coded segments. Looking at the detail- and context- focused segments independently, we found that participants focused more on detail-focused, or technical aspects, segments. The Mann-Whitney test revealed there was a statistically significant difference between the detail and context-focused segments overall. It was also observed that, on average, all four of the detail-focused nodes were covered and 10 out of 12 context-focused nodes were covered by the participants.

C. *Integrating the data*

From the purposive sampling, the data from 16 low spatial visualizers (6 Female and 10 Male) and 15 high spatial visualizers (2 Female and 13 Male) was included in this analysis. Following the coding scheme for design problem scoping behavior, we also studied how the time taken to solve this design problem varied between high and low spatial visualizers.

To investigate and characterize the breadth of design problem scoping behaviors among high and low spatial visualizer groups, we averaged the coded segments for the physical location and frame of reference and plotted them in a two-dimensional coding space. Figures 3 and 4 provide a detailed comparison of the coded responses from high and low spatial visualizers, showing what kind of factors were discussed while completing the design task. Each figure presents the average number of segments inside a circular disc by code pair for high and low spatial visualizer group. The circular disc size was proportional to the number of average numbers of coded segments at that node.

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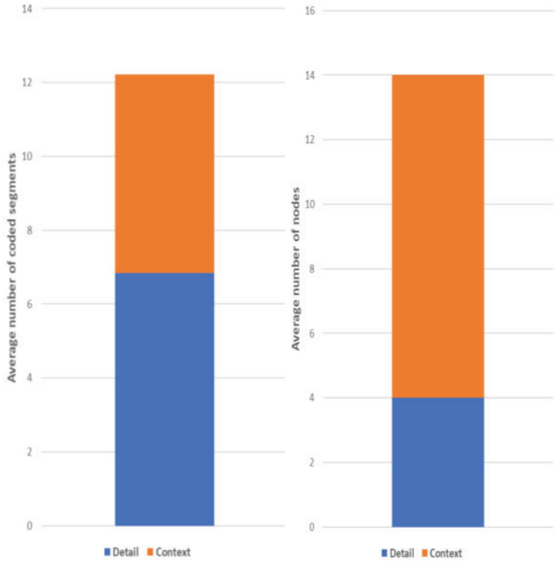


Fig. 2. (a) Average code pair segments by spatial visualizer groups. The bar division shows the average of detail- and context-focused segments. (b) Mean nodes covered by spatial visualizer groups for comparison. The bar division shows the average of detail and context-based nodes covered.

Upon plotting, it was inferred from the figure that high spatial visualizers focused more on the details of the Midwest flood listing problem as compared to the context of the problem when compared to low spatial visualizer group. This implies that the high spatial group focused more on the core engineering design problem because they generated more detail-focused segments. It was also very clear that the segments were not spread evenly across the coding space. Both high and low spatial visualizers tended to discuss more factors that were related to the wall and water compared to the bank and surroundings.

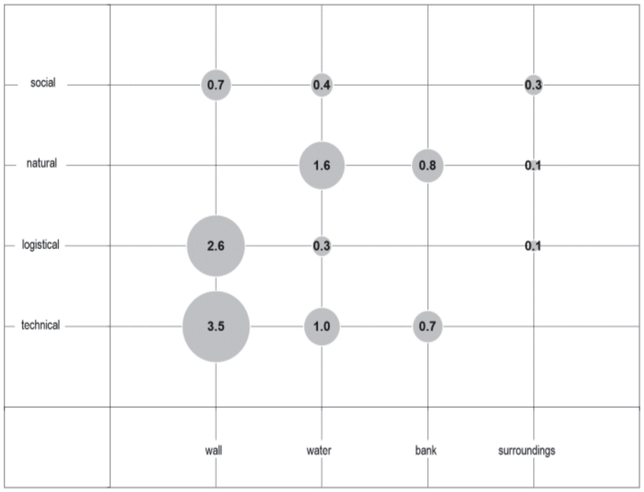


Fig. 3. Average code pair segments count for high spatial visualizers

The discussion of the wall factors focused on the technical details like wall dimensions and logistical considerations like cost and timeline of the project. The discussion of the water incorporated topics like flooding and wildlife. Contrasting these two figures (Fig.2 and Fig. 3.), it is clear from the averaged segment code values at each node that high spatial visualizers focused more on detail-oriented codes (WALL, technical and logistical) compared to low visualizers.

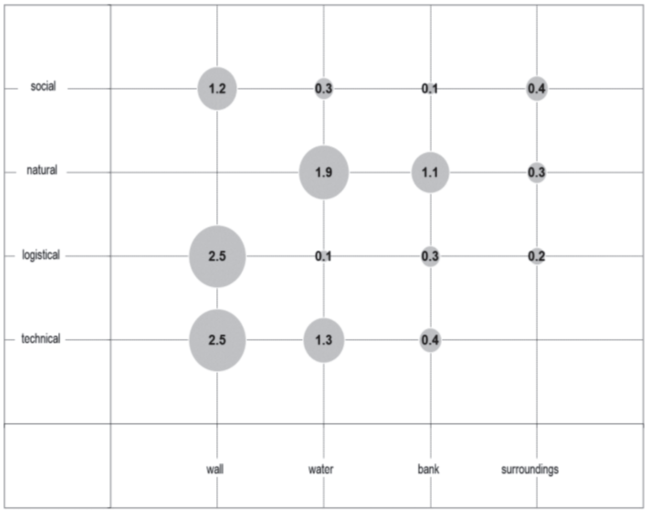


Fig. 4. Average code pair segments count for low spatial visualizers

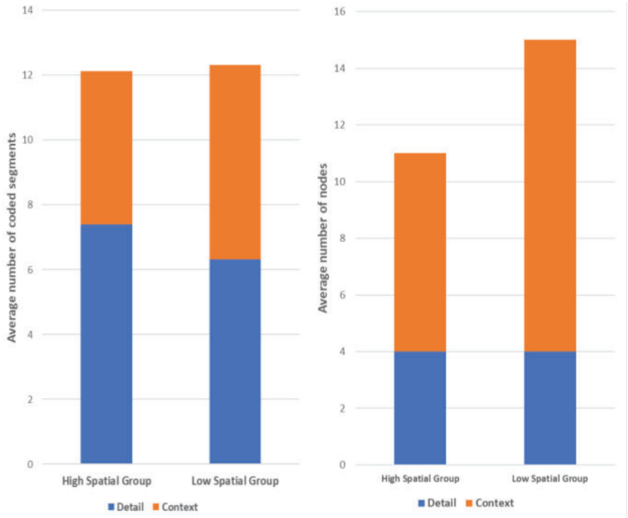


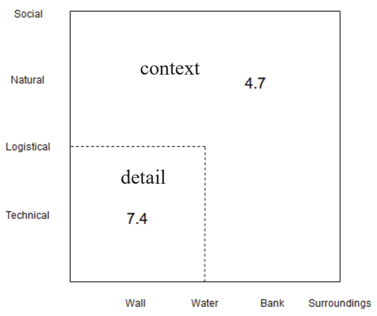
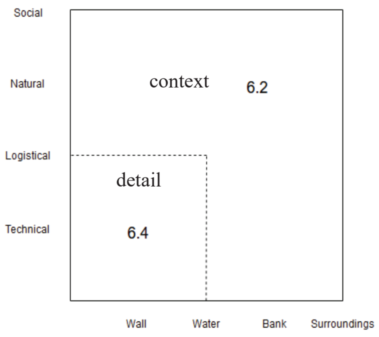
Fig. 5. (left) Average code pair segments by spatial visualizer groups. The bar division shows the average of detail- and context-focused segments. (right) Mean nodes covered by spatial visualizer groups for comparison. The bar division shows the average of detail and context-based nodes covered.

As shown in Figure 5 (left), high spatial visualizers generated an average of 12.13 coded segments and low spatial visualizers contained an average of 12.31 coded response segments. Looking at the detail- and context- focused segments independently, we found that high spatial visualizer group focused more on detail-focused segments. A Mann-Whitney test revealed there was a statistically significant difference in detail-focused segments between the two groups. Also, it was inferred from the plot that the low spatial visualizer group focused more on context-focused segments as compared to the high spatial visualizer group. The Mann-Whitney test revealed that there was a statistically significant difference in context-focused segments between these groups ($p<0.05$).

As shown in Figure 5 (right), high and low spatial visualizers covered all nodes in the detail nodes. Meanwhile, low spatial visualizers had more nodes covered in the context nodes. This signifies that low spatial visualizer considered more factors that were away from the core issue of the problem. Also, it was found that low spatial visualizers took one minute more time on average to complete the problem when compared to high spatial visualizers.

Table II shows the results broken down by level of spatial skills. While looking at the high spatial group, it is inferred that they focus more on the technical issues which are related to the typical engineering problem. Whereas, the low spatial group focused more on the context issues, focusing on interactions between the design and the broader system such as social, environmental, and urban impacts.

TABLE II
INTEGRATING THE RESULTS

Level Spatial Skills	**Avg. Scores**	**Average number of coded responses in the two-dimensional coding space**
High	61.2	
Low	23.6	

IV. DISCUSSION AND CONCLUSION

There is a strong consensus among researchers that spatial skills are important for success in engineering, but there has been limited research on the connection between engineering design behaviors and spatial skills. As described earlier in this paper, we sought to understand the relationship between spatial ability on the design problem scoping behaviors of undergraduate engineering students.

We found that the high spatial visualizers focused more on the core technical engineering and low spatial visualizer group generated more context-based segments. This indicates that high spatial visualizer emphasizes more on the technical issues of the phenomenon and low spatial visualizers focus on issues that are interactions from the proposed solution and broader system. One limitation is the fact that participant's year of study and gender were not considered during the analysis. So, future analysis is necessary to understand the impact of spatial skills based on their expertise level, gender and their impacts on design scoping behaviors. Currently, we are analyzing the data from a second year of data collection, which is anticipated to partially address the limitations of the ongoing study.

The Midwest flood listing task could serve as a valuable tool to understand the breadth of design problem-scoping. This research has helped us to understand how spatial visualization skills are related to engineering design skills. This understanding could be used to improve educational approaches to developing design capability in engineering education programs by helping the educators develop assessments and interventions to support design education.

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