2023 Annual Conference & Exposition
Baltimore Convention Center, MD | June 25 - 28, 2023
The Harbor of Engineering Education for 130 Years
Paper ID #37759

Learning Styles Impact on Ill-Structured Problem Solving Processes of Engineering Students, Faculty and Professionals

Kyle P. Kelly, Michigan State University
Secil Akinci-Ceylan, Iowa State University

Secil Akinci-Ceylan is a PhD student in Educational Technology in the School of Education at Iowa State University.

Xiangxiu Zhang
Dr. Kristen Sara Cetin, P.E., Michigan State University

Dr. Kristen S Cetin is an Associate Professor at Michigan State University in the Department of Civil and Environmental Engineering.

Dr. Benjamin Ahn, The Ohio State University

Dr. Benjamin Ahn is an Associate Professor at The Ohio State University in the Department of Engineering Education.

Learning Styles Impact on Ill-Structured Problem Solving Processes of Engineering Students, Faculty and Professionals

Abstract

Ill-structured problems are problems that are complex and open-ended in their design and as such they do not have a prescribed solution. They are generally more representative of the situations engineers face post-degree, in the “real world”. As these types of problems are integrated into college engineering classrooms, it is important to consider how the learning styles of the faculty and students involved may impact this problem solving process, and if this is similar or different to that of engineering professionals. Specifically, for faculty, their personal learning basis may impact the implementation and design of such problems within the curricula. Similarly, engineering students’ range of learning styles may influence how they solve or learn to solve design problems. Finally, engineering professionals’ learning styles may relate to the problem solving processes and external constraints seen in their professions, but may be different from those seen in the classroom. This research thus seeks to better understand variations in students, faculty and professionals’ learning styles, and how their learning styles relate to the steps and time taken to solve various steps of the problem solving process when presented with an ill-structured engineering problem.

As part of a larger study, 60 undergraduate students, academic faculty, and practicing engineers within Civil Engineering were asked to solve an ill-structured problem during which they were required to verbalize what they were doing. Prior to doing this, participants were asked to complete an Index of Learning Style (ILS) survey. Recordings of their verbalization were then transcribed and coded to divide the problem solving process into steps. Analysis of this data suggests there are some differences in learning styles between undergraduate students, academic faculty, and practicing engineers. Moreover, trends suggest that certain components of a participant’s preferred learning styles are predictors of the relative amount of time a participant will take to complete different steps of the problem solving process. This has implications for the teaching of such problems, since learning styles are likely to affect how a faculty teaches. This also has implications for how students learn the problem solving process. More research is needed to understand what factors and experiences may result in these differences. This includes how ill-structured problems and the process used to solve them in the classroom may or may not accurately represent professional engineering problem solving processes.

I. Introduction

The current body of academic knowledge has highlighted a disconnect between the problem types which students experience during the collegiate studies and those that occur in the field. Professionals within the engineering industry encounter problems which are described as *ill-structured* [1], *wicked* [2, 3], *ill-defined* [4], *complex* [5], or *workplace* [1]. While a diverse use of terms are employed, with varying amounts of use, all share similar meanings. That is, they describe problems which do not have defined correctness in solutions (no right or wrong answers), are not easily described, lack defined rules, and often necessitate iteration to generate a final solution.

Alternatively, the sorts of problems that are commonly experienced with engineering classrooms are "Engineering Classroom Problems." These problems are often presented by the course instructor in a manner such that the scenario is well described in a written manner with well-defined constraints such that there exists a singular "correct" answer [3]. In order to more effectively prepare students for careers within the field of engineering which necessitates that graduates have the ability to generate solutions to ill-structured problems, the ABET Engineering Accreditation Commission (EAC) [5] has emphasized the importance of integrating such ill-structured problems within civil engineering curriculum. ABET EAC has identified complex problem solving skills (Outcome 1) as one of its defined learning outcomes. Specifically, this includes the "ability to… solve complex engineering problems by applying principles of engineering, science, and mathematics." Concurrently, ABET EAC has denoted the importance of understanding non-engineering (i.e., non-technical) constraints (Outcome 2). More specifically, this includes "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."

A broad diversity of students enroll in engineering programs throughout the country and the world, and this demographic diversity has increased over time [6]. Many of these engineering students ultimately become industry professionals, professors, and/or instructors. To support the learning of engineering concepts, and in this case, complex problem solving processes, it is important to consider the diversity of learning styles [7] that exist within this population. Learning styles according to Felder and Silverman [8] are preferences in the way one learns that can be defined in four dimensions: Active-Reflective, Sensing-Intuitive, Visual-Verbal and Sequential-Global. Some research suggests that a good way to understand differences in individuals to support classroom learning is through the understanding of each person's learning style [9]. It is noted that learning styles are not necessarily the only way that students can learn, but suggest their preferences in learning. Research also suggests that if the teaching style of teachers and learning styles of students match, learning can best be achieved [10].

Among literature on learning styles in engineering, the majority of engineering education literature that relates to learning styles focuses on students [13,14]. For example, a study of engineering students in Malaysia suggests that engineering students were more strongly Active, Sensing, Visual, and Sequential learners [15]. The same finding of learning style preferences was found in a research study that included students in computer science, civil, electrical, and mechanical engineering in India. These more recent studies are consistent with prior studies as well. Among these studies, a key finding to note, however, is that while overall the populations were more inclined to be Active, Sensing, Visual, and Sequential learners, the reported learning styles across students span the spectrum in each of the four dimensions, and in some cases only slightly favored one side of each dimension over the other. For example, Kuri [16] found, among the students surveyed, a balance between Global and Sequential learners. Tulsi [17] found a near-even split between Active and Reflective learners specifically in civil engineering. These suggest that while research indicates that engineering students, on average, have preferences for certain types of learning styles, these learning styles also vary.

Beyond students, the stronger focus on students in the literature also means more limited information on academic professionals and especially practicing engineers. Research does suggest, however, that in many cases the methods of teaching in engineering courses are incompatible with engineering students' learning style preferences [18]. In addition, little research has included academic faculty and practicing engineers as two distinct groups. Commonly these groups are combined and defined as professionals.

In order to better integrate ill-structured problems within the curriculum, the approach to these problems associated with a person's learning style should be examined, as well as the differentiation between learning styles among participant (faculty, student, practicing engineers) groups. This is important as differences between groups can be the result of significant external factors as well as influence educational instruction. The goal of this study is to explore learning styles representation among students, faculty, and practicing engineers as well as understand how each learning style spends their time while solving ill-structured problems. Analyzing the interplay between these factors will help to identify opportunities for improvements to undergraduate instruction that teach and utilize ill-structured problems in the classroom environment.

II. Methods

Participants

Sixty undergraduate students (freshman to senior), academic faculty, and practicing engineers (5+ years experience) within civil and environmental engineering were asked to individually solve an ill-structured problem as well as complete an Index of Learning Style (ILS) survey. All faculty, students and professionals lived and/or worked in the United States during the time of the data collection. This was part of a larger study on ill-structured civil engineering education that occurred between 2017 and 2021. All participants who took part in the study did so on a voluntary basis and were compensated for their participation.

Data Collection

Participants were asked to complete the Index of Learning Styles Survey (ILS). This survey was chosen due to its high validity and reliability [6,7] as well as its consistent use in studies within the broader scope of engineering education [8-10]. After completion of the ILS survey, participants were given a 35-minute period to solve an ill-structured engineering problem. As participants engaged with this task a verbal protocol analysis (VPA) was used to collect collaborating data. VPA has been used extensively within literature as a method by which to examine problem solving

[19-24]. This method requires that participants vocalize their thought process while working on the problem. Besides the problem itself, participants were limited to only blank “scrap” paper on which they could visualize. During the task participants were not allowed access to reference literature (physical or digital). The ill-structured problem that participants were asked to solve was to construct a solution focused on removal of trash from a river [19]. This problem was generated by members of the research team along with other ill-structured problems. This problem was chosen for use in the final study based upon the input of the project’s advisory board members and discussion among the research team.

Data Analysis

Data for this study is from 60 Index of Learning Styles survey as well as transcripts generated from the ill-structured problem solved by each participant via VPA. The index of learning styles survey generates a profile for each participant based upon 4 dimensions. These include: Active-Reflective, Sensing-Intuitive, Visual-Verbal, and Global-Sequential. The first dimension is associated with the way a participant processes information. Active learners best learn information by working actively, and applying the material while reflective learners like to think and reflect on the material. For the second dimension, those who prefer a sensing learning style like facts and following standard approaches whereas an intuitive thinker prefers to do what feels right. For Visual-Verbal, visual learners like to see what they are learning about as compared to verbal learners who prefer text and talking. Finally, for Global-Sequential, sequential learners prefer learning and solving problems in small sequential steps, versus global thinkers who absorb a lot of different information.

Within each of these dimensions, participants are categorized based upon where their responses ranked on either side of the dimension (very strong preference, moderate preference, balanced). For example, across the four dimensions, a participant may be a “very strong Active learner” with balanced Intuitive, moderate Visual, and very strong sequential preferences. This data was then reclassified such that participants were considered to show expression to either side of a dimension or considered to be balanced. For example, within the dimension of Active-Reflective, a participant would be defined as active (includes both very strong Active” and “moderate Active”), reflective (includes both “very Reflective” and “moderate Reflective”), or Balanced. This process was followed because the number of participants that fell into the “very strong” category in each of the four dimensions was minimal. This best captures trends while minimizing categories of data that have a smaller number of participants.

After participants finished the ill-structured problem audio recordings of participants were transcribed for data analysis. Each of these transcripts were coded by a team of three coders using methodologies outlined by Corbin & Strauss [25]. Open, axial, and selective coding was used as a basis to generate a codebook. During the open coding stage, transcripts were read several times then using the participants own words as a basis labels were generated by each team member such that it summarized the participants thoughts while problem solving. Each team member went line by line within each transcript reading what was said explicitly and what such statements represented in one's solution generation process.

Following open coding, team members applied axial coding. During axial coding, relationships between open codes were identified such that categories and related subcategories were increasingly developed. Via axial coding a reduction in the total number of open codes was made by merging codes that express similar statements/sentiments. During selective coding a foundational category is chosen such that related subcategories become unified. This step is the conclusionary step, as defined by Corbin & Strauss [25], in developing a codebook. In total, the codebook went through 18 iterations, ultimately resulting in 13 code categories, and a total of 24 subcodes across all categories. It was determined that *Idea Expansion*, for example, was considered a core category. Within this category were the subcategories of *Expand Idea Details*, *Make Assumptions*, and *Calculations*. Table 3 shows a few of the codes utilized in this paper associated with the broader research study, along with some examples of quotes representing what is included in each type of code. For a full set of codes developed, please see [26-28]. The codes/subcodes shown in Table 3 are included in this paper because they were found to most strongly correlate with participants' learning styles.

Table 3 Selected *Coding Schemes for Verbal Protocol Analysis for Ill-structured Problem Solving Process*

Code	Definition	Example(s)
Problem Statement	The participant is reading the problem (paraphrasing, summarizing, interpreting, or repeating verbatim)	*"All right, so reduce the level of trash. Range of options to consider. Implement solutions in the streams," so the streams- streams, um, have a depth of 1 to 5 feet, a width of 5 to 10 feet and- and the river- river- river is- depth is 10 to 25 feet and it's 30 to 50 feet."* *"Essentially, since we are trying to test a small area, find a, find a process, whether it's a chemical, physical, whatever type of process mechanical uh, to do this. And, then from that, based on-on that find a solution that is-that is um easy."*
Workability	Discussion of if the *detailed idea* itself or its specific details are possible to do/likely to work	*"They're not concrete stakes anymore, tho-those are not gonna work."* *"What if you incentivize tourists to remove gum? I can't see-I can't see New York tourists doing that."* *"I'm trying to envision how much gum there is. So that's you know, it may not be enough to where you could just do it."*

Expanding Ideas	When the participant develops the initial *idea* into a *detailed idea*.	*"So, you could do the sidewalks to get the gum off -- we're just gonna like take a- a big scraper thing, that's beveled kind of at the edge of it, you know, almost like a knife and that-- that's going to be pretty wide. That two people probably will operate. And they're just gonna - There's two of them. It's going to be like a, uh-- It's going to have like a bar thing- And both wanna come down to like the blade. They'll be like, however wide the sidewalks are and that they're really wide, they might have to go by twice."* *"Um, and uh, and if we could automate that somehow, where you'd have a-a, uh, where it wouldn't be piece by piece, maybe it could just, uh, have a you know, a-a small piece of equipment that just goes along and freezes the ice."* *"Um, so can we, uh, um, can we end up developing a-a-a more mechanical where we can go through and at night-at night to do some type removal with limited numbers of people and so on."*

The codes were developed by a subteam within the larger research team. Three coders met weekly to discuss each transcript and compare codes. In the event a disagreement between coders occurred or a question was raised, the group would consult an additional coder in order to reach a consensus. In utilizing this method the study was able to achieve high inter-coder reliability. In order to more effectively code transcripts, a data analysis tool, MaxQDA [28] was employed. Using MaxQDA's "Code Coverage - Text, Tables, and PDF's" operation each transcript's code was quantified. This operation generates a percent for each subcategory code such that when added it totals the percentage of the entire document that was coded. In order to ensure the percentages used represent that of the coded text, each was divided by that transcripts' total percentage of text coded. To represent the distribution of data, this was then plotted using box plots to visually define the range, maximum and minimum values as well as the average and median.

III. Results & Discussion

For the overall dataset, the count and percentage of participants with each of the four dimensions of learning styles is shown in Table 1. The ILS survey data was also grouped based upon the role each participant belongs to: student, practicing engineer, or academic faculty. Table 2 shows the finalized form of ILS data. This is also graphed in Figure 1 to more easily understand the data through data visualization.

Table 1. *Count and Percentage Breakdown of Learning Styles (Note: *bold* indicates most common category)*

	# Participants (% of role total)		# Participants (% of role total)		# Participants (% of role total)		# Participants (% of role total)
Active	15 (25)	*Sensing*	24 (40)	***Visual***	**34 (56.67)**	*Global*	11 (18.33)
Balanced	**36 (60)**	***Balanced***	**29 (48.33)**	*Balanced*	26 (43.33)	***Balanced***	**36 (60)**
Reflective	9 (15)	*Intuitive*	7 (11.67)	*Verbal*	0 (0)	*Sequential*	13 (21.67)

In the overall dataset, for Active-Reflective, most participants were considered to be

Balanced; this same trend is observed for Sensing-Intuitive, and Global-Sequential. For these three, second to the Balanced category is Active, Sensing, and Sequential, which is in agreement with prior literature that collected data from engineers. For Visual-Verbal, the majority of participants were considered Visual, with Balanced being second. Notably, there were no participants that would be considered Verbal. Therefore overall, it can be said that on average, participants in this study generally favored Active, Sensing, Visual, and Sequential learning styles, with many considered to be balanced between both extremes.

Table 2. *Count and Percentage Breakdown of Learning Styles sorted by Role (note: *bold* indicates most common category)*

Role	*Active/Reflective*		*Sensing/Intuitive*		*Visual/Verbal*		*Global/Sequential*	
	# Participants (% of role total)		*# Participants (% of role total)*		*# Participants (% of role total)*		*# Participants (% of role total)*	
Undergraduate Students								
	Active	*8 (23.53)*	*Sensing*	*13 (38.24)*	***Visual***	***20 (58.82)***	*Global*	*4 (11.76)*
	Balanced	***21 (61.76)***	***Balanced***	***16 (47.06)***	*Balanced*	*14 (41.18)*	***Balanced***	***23 (67.65)***
	Reflective	*5 (14.71)*	*Intuitive*	*5 (14.71)*	*Verbal*	*0 (0)*	*Sequential*	*7 (20.59)*
Practicing Engineers								
	Active	*3 (33.33)*	*Sensing*	*3 (33.33)*	*Visual*	*3 (33.33)*	*Global*	*2 (22.22)*
	Balanced	***6 (66.66)***	***Balanced***	***5 (55.56)***	***Balanced***	***6 (66.66)***	***Balanced***	***5 (55.56)***
	Reflective	*0 (0)*	*Intuitive*	*1 (11.11)*	*Verbal*	*0 (0)*	*Sequential*	*2 (22.22)*
Academic Faculty								
	Active	*4 (23.53)*	***Sensing***	***8 (47.06)***	***Visual***	***11 (64.71)***	*Global*	*5 (29.41)*
	Balanced	***9 (52.94)***	***Balanced***	***8 (47.06)***	*Balanced*	*6 (35.29)*	***Balanced***	***8 (47.06)***
	Reflective	*4 (23,53)*	*Intuitive*	*1 (5.88)*	*Verbal*	*0 (0)*	*Sequential*	*4 (23.53)*

Table 2 shows that practicing engineers were majority Balanced in all categories, with active, sensing, and visual being second most common (Global/Sequential were tied). Among faculty, Balanced was most common for the Active/Reflective, Global/Sequential, and Sensing/Intuitive (tied with Sensing). Visual was most common for the Visual/Verbal category. For students, most were considered Balanced, except for Visual/Verbal, in which the majority were Visual. Overall, the distribution of results is somewhat similar across categories, as visually represented in Figure 1.

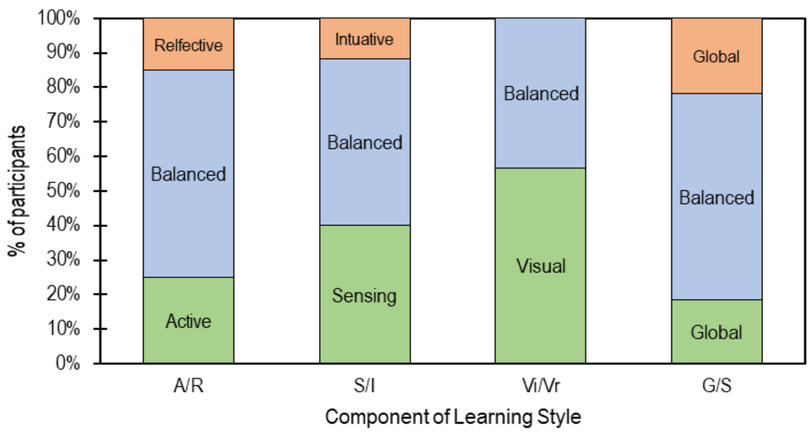

Figure 1. Visual representation of overall distribution of learning styles for the overall dataset

Three key trends were found when comparing participants' learning styles and the amount of time spent in various components of the problem solving process. For inclusion in this paper, the relationship between learning style components and codes from the problem solving process, must indicate a clear differentiation in time spent based upon one's learning style.

As shown in Figure 2, a person that is classified as having an Active learning style, spent less time (12.1%), on average, on the *Problem Statement* (as defined in Table 3, which is the period in the problem solving process where the participant is reading the problem) compared to those that are classified as Balanced (13.4%) or Reflective (18.7%). Active learners are considered those that process information by doing whereas a Reflective learner processes information via contemplation [7]; Balanced learners are in between these two extremes. Therefore this trend makes sense when considering that Reflective learners tended to take more time to think through the problem, in this case, by reading through the problem statement, before proceeding with solving the problem.

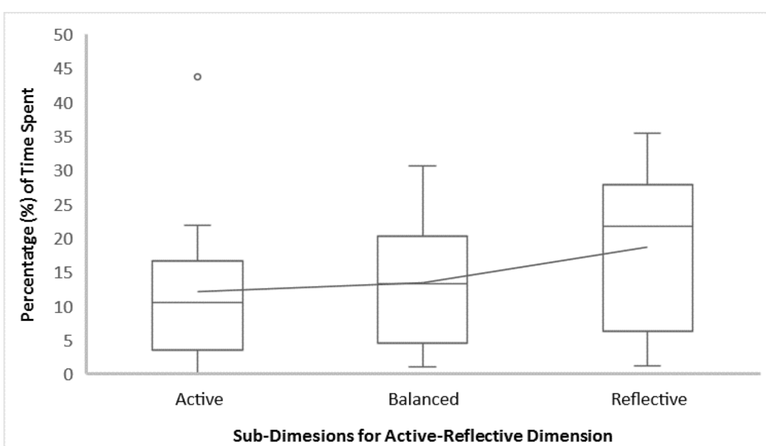

Figure 2. Percentage of time spent on the **Problem Statement**, across the Active-Reflective dimension of learning styles *(Note: Active (n = 15), Balanced (n=36), Reflective (n=9))*

When considering the possible implications of this in the engineering classroom, this may suggest that using active learning methods, such as think-pair-share (TPS), there may be variation in how much time students may need to think through their answer to a question. In TPS, students think on their own on how to answer a question, then talk with a classmate about what they thought about, then share with the rest of the class. This suggests it may be beneficial to give slightly more time in the “think” to support the reflective learners.

This difference among the Active-Reflective dimension of learning styles is inversely expressed when considering time spent on *Workability* (as defined in Table 3, which is the period in the problem solving process where the participant is evaluating if a detailed idea itself or its specific details are possible to do/likely to work), as shown in Figure 3. Spending time considering *Workability* in this study is more aligned with Active learners as compared to Reflective learners, where Active learners took approximately 5.2% of the time to consider *Workability*, while Reflective learners only took approximately 2.9% of the time.

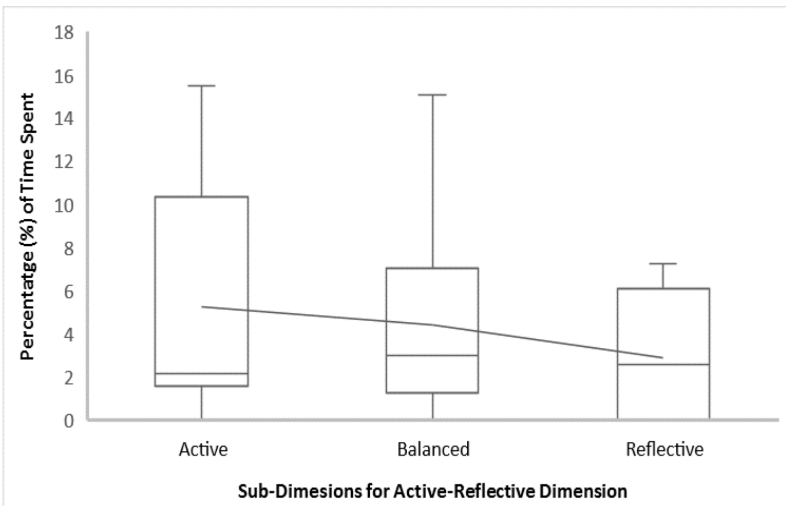

Figure 3. Percentage of time spent by participants on the **Workability** grouped by sub-dimensions within the larger Active-Reflective dimension *(Note: Active (n = 15), Balanced (n=36), Reflective (n=9)).*

Differences in time spent during the problem solving process considering *Workability* are also expressed within the Global-Sequential dimension of learning styles. Global learners are those that learn by exposing themselves to a totality of information and then learn by synthesizing this information together; conversely Sequential learners build upon small units of information over time in which by the end the learner understands (“learns”) the totality of the information. Balanced learners include components of these two extremes. In Figure 4 it is shown that Global learners, on average spend slightly less time on *Workability* than Sequential learners. This may reflect how such learners approach the solving of an ill-structured problem. Global learners may not spend as much time following different steps that focus on refining a *detailed idea* since they would likely generate a more refined *detailed idea* all at once. Conversely, a Sequential learner may take more time to consider *Workability* as one or multiple steps in the development of a refined solution after the initial generation of the detailed idea.

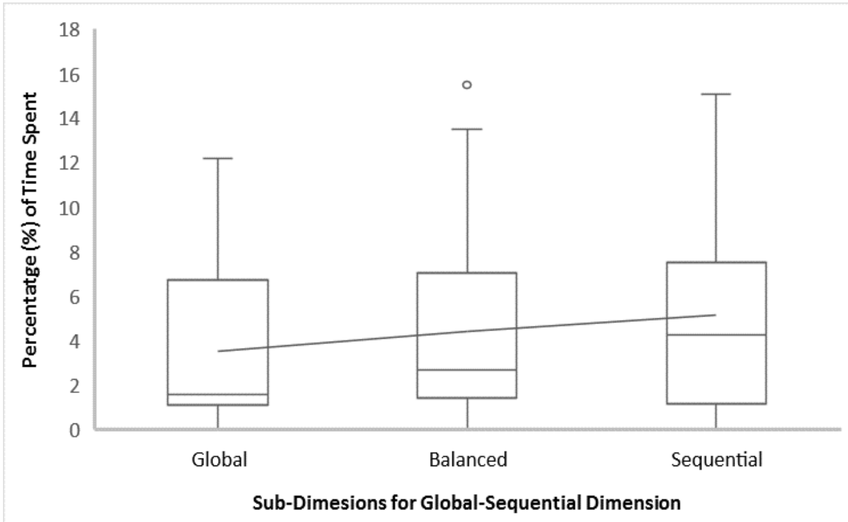

Figure 4. Percentage of time spent by participants on the **Workability** grouped by sub-dimensions within the larger Global-Sequential dimension. *(Note: Global (n = 11), Balanced (n=36), Sequential (n=13))*

The third trend observed is that Visual learners on average spend more time on the *Expanding Ideas* (as defined in Table 3, which is the period in the problem solving process where the participant is taking their *initial idea* and developing it into a *detailed idea*) step in the problem solving process than Balanced learners. Prior to further discussion, we note that this research as well as others has shown that engineers are generally skewed to the Visual side of the Visual-Verbal dimension. In this study all participants were either classified as Visual or Balanced, as shown in Figure 5. As such this study is only able to compare these groups.

Visual learners spend more time *Expanding Ideas* (~48.1% of time) as compared to Balanced participants aligns with what is generally known about Visual versus Verbal learners. Visual learners rely significantly on visuals (e.g. pictures, diagrams, flow charts, time lines, films, and demonstrations) to learn information, while Verbal learners benefit most from words, either written or spoken explanations. While the ill-structured problem presented to participants included both verbal (written words) and visual (pictures and diagrams) components, Visual learners would likely still require further visuals to generate and develop their ideas. This suggests that Visual learners may need to spend more time drawing pictures, and diagrams to help them process information and generate solutions. Balanced learners are more likely to rely on both visual and verbal information to learn and solve problems. Balanced learners may therefore employ both visual and verbal processes when developing solutions. In doing this, Balanced learners may be able to reduce the time spent on *Expanding ideas* by writing down information that visual learners may need to draw.

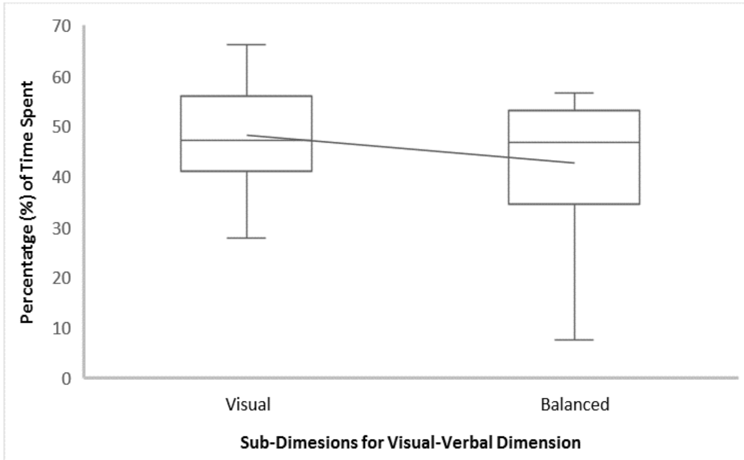

Figure 5. Percentage of time spent by participants on the **Expand Idea** grouped by sub-dimensions within the larger Visual-Verbal dimension *(Note: Visual (n = 34), Balanced (n = 26)).*

As shown in this study, variation in time spent in different steps of the problem solving process when solving ill-structured problems in some cases has a relationship to a person's learning style. Table 2 denotes variation in representation of these dimensions based upon that person's position, namely: Undergraduate Student, Practicing Engineer, or Academic Faculty. Along with identifying one's learning style the Learning Style Index also suggests the instructional approach that may be most comfortable for that person to use to teach, and to learn from. This is based on the assumption that if one learns in a specific manner, they are more likely to instruct in a way that matches/supports the manner in which they learn [7, 30], however since the ILS was first created there has been an increased emphasis on the use of teaching in a manner that caters to diverse learning styles. Using this information, assumptions related to misalignment in instructional methods and the post college careers can be highlighted.

Thus far this research has suggested that if a person is less of an active learner, they spend more time on reviewing the problem statement as a part of the problem solving process. While the majority of both practicing engineers and academic faculty are considered Balanced (on the Active-Reflective scale) in this study, only academic faculty contain reflective learners. Given this, instructional practices within undergraduate classes that employ ill-structured problems, particularly as taught by this group of faculty, may over emphasize a reflective style when it comes to thinking through the problem statement.

Within the Visual-Verbal dimension, practicing engineers are the only group that has more participants classified as Balanced than Visual. This is notable related to instructional methods, i.e. if faculty generally prefer a Visual learning style, it is likely they are using this in the teaching of classes via the use of visuals in classroom teaching. For example, when helping to guide students through ill-structured problems, academic faculty may more strongly emphasize methods for expanding ideas that appear to correlate more with the Visual learning style. While this appears to align well with students' preferred learning style as well, it also suggests that overly Visual-reliant teaching may be teaching students in a way that is different than what might be expected to be seen by practicing engineers. It is suggested by other research that a person's learning style can change over time, and can be influenced by external factors such as a person's profession [31]. Therefore, the difference seen between engineering professionals and faculty/students may suggest that professional engineers' learning styles may be adapted to meet the profession's need for conducting work in both the Verbal and Visual dimensions.

V. Conclusion

This research has focused on better understanding variations in how engineering students, faculty and professionals preferred learning styles relate to their problem solving processes. Specifically, this research focuses on key trends seen that relate time spent on different steps in the problem solving process to one or more of the 4 dimensions of learning styles.

While academic faculty play an important role in educating the next generation of engineers, it is important for academic faculty to consider how their own learning style frames their instruction. Similarly, it is important to note that faculty and students' learning styles may not be the same as professional engineers' learning styles. Given that faculty are training students to become, in large part, professional engineers and solve the future's challenging and highly ill-structured engineering problems, if there is a misalignment in the learning styles among these three groups, there is a need to ensure that the way that students are taught to solve these problems is conducive to supporting a successful future engineering career. Given that learning styles can change over time (e.g. [32]), including throughout a student's education, this research suggests that there are some differences in both professional engineers problem solving processes and their learning styles that may be beneficial to further understand. By better understanding these differences, the engineering classroom can help to better reflect these and teach to the likely future methods of problem solving that students are likely to use as professional engineers.

Moving forward, further research is needed to understand how a person's role and the environment in which that role exists impact a person's learning style. This can also further help support defining how to best instruct students on the solving of ill-structured problems such that it more accurately reflects the process of practicing engineers.

Acknowledgements

This work was funded by the National Science Foundation Grant #1712195/2013144. Data, findings, and conclusions or recommendations are those of the authors, only.

References

[1] Jonassen, D., Strobel, J., & Lee, C. B. (2006). Everyday problem solving in engineering: Lessons for engineering educators. Journal of engineering education, 95(2), 139-151.

[2] Regev, G., Gause, D. C., & Wegmann, A. (2008, September). Requirements engineering education in the 21st century, an experiential learning approach. In 2008 16th IEEE International Requirements Engineering Conference (pp. 85-94). IEEE.

[3] Regev, G., Gause, D. C., & Wegmann, A. (2009). Experiential learning approach for requirements engineering education. Requirements engineering, 14(4), 269.

[4] Reitman, W. (1964). Heuristic decision procedures, open constraints, and the structure of ill defined problems. In W. Shelley and G. L. Bryan, eds., Human judgments and optimality. New York: Wiley.

[5] Accreditation Board for Engineering and Technology (ABET EAC), (2022, October 29). Criteria for accrediting engineering technology programs. Retrieved from https://www.abet.org/wp-content/uploads/2023/03/23-24-EAC-Criteria.pdf

[6] Science and Engineering Labor Force | NSF – National Scicene Foundation. (n.d.). Ncses.nsf.gov https://nces.nsf.gove/pubs/nsb20198/demographic-trends-of-the-s-e-workforce

[7] Felder, R. M., & Soloman, B. A. (2000). Learning styles and strategies.

[8] Felder, R.M. & Silverman, L.K. (1988), Learning and teaching styles in engineering education, Engineering Education,78:7, 674-681.

[9] Hall, J. (2005), Neuroscience and education:A review of the contribution of brain science to teaching and learning, Scottish Council for Research in Education.

[10] Rohrer, D., & Pashler, H. (2012). Learning Styles: Where's the Evidence?. *Online Submission*, *46*(7), 634-635.

[11] Felder, R. M., & Soloman, B. A. (2000). Learning styles and strategies.

[12] Felder, R. M., & Spurlin, J. (2005). Applications, reliability and validity of the index of learning styles. *International journal of engineering education*, *21*(1), 103-112.

[13] Mohamad, M. M., Jamali, A. R., Mukhtar, M. I., Sern, L. C., & Ahmad, A. (2017, November). Learning styles and critical thinking skills of engineering students. In *2017 IEEE 9th International Conference on Engineering Education (ICEED)* (pp. 54-58). IEEE.

[14] Miskioğlu, E. E., & Wood, D. W. (2014, October). That's not my style: Understanding the correlation of learning style preferences, self-efficacy, and student performance in an

introductory chemical engineering course. In *2014 IEEE Frontiers in Education Conference (FIE) Proceedings* (pp. 1-3). IEEE.

[15] Kapadia, R. J. (2008, October). Teaching and learning styles in engineering education. In 2008 38th Annual Frontiers in Education Conference (pp. T4B-1). IEEE.

[16] Kuri, N. P., & Truzzi, O. M. S. (2002, August). Learning styles of freshmen engineering students. In Proceedings, 2002 international conference on engineering education. International Network for Engineering Education and Research.

[17] Tulsi, P. K., Poonia, M. P., & Anu, P. (2016). Learning styles of engineering students. Education, 1(1), 2

[18] Felder, R. M. (2002). Learning and teaching styles in engineering education.

[19] Atman, C. J., Cardella, M. E., Turns, J., & Adams, R. (2005). Comparing freshman and senior engineering design processes: an in-depth follow-up study. Design studies, 26(4), 325-357.

[20] Dixon, R. A., & Johnson, S. D. (2011). Experts vs. Novices: Differences in How Mental Representations Are Used in Engineering Design. Journal of Technology Education, 23(1), 47-65.

[21] Atman, C. J., Chimka, J. R., Bursic, K. M., & Nachtmann, H. L. (1999). A comparison of freshman and senior engineering design processes. Design studies, 20(2), 131-152.

[22] Taylor, K. L., & Dionne, J. P. (2000). Accessing problem-solving strategy knowledge: The complementary use of concurrent verbal protocols and retrospective debriefing. Journal of Educational Psychology, 92(3), 413–425.

[23] Douglas, E. P., Koro-Ljungberg, M., McNeill, N. J., Malcolm, Z. T., & Therriault, D.J. (2012). Moving beyond formulas and fixations: solving open-ended engineering problems. European Journal of Engineering Education, 37(6), 627-651.

[24] Akinci-Ceylan, S., Cetin, K. S., Fleming, R., Ahn, B., Surovek, A., Cetin, B., & Taylor, P. (2018, January). Bridging the Gap between Academia and Industry in Approaches for Solving Ill-Structured Problems: Problem Formulation and Protocol Development. In ASEE Annual Conference proceedings

[25] Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. Qualitative sociology, 13(1), 3-21.

[26] Bir, D. D., Ahn, B., Cetin, B., Akinci-Ceylan, C., Cetin, K. S., Surovek, A. E., ... & Thompson, K. R. (2019, June). Connecting dots: Coding multiple data sources to enhance qualitative analysis. In *ASEE Annual Conference proceedings*.

[27] Akinci-Ceylan, S., Cetin, K., Ahn, B., Cetin, B., & Surovek, A. (2020, July). A Qualitative Analysis of How a Student, Faculty, and Practicing Engineer Approach an Ill-structured Engineering Problem. In Proceedings of the *2020 American Society of Engineering Education Virtual Conference.*

[28] Akinci-Ceylan, S., Cetin, K. S., Ahn, B., Surovek, A., & Cetin, B. (2022). Investigating Problem-Solving Processes of Students, Faculty, and Practicing Engineers in Civil Engineering. *Journal of Civil Engineering Education*, 148(1), 04021014.

[29] VERBI Software. (2021). MAXQDA 2022 [computer software]. Berlin, Germany: VERBI Software. Available from maxqda.com.

[30] Felder, Richard, "Reaching the Second Tier: Learning and Teaching Styles in College Science Education." J. College Science Teaching, 23(5), 286-290 (1993).

[31] Kolb, D. (1984). Experiential learning experience as the source of learning and development. New Jersey: Prentice-Hall, Inc

[32] Koohestani, H. R., & Baghcheghi, N. (2020). A comparison of learning styles of undergraduate health-care professional students at the beginning, middle, and end of the educational course over a 4-year study period (2015–2018). Journal of education and health promotion, 9.