Using Evidence Based Practices and Learning to Enhance Critical Thinking Skills in Students Through Data Visualization

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***Abstract*—This research-to-practice work in progress paper outlines the use of evidence-based practices and learning to enhance critical thinking skills in students through data visualization. Data visualization is a multi-stage process that enables the transformation of complex data into visual representations that inform without overwhelming its audience. The purpose of this study is to investigate how data visualization learning experiences enhances students' critical thinking skills. In this paper we identify the conceptualization of critical thinking in the data visualization process. A design-based research approach is used to empirically investigate the main research question: after participating in data visualization learning experiences, in what ways do students engage in design practices that enhance development of critical thinking skills? The working hypothesis is students experience greater learning gains when instructions include design challenges integrated with the data visualization process and mapped to critical thinking that requires them to exhibit higher-order-thinking skills. The first aim of the study is to identify critical thinking skills that are evident in the data visualization process. The second aim is to identify habits of the mind competencies that are evident in the data visualization process. The implications of this work will inform the implementation of the Paul-Elder critical thinking framework into the data visualization process with the goal of building essential intellectual traits in undergraduates. In this work, the data visualization process facilitates the logical structure of connected elements of higher-order thinking that relate to one another within the theoretical frameworks of critical thinking and habits of the mind. This research is significant because it informs the practice of engineering through a problem-solving activity and computing education by introducing data visualization as method for improving critical thinking skills; a requirement for STEM students, a desired skill for all students.**

Keywords—data visualization, critical thinking, evidence-based practices

I. Introduction

The teaching of critical thinking (CT) skills has been identified as one of the 21st century skills [1]. There are several conceptualizations of critical thinking depending on the field it is studied [2]. Critical thinking is often described as a metacognitive process, consisting of a number of sub-skills (e.g., analysis, evaluation and inference) that, when used appropriately, increases the chances of producing a logical conclusion to an argument or solution to a problem [1].

Critical thinking is becoming increasingly important, together with other '21st century skills' on which educators are starting to focus [3]. As such, educators are seeking ways to develop in their students critical thinking capabilities. Astleitner [4] defined critical thinking "as a higher-order thinking skill which mainly consists of evaluating arguments. It is a purposeful, self-regulatory judgment which results in interpretation, analysis, evaluation, and inference, as well as explanations of the evidential, conceptual, methodological, or contextual considerations upon which the judgment is based" (p. 53). In an increasingly technological and information driven society the ability to think critically has become a cornerstone to both workplace development and effective educational programs [5]. In other words, CT is an essential component of current workforce practices since individuals in STEM fields (e.g. educators, engineers, scientists, and computer technologists) always encounter data-driven, complex situations, which demand accurate judgments, precise decision-making and continuous learning. The application of critical thinking helps students solve common occurring errors found in ill-defined, open-ended, complex problems through the analysis and evaluation of information, evaluating arguments, and developing conclusions resulting from sound reasoning [6]. Douglas ([7]- [8]) reported there is a disconnect between understanding what critical thinking is in engineering and how engineering students use critical thinking. As such, the aim of this work was to explore students' experiences in data visualization as a possible option for introducing critical thinking into a process (data visualization) that parallels with the engineering design process [9].

II. Background

A. Data Visualization

Data visualization is a multi-stage process that enables the transformation of complex data into visual representations that inform without overwhelming its audience. There are numerous data visualization workflows ([10] –[11]), varying in the number of steps depending on the data and domain. Byrd ([9], [12]) has adopted the 7-stage data visualization process presented by [13] for introducing data visualization to undergraduates. For beginners, the seven stages are introduced as a linear process and in a sequential manner: acquire, parse, mine, filter, represent, refine, and interact. Once students are familiar with the process and the tasks required at each stage, the concept of non-linear, iterative nature of the process is introduced. The non-linear, dynamic flow of the process necessitates deeper understanding of the role of each stage, the impact of each stage and the complex nature of the process. The task of transforming data into sight utilizing data visualization techniques presents opportunities for metacognitive and critical thinking throughout the process. A common process used to introduce data visualization to beginners is one presented by [13]. Fry's method illustrates seven stages for manipulating and making sense of data from acquisition to interpretation and demonstrates the iterative nature of the visualization process through the interdependencies between stages. These seven stages of visualization are the framework used in an introductory data visualization course in a research intensive Midwest University in USA to introduce the data visualization process. For learning the intricacies of each stage, the visualization process is introduced as a direct path starting with the acquire stage and ending with the interact stage as shown. However, it is important to note that the process is flexible and more often than not, takes on a non-linear structure resulting in a visualization project that can be in any stage, or combination of stages depending on the questions to be answered. In this work, the data visualization process serves as a vehicle for critical thinking through which evidence-based practices are studied and assessed.

In this work we adopt and align our data visualization process to the Critical Thinking Competency Standards (CTCS) and Principles [14], and evidence based practices for assessing critical thinking skills in undergraduates after completing a data visualization course. This alignment will facilitate realization that CT involves a larger process of reasoning and problem solving whereby all judgments and decision making is based on evidence. Evidence based practice is the conscientious, explicit and judicious use of current best evidence in making decisions about the case of individual students [15].

B. *Theoretical Framework*

The theoretical framework that guides this work is grounded in educational theories directly related to learning and evidence based practices and their effects on conceptual understanding that lends to critical thinking as defined by the Framework [16] and Habits of the Minds [17]. Constructivism and incremental theory (growth mind-set) and intelligent behaviors underpin our approach. Constructivism as a learning and memory theory focuses on the construction of knowledge and meaning by individuals [18]. "The central principles of [constructivism are] that learners can only make sense of new situations in terms of their existing understanding. Learning involves an active process in which learners construct meaning by linking new ideas with their existing knowledge" [19].

For this project, we utilize the Paul- Elder Framework to (a) identify parallels between the data visualization process and critical thinking, (b) assess students acquisition of higher-order thinking skills [20] as described by [17] and [21]. The Paul-Elder framework isolates critical thinking into three constructs being: standards, elements, and intellectual traits. It also imposes the following relationship on that decomposition: standards are applied to the elements as we learn to develop intellectual traits [22]. The purpose of the framework is to aid in the analysis and evaluation of thought and to provide a common vocabulary for critical thinking.

A benefit of this framework is that it is a discipline neutral, general framework for critical thinking. For students and instructors, the framework provides a common language for defining and operationalizing critical thinking by defining eight elements of thought which capture how critical thinking examines, analyzes, and reflects on intellectual work. These elements lead to eight categories of questions present, to some degree, in all critical thinking: (1) what is the purpose? (2) what is the point of view? (3) what are the assumptions? (4) what are the implications? (5) what information is needed? (6) what inferences are being made? (7) what is the most fundamental concept? and, (8) what is the question that is being answered? The intellectual standards describe the criteria used to evaluate the quality of the critical thinking. For example, the thinking has a clear purpose or makes relevant assumptions. The intellectual traits are the characteristics associated with a mature critical thinker and developed by individuals over time. The intent is that students will develop and exhibit these traits as they proceed through the data visualization process and engage in solving design challenges.

The underlying assumption arising from this framework is that deeper understanding of the concept means a greater ability to think critically. In the context of this work, more practice thinking critically while implementing the data visualization process helps in the development of a deeper and more complete conceptual understanding of data, and improves problem-solving skills.

C. *Evidence –based Practices*

Argument skills have a central role in STEM education ([23] – [24]). Advanced argument skills are associated with appreciation of STEM as an enterprise that advances through coordination of evidence with theories rather than the accumulation of facts [25]. Key means to achieving this goal are the employment of argumentative strategies that enhance student's critical thinking skills through the effective use of evidence [26]. Yet, studies of students' argument skills in science contexts report these skills to be under-developed at best, even at the college level ([27] –[30]). Questions such as the degree to which educational interventions can promote the development of students' argument skills, and especially their ability to use evidence in argumentation, remain unresolved. Evidence lies at the heart of science. It constitutes the foundation of science and the mechanism through which it advances [31]. Argumentation, used here synonymously with evidence-based reasoning, is a process of reasoning with evidence to justify and refine claims, through evaluation of data [32]. We use the term evidence-based argumentation to stress the focus of our study in developing in student's critical thinking skill of using proof to support their decisions making through argumentation in the context of data visualization. Evidence-based argumentation involves both the ability to use evidence in argument production that is when one uses evidence to support his/her own position and the evaluation of evidence in argument reception that is when one weighs evidence offered by another student with differing views.

This element of our work is captured in Figure 1. Figure 1 (adapted from [13]) shows the iterative nature of the data visualization process. In this workflow the revised Bloom's taxonomy [20] of higher-order thinking skills are leveraged to elicit meta- cognitive [17] reflective activities that support development of habits of the mind level (e.g., Thinking flexibly, metacognition, and Questioning and posing problems) as a consequence inform critical thinking practices as described by Paul Elder framework. [23] shared that meta- cognition levels helps individuals recognize evidence which in turn supports execution of the knowing strategies, such as argument and inquiry. This implies that an individual develops procedural critical thinking skills that seeks to answer questions such as "What do knowing strategies accomplish?" and "When, where, why to use them?" which in turn informs one's declarative knowing based on evidence presented in recognition of an accomplished task or possible solutions to a given design problem. Our approach students' development of CT skills (see Higher Order Thinking stages in Figure 1) through meta-level awareness through Fry's [13] data visualization process. Students are engaged in reflective activities on problem-solving tasks based on data visualization evidence and their experience using the data visualization process. Thus, successful argumentation requires a solver to develop and articulate a reasonable solution, support it with data and evidence, identify alternative solutions, and rebut these alternatives [33]. It shifts the focus from answer-oriented problem solving to process-oriented scientific practice of constructing and justifying claims [34].

The application of CT in STEM related fields and workforce helps individuals solve ill-defined, open-ended, complex problems through the analysis and evaluation of information, evaluating arguments, and developing conclusions resulting from sound reasoning. In this process, there is an active ingredient of intuition, emotional intelligence, and reflection. One way for educators to cultivate problem-solving skills is to intentionally create an active and engaged learning environment where students are more likely to make connections and see the value of the content. Despite the central importance of CT in the workplace and STEM education, existing assessment tools are plagued by problems related to validity, reliability, and cultural fairness [35]. According to [36] a challenge for educators is to provide an instructional framework that links assessment practices to higher-order thinking skills and habits of the mind that may support development of CT skills in STEM learning environments. This project investigates how students enrolled in STEM courses make meaning of data that informs their decision-making in the problem solving process. Similarly, this project establishes a strong evidence-based foundation for continuous research and effective training through data visualization technologies. The project also contributes to identifying the role of technological and digital tools in STEM learning environments [37].

III. METHODOLOGY

The epistemology for this study was constructionism, the focus being the construction of meaning from the perspectives of students experiences in data visualization as a possible option for introducing critical thinking into a process (data visualization) that parallels with the engineering design process. Crotty [38] stated that constructionism is the view that all knowledge, and therefore all meaningful reality as such, is contingent upon human practices, being constructed in and out of interaction between human beings and their world and developed and transmitted within an essentially social context. This inquiry was designed to be a qualitative focus group case study [39] that explored, what problem solving and critical thinking meant to students, and how skills learned in the data visualization course in the prior semester has helped them in subsequent courses.

A. Study Design

In Fall 2019 two sections of an undergraduate course in data visualization was offered at a research intensive university in Midwest United States. In the course, the data visualization process is introduced as a 7-stage process. Students learn the key elements of each stage and demonstrate their understanding, competency, proficiency and ultimately mastery of the process by completing visualization exercises that increase in difficulty to challenge their knowledge and skills. The underpinnings of the critical thinking framework are utilized to examine the reflective judgement of students' analysis, evaluation and inferences of the data visualization process informed by self-regulatory functions of metacognition. Thinking flexibly, metacognition and questioning and posing problems are key elements of the habits

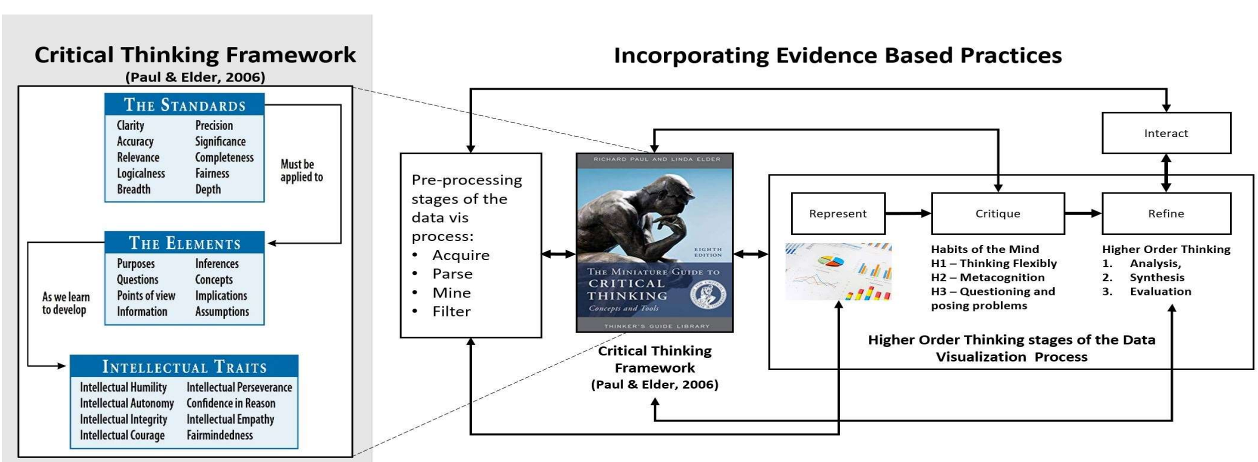

Fig. 1 Data visualization workflow incorporating evidence-based practices.

of the mind framework that maps to the critique/feedback stage of the data visualization process and enables higher-order thinking (analysis, synthesis and evaluation). The data visualization process is a non-trivial process which can be overwhelming to a novice. Each stage is introduced incrementally to allow students to process the required elements of each stage. The introduction of each stage is supplemented with hands-on exercises to reinforce learning. To assess student's understanding, at each stage of the process, students were asked to complete an activity worksheet which mapped key elements of each stage in the data visualization process to higher order thinking skills. Table 1 shows how the 7-stage data visualization process aligns with Bloom's Taxonomy [20] and higher order thinking skills shown in the objectives column.

TABLE I. HIGHER ORDER THINKING OBJECTIVES MAPPED TO THE DATA VISUALIZATION PROCESS (DVP).

DPV	*Higher Order Thinking Objectives*
Acquire	Students will demonstrate appropriate data acquisition skills – planning, generating and producing data.
Parse	Students will demonstrate their ability to change data into a format that tags each part of the data with its intended use.
Mine	Students will demonstrate their ability to identifying patterns, extreme and subtle features about data.
Filter	Students will demonstrate their ability to identify and extract data of interest for use.
Represent	Students will demonstrate their ability to choose the appropriate chart and layouts for data.
Refine	Students will generate/produce new and/or improved data visualizations.
Interact	Students will demonstrate their ability to assess the data visualization process for creating interactive visualizations for insight.

B. Participants

Participants of the study were recruited from an introductory data visualization course offered in Fall 2019. Students enrolled in the course had little to no data visualization experience, and are typically at the sophomore level or higher in their undergraduate studies. Six uundergraduate students who successfully completed the data visualization course were interviewed individually for 25 mins, and they later all participated in half an hour focused group interview in an attempt to triangulate their interview responses. Participant characteristics are given in Table 2. Participation in the study was voluntary with the option to discontinue the study at any time. The focus group convened in week 9 of the Spring 2020 semester.

TABLE II. PARTICIPANT CHARACTERISTICS

Participant	*Gender*	*Year of study*
S1	Male	Sophomore
S2	Male	Sophomore
S3	Male	Freshman
S4	Female	Sophomore
S5	Female	Sophomore
S6	Female	Sophomore

C. Data Collection

Data collected for this research include post-interviews with students who enrolled in the course in Fall 2019 and their responses to class exercises from the fall 2019 semester. The interviews were conducted by the graduate teaching assistant (TA) who was the teaching assistant for the Fall 2019 data visualization class. The interview and focus group questions were semi-structured, and focused on students' reflection on their perceived impact of learning the data visualization process in the previous semester and impact the transferable skills have had on the problem solving and critical thinking in other classes. Specifically, the interview and focus groups questions explored what problem solving meant to students, the main purpose of data visualization in solving design/visualization challenges, how the seven steps of data visualization helped students solve a given design/visualization problem, what kind of information/process that problem solvers used in finding solutions to given data visualization challenges, what were implications and consequences of utilizing the data visualization process to solve problems, and what main concepts of data visualization they learned in the course would transfer to other situations they had experienced that relate to problem solving?

D. Data Analysis

One of the researcher's challenges is to obtain and verify the true meaning of each participant's responses to the questions asked [40]. To begin making meaning of collected data (i.e., the interview and focus group data from the six students), the interviews were analyzed separately using text analysis as described [41]. McKee [42] shared that, qualitative textual analysis is interested in gathering information about how individuals in particular contexts make sense of the world around them. This approach recognizes the variety of ways that text can be interpreted and utilized by those who view it.

In our work, we were guided by [43] five stages process for studying texts, that include: (1) selection of a problem worth investigating, and familiarization of context of study setting, (2) review of literature in establishing particular themes that may guide data collection, for example in our work we utilized the seven steps of data visualization and our theoretical frameworks as a basis for semi structured interview guide and data collection, (3) coding in this process is reflexive and continually ongoing. Pre-established codes, for example in our work, in vivo code "*process*", informed our analysis as we further engaged with the textual data from participants' transcripts. (4) Conceptual refinement to distinguish categories and themes that begin to answer the problem that was first posed in step (1) above. For example, in our work we, (the researchers) read the transcripts twice to refine our in vivo codes, and (5) Compiling findings.

To gain a broad understanding of text provided by participants, transcripts were proofread and key phrases underlined [44]. A second read of transcripts provided deeper understanding of participants' cores thoughts.

We then compared and reconciled our markings of text on transcripts, including focus group data as a form of triangulation. The idea is to see whether the constructs being investigated are shared and whether researchers saw the same constructs as applying to the same portions of text [45]. Denzin [46] referred to this as investigator triangulation, where two or more researchers in the same study provide multiple observations and conclusions. According to [46], this type of triangulation can bring confirmation of findings and different perspectives, adding breadth to the phenomenon of interest. Detailed notes were developed about participants' ideas in response to the aim of our study. The researchers then identified text segments that contained the same meaning and sought to derive *in vivo* codes from transcripts by identifying repetitive, descriptive, and interpretive phrases of participants' experiences [45]. The researchers identified 16 initial *in vivo* codes in no order of priority (i.e., *process, past experiences*, *prior knowledge, problem solver, issues, different tools, conduct research, complex to easy, filtering, methodical mindset, predictability, translator, analytical tools, logical, visualize and identity*). We then grouped these initial codes with accompanying text as suggested by participants into relevant categories. This process further affirmed the initial codes that had emerged from the interviews into categories and subcategories. Afterward the researchers wrote memos describing identified categories to further reduce the data. Participants' explanations and ideas that had similar meanings were then collapsed into key categories informed by subcategories identified by reviewing the initial categories and participants' transcripts again. However, it should be noted that emergent categories had text descriptors in identified subcategories that overlapped. During this process we reduced the initial codes to four, again in no order of priority to; *prior knowledge, problem solver, methodical mindset, and visualize.* This process helped us group these codes with accompanying text that captured participants' thoughts into relevant categories. These four codes then formed our core themes. Table 3 provides the themes identified during this stage of analysis; they are termed as categories, along with subcategory labels.

TABLE III. CATEGORIES THAT INFORMED THEMES GENERATED BY RESEARCHERS

Category	*Subcategory*
Methodical mindset	Process; logical; conduct research; understanding; predictability
Prior knowlegde	Understanding, past experiences, thinking through; avoid biases
Problem solver	Conduct research; know audience; filter; reflect
Visualize	Translate; insights; trends, choice of tools, present in another way

IV. RESULTS

This study sought to explore students' experiences in data visualization as a possible option for introducing critical thinking into a process (data visualization) that parallels with the engineering design process. Quotes from study participants have been used throughout this section to emphasize core themes that emerged with no observed priority or order. Four core themes (methodical mindset, prior knowledge, problem solver, and visualize) were identified from the reduced meanings of participant verbatim transcripts. Verbatim quotes from participants were used throughout this section to emphasize core themes.

Core theme Methodical mindset: Responses supporting this theme offer insights into how students logically solve design related challenges using given a set of tools. Participants shared that one has to develop and form a habit, and reflect all the time as they use available tools, e.g. statistical software or even data visualization software like Tableau. Such an approach, according to participants of this study offers a method to solve a given issue. For example, Participant S1 shared that one had to "constantly look at the whole process when you're going throughout as opposed to where you currently are, I'd say is probably the biggest tool you have is just retrospectiveness." Likewise, Participant S2 posited that such requires a process, for example by "following the seven steps of data visualization, you're able to organize your data" and filter through information. This view was also shared by Participant S5; they stated that instead of just going blindly into solving a problem, a process lets you know you that you have a skeleton to work with. These insights reveal that participants' experiences in the course offered them a process to solve problems. In essence, all the participants shared that the seven steps for data visualization offered them a structured way of solving a problem every single time, because once could follow that process. In light of this view, Participant S4 shared that such a process needs to translate to other situations as well.

Core theme Prior knowledge: Participant S4 noted that one's past experiences, and tacit knowledge can help understanding an issue at hand, its relevance and why and how to solve that problem. Such thinking and perspectives then gives individuals the ability to better understand the problem. In the same vein, Participant S1 shared that having past experiences offered individuals the ability to have better problem solving and critical thinking abilities outside of the visualization process. According to Participant S6 working backwards on a given problem, offers individuals opportunities to reassess their previous experience, review existing, or finding new data and make sure that they are actually focusing on the solving the given problem. This theme was shared across the interviews as well as the focus group.

Core theme Visualize: All participants shared that when solving problems, visualization as an area of study offered individuals an opportunity to envision a trend/s that you wouldn't be able to examine otherwise. Specifically, Participant S3 shared that visualizations showed what could not be possibly shown through various innovative formats (e.g. graphs, etc.) that are analytical, and sometimes offer a sense of predictability, that wouldn't be able to be observed in different settings. Similarly, Participant S4 posited that "visualizations helped answer those "If" questions throughout the entire process rather than just going off of a gut feeling and be like, Oh, the best graph for this is going to be a Venn diagram or something." Focus group data offered a cohesive insight about this theme. Participants were of the view that visualize helped individuals to posture and think about, "what kind of data they were working with," "will the data change over time" "was it some kind of comparison data," Such questions would then lead individuals to start thinking of possible visualizations that have already been created, or possibly think of combining a few. Further the focus group clarified that sometimes one visualization might not be able to answer a detailed research question or very broad research question if you're trying to figure out a few things. As such, visualization offered problem solving opportunities to take time and carefully think the scope of the problem at hand. As a consequence, think through the visualizations that could best be used.

Core theme Problem solver: Each study participant was asked to define problem solving in their own words during interviews and relate their insights to data visualization. Based on participant key words, thus in vivo codes, problem solving was, "a process", "a way to attack difficult scenarios or issues", "problems are abstract or defined and it's kind of how you handle them, fix them", "meant completing a certain task or by finding probable solutions in response." Participants offered that a lot of focus and research went into problem solving, and data visualization and analysis was a tool. Participant S2 shared it might take the form of basic statistics when solving problems, he further shared that one should use all the different tools that you've learned in a data visualization course to try and find a solution to the problem. By the same token, Participant S5 likened the seven steps as a tool that may transcend to other fields but different terminologies might be used, but it's still problem solving. Participant S3 was the view that to problem solve meant that one had to identify the issue by conducting research, and then use whatever tools or knowledge you have to try and solve that the best you can. In the same way, Participant S6 stated:

> being open when you are going through the process really is beneficial because you don't know what problems might arise, you might kind of have a general direction you want to go. I think going through that process really makes people think about possible biases that might exist or other avenues that might actually affect what you're thinking to solve the problem

In summation, all participants were of the view that data visualization offered an opportunity to filter out information to use and hence focus on problem solving.

V. Discussion

In today's economy, the need for data visualization experts who think critically and can represent ever increasing data points in more meaning-full or understandable ways cannot be underestimated. Researchers ([47] – [48]) recognized that critical thinking skills are linked to one's ability as related to decision-making thus problem solving. In light of this view, ([49] – [51]) shared that problem solving has been used as a strategy to develop and impart in students critical thinking skills in engineering and technology. Writing reflectively, promotes critical thinking by having students digest given data, analyze the content and the thinking, which translates to metacognition, i.e. think about their own thinking, and then articulate their thoughts. These strategies mirror the instructional approach utilized in our introductory data visualization course. Findings of the study reveal that participants' experiences crystallized into four themes that highlighted the aspects of constructionism, as well as the conceptual framework that guided our work. Jonassen [52] stated that, how we construct knowledge depends upon what we already know. This has been captured through participants shared experiences by, core theme prior knowledge, which highlights insights that participants have had, how they have internalized and classified those experiences into knowledge structures that inform their understanding of new situations they anticipate or face, and what they believe about what they know. In other words, the meaning that each of us finds in an experience, resides in the mind of each individual.

These findings also present how participants' experiences in our introductory data visualization course demonstrated the elements of the [53] and habits of the mind [17]. Costa [17] shared that these habits are dispositions that empower creative and critical thinking. In our work, core themes "methodical mindset" and "problem solver" elucidated dimensions of higher order thinking skills which are a hallmark for critical thinking as described by [20]. Thus these core themes revealed that participants' deeply reflected on the purposes as well as the context of a given problem, what assumptions they had to make with regard to data needed to solve a problem, in addition to different set of tools they may have utilized for this purpose. Participants also alluded to the logical process which they might utilize into solving the problem, and if their assumed solution could help predict different scenarios, and implications based on the data presented, including visuals they would generate to offer differing perspectives of predicted solution. As such, our work and findings exemplify what other researchers have shared (e.g., [54] – [56]) that critical thinking promotes creative problem solving through creativity and innovation, and it's a central component of learning in engineering classrooms. As such, the logical process described by our participants in this study may also be tantamount to the engineering design problem solving process utilized by engineers to solve everyday challenges that society faces.

Implications for engineering and computer science. Development of critical thinking skills has been recognized as an important aspect of undergraduate education; however, work remains to be done to define critical thinking specifically within the context of engineering ([7] – [8]). For the most part, studies have considered critical thinking in the context of engineering problem-solving ([57] – [59]). What is missing from the literature is an understanding of what critical thinking is in engineering and how students use critical thinking [7].

The process of data visualization encompasses transferrable 21st century skills that are indicative of critical thinking, computational thinking, problem-solving and habits of the mind. The impact of the process of visualizing data is far-reaching; irrespective of discipline, understanding the data visualization process could benefit students in the classroom, professionally, in research and in daily practice.

Evidence of the importance of visualization can be seen in the role visualization plays in informed decision making [60 – 63], data analysis [64], explanations of complex data sets [65 – 67], detection of trends and patterns [68], and storytelling [69 – 71]. The need for early exposure to a field with such far-reaching influence is imperative [72].

The concept of visualization in engineering education has been either in the use of static versus dynamic visualization in multimedia learning in technology [73], or as a tool for computer-aided design) applications [74]. The stages of visualizing data and the elements of computational thinking [75] are largely congruent; however, a significant gap exists between understanding what happens to data as it transforms from a raw complex state to a visual representation in engineering design scenarios. Failure to integrate data visualization into the engineering design workflow can result in students unprepared for tomorrow's engineering jobs that require an understanding of the data visualization process. An understanding of and experience with the data visualization process may help deepen students' engineering design experiences for the purpose of optimization in design decisions, enhance their computational thinking skills in engineering and computer science and ultimately aid them in developing better design solutions. Such capabilities can promote competitiveness in global markets where data is currency. Themes identified from the focus group results in this study makes a case for building data visualization capacity in engineering and computer science curriculums as another tool to facilitate critical thinking.

VI. CONCLUSION

Findings of this study are views and experiences of two faculty members who are exploring with new ways of teaching across STEM fields using data visualization to enhance problem solving techniques in students. Findings of this study suggest that data visualization opens a range of possibilities by which educators may utilize to develop critical thinking skills in students. As with all exploratory research, this study was limited to a small number of participants who were purposefully chosen thus limiting the ability to utilize sophisticated statistical methodologies and generalize our findings. However, the core themes generated provide educators with a platform to discuss the role of data visualization in promoting critical thinking skills through problem solving as an instructional approach.

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