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How Aerospace and Mechanical Engineering Undergraduate Students Define and Develop Data Proficiency

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1. ABSTRACT

This paper examines how mechanical and aerospace engineering (MAE) students conceptualize and develop data proficiency within their engineering curriculum. The growing importance of data across all engineering fields means students must master data skills – including advanced techniques – to remain competitive. However, there's limited research on how non-computer science majors understand data proficiency and seek opportunities for skill development. We investigate the nature of data proficiency from the perspective of undergraduate MAE students, conducting 27 qualitative interviews at a research institution in the southeastern United States. Using the How People Learn framework with a postpositivist approach, we employed thematic analysis to evaluate the data within this study's context. Results indicate that MAE students perceive data proficiency as vital for their careers and evidence-based engineering decisions. Moreover, despite data proficiency being a "hidden competency," MAE students actively seek various ways to improve their skills. These findings offer insights for engineering educators, allowing them to tailor instruction, address misconceptions about data, and prepare a data-literate workforce.

2. INTRODUCTION AND LITERATURE REVIEW

The engineering landscape is experiencing a data-driven transformation. Data underpins new paradigms, enabling the precise simulation of complex systems and fueling breakthroughs across science, technology, and industry. This revolution calls for data-savvy engineers who can extract insights from information and apply them strategically. Data skills range from fundamental manipulation to advanced machine learning and AI [1]. Proficient engineers, able to contextualize and interpret data, will be indispensable in the landscape of data-driven technologies. While data has always been important in engineering, today's unprecedented volume and quality represent a paradigm shift [2]. Data itself now dictates hypotheses, making nearly every engineering discipline data-intensive [3].

This study investigates Mechanical and Aerospace Engineering (MAE) students' experiences navigating this data-centric field. Understanding their development of data skills will offer insights for preparing the next generation of engineers to thrive in this era.

Research underscores the importance of a strong engineering identity for student retention and success [4]. Motivation is influenced by an individual's perceived value, expected outcomes, and potential costs of fulfilling educational requirements [5]. The growing emphasis on data skills within engineering curricula makes exploring the relationship between data proficiency, engineering identity, and motivation crucial for maintaining a competitive workforce. This is the focus of our ongoing research, seeking to bridge the gap between data skills and engineering identity development.

Researchers have investigated how competencies like problem-solving, systems thinking [6], design thinking [7], and computational thinking [8] shape engineering identity. Computational thinking, with its focus on algorithmic problem-solving, is a vital skill for engineers [9]. Integrating computational skills early and regularly in engineering curricula has been shown to improve student outcomes [10]. Similarly, we propose that incorporating data skills throughout the curriculum can also strengthen engineering formation.

Data skills refer to the ability to collect, organize, analyze, visualize, and communicate data effectively and ethically. Engineering students practice data skills in various assignments, such as conducting experiments, designing solutions, and evaluating results. These assignments mirror the real-world tasks of practicing engineers, who rely on data to make informed decisions and solve complex problems. However, the literature has not yet established how data skills relate to engineering identity and motivation. Understanding these links could help inform the best practices for introducing data skills in the engineering curriculum and fostering a positive engineering culture. Moreover, the field of data literacy is still emerging, and there are gaps in the existing knowledge about how engineering students perceive and develop data skills. Therefore, this study aims to answer the following research questions:

1. How do mechanical and aerospace engineering (MAE) undergraduate students conceptualize data proficiency?
2. How do MAE undergraduate students identify the opportunities to develop data proficiency in their academic trajectory?

3. THEORETICAL FRAMEWORK

This study adopts Bransford's foundational How People Learn (HPL) framework as its theoretical basis [11], in a unique and novel application of the framework. This study adopts Bransford's foundational How People Learn (HPL) framework as its theoretical basis. HPL, known for its learner-centered approach, outlines key principles for designing effective learning environments. The framework emphasizes the learner, knowledge, assessment, and community aspects. Traditionally used to craft and evaluate specific learning environments, our study takes a novel approach. Instead of focusing on the design or assessment of a particular teaching approach, we leverage the insights of the HPL framework to explore how undergraduate engineering students interact with data skills in relation to the HPL elements when reflecting on their own data skills learning experiences. Our interview protocol, guided by the HPL framework, delves into student perspectives on self-reflection, knowledge acquisition, and assessment related to data skills.

4. METHODS

4.1 Participant Recruitment and Selection.

In this study conducted at a southeastern United States institution, 177 students completed a recruitment survey. All interested mechanical engineering (ME) students were automatically selected, as only a small number of participants were ME students. Meanwhile, interested aerospace engineering (AE) students were sampled for diversity. The final qualitative study included 27 MAE students: 7 ME students and 20 AE students.

Table 1: Demographics of Study

Gender	Number of Participants
Man	14
Woman	13
Year	**Number of Participants**
Freshman	3
Sophomore	6
Junior	10
Senior	8
Race/Ethnicity	**Number of Participants**
Asian	1
Black/African American	3
Hispanic	4
White/Caucasian	19

4.2 Data Collection

To refine our interview protocol, we piloted it with four participants. Analysis of the pilot data allowed us to identify ambiguities, adjust question flow, and ensure the protocol captured the desired perspectives. In the full study, we conducted individual interviews using the refined, semi-structured protocol. These 45-minute interviews fostered conversation about participant experiences with data skill acquisition. Participants chose pseudonyms for anonymity and received a $20 Amazon gift card as compensation. Interviews were securely transcribed with all identifying information redacted.

4.3 Data Analysis

We employed thematic analysis [12] to analyze interview data and answer our research questions. Following familiarization with the transcripts, we used NVivo 14 to conduct open coding on five transcripts, generating initial codes. We then applied open coding to identify themes related to student conceptualizations of data proficiency and skill acquisition within their academic journeys. Through an iterative process of coding, refining, and thematic development, we arrived at a set of themes that condense the data into coherent findings addressing the research questions.

4.4 Limitations

This study offers valuable insights, but limitations exist. The sample of 27 MAE students may not generalize to the broader engineering population or different university contexts. Additionally, the single-institution design limits generalizability across engineering education. Finally, inherent to qualitative research, researcher interpretation shapes the findings.

5. FINDINGS

Our interviews revealed participants' shared experiences in acquiring, using, and improving their data skills. By analyzing their responses, we identified recurring themes that addressed both research questions. Each of these themes is explored in greater detail throughout this section.

5.1 How do mechanical and aerospace engineering (MAE) undergraduate students conceptualize data proficiency?

Our first research question focused on how undergraduate MAE students define data proficiency. To capture their authentic understanding, we used an inductive approach, avoiding pre-defined examples. This allowed us to prioritize student-driven perspectives throughout the process. Our analysis revealed four key themes characterizing data proficiency: information literacy, data interpretation and presentation, data application, and computation. Themes were crafted to describe the qualities of a data-proficient individual.

5.1.1 *Information Literacy*

Across the board, participants identified information literacy as a fundamental element of data proficiency. They defined it as the ability to acquire, synthesize, and critically evaluate information from diverse sources, leveraging background knowledge to draw informed conclusions. The importance of theoretical understanding was repeatedly emphasized. As one student stated, “you need enough background knowledge... because there’s a lot of cause and effects that could be happening.” The ability to apply theory to interpret raw data, draw informed conclusions, and identify potential implications was emphasized.

The students further stressed the importance of synthesizing information from diverse sources to gain a deeper understanding of the subject matter, whether it involves consulting a textbook, looking through datasheets, or simply asking questions. One participant noted, “through the action of asking questions, one is able to confirm their thoughts or train of thought.” Lopy’s insightful quote shows this concept:

> *“I’m thinking about if you put a sensor on whatever the product is if you’re measuring temperature for whatever reason. You’re getting a ton of data points of temperature. And then your job is to look at all the data given in whatever graph plot or whatever it is and try to find patterns, find things that make sense or cause an effect. If you realize that the distance between the sensor and the object causes a significant difference, why is it so and what could it possibly mean? And what can you do with that result?” - Lopy*

Lopy exemplifies the essence of information literacy right from the outset by actively seeking information and questioning the outcomes when measuring temperature with a sensor. They recognize the importance of diverse data sources, considering data in “whatever form” it might present itself. This approach emphasizes the critical role of inquiry: “If you notice… why is it so… what could it possibly imply?” Lopy’s inquisitive stance showcases their ability to challenge assumptions and delve deeper into the data’s meaning, a key aspect of information literacy. Finally, Lopy contemplates the practical implications: “what can be done with these findings?” This demonstrates their ability to apply the analyzed data to inform decisions and solve problems, further highlighting their information literacy skills.

5.1.2 *Data Interpretation and Presentation*

This theme delves into the art of data interpretation and presentation, a skill highlighted by all participants as a crucial marker of data proficiency. They expressed this as the ability to not only explain the essence of your data but also the ability to communicate it to people of different understandings. Tracy continually emphasized how data proficiency isn't just about "crunching numbers". She further elaborates on the essence of data proficiency by adding:

> *"I would say that would be being able to take lab results, raw data and dialing it down, kind of going through it, pulling out the important stuff. Maybe not considering some things that are not as important, but also taking into account the outliers and stuff. So I guess I would say lab data and being able to look at it, understand it, and then explain it in a report source"-Tracy*

She highlights the crucial ability to discern the signal from the noise. She asserts the importance of clear and concise communication for example through reports emphasizes identifying key findings and accounting for outliers which further demonstrates a grasp of data nuances.

When discussing data interpretation and presentation, students across the board placed significant emphasis on the power of visual representation. In their experiences within engineering, they consistently identified the ability to use images, graphs, and charts as an essential data skill. They articulated a strong belief that data proficiency demands proficiency in utilizing visuals to present, communicate, and interpret information effectively. Beyond communication, students also highlighted the benefits of visuals for enhancing their own understanding and memory retention. Visual representations served as powerful tools for internalizing complex data and extracting key insights. For example, Foresight echoed that visuals such as pictures and graphs "make it easier to follow" for everyone. She further explained:

> *"I make an extra effort to visualize the graph, because I want to understand it, and the image tends to linger in my memory longer. If I merely state that the curve is there, or the stress and strain values are such and such, I won't retain that information as effectively. I need a visual reference to remember it more vividly."-Foresight*

While Foresight emphasizes the significance of visual aids such as plots and graphs, the concept of visual representation extends beyond just these elements. Hitman, a sophomore, provides an example of how he leverages computer-aided design (CAD) software to visualize the calculations he is performing. Hitman shares his experience:

> *"The biggest part I had was doing the CAD software. My partners would give me the numbers, and we would kind of sketch it out together. Then, I had to enter the airfoils, put in all the numbers, and extrude it all. So, mine was basically just using the CAD software and getting all the data into it."-Hitman*

The emphasis on data representation and interpretation as a crucial aspect of data proficiency was so pronounced that one participant, Foresight, proposed a simple experiment for subsequent interviews. She posited that nearly every student who had taken a Materials class to some extent would be able to estimate the stress/strain curve of a material. Accepting this challenge, all following interviewees who had taken a Materials class were asked to describe the stress/strain curve of Jell-O. To our delight, most students were able to accurately describe the stress/strain, particularly using key terms such as brittle, yield strength, and ultimate tensile strength.

5.1.3 *Data Application*

As the MAE students shared their experiences, a consistent theme resonated loud and clear: the capacity to utilize data as a potent tool for decision-making. They shared experiences that exemplified an ability to effectively and efficiently apply data to guide actions and outcomes, while considering the context, purpose, and limitations of the data. For example, Uno describing her team building an RC plane perfectly embodies this theme:

> *"Yes, at the moment, we are conducting tests on the foils that will be used on the hydrofoil. In terms of data, we have just completed wind tunnel tests. As expected, we obtained lift curves, drag curves, and coefficients of lift (Cl) and drag (Cd), among other things. These were measured at various angles of attack and two different speeds. That's the data we are analyzing this week."*

She explains how they collect specific data (lift, drag, etc.) that directly relates to their goal of choosing the right hydrofoils. The quotes highlighted demonstrate the fundamental importance of data proficiency in decision-making. The interviews further indicated that intuition plays a crucial role in the application of data, reinforcing its significance in data proficiency. Participants repeatedly emphasized the importance of intuition in making effective data-driven decisions, particularly when dealing with incomplete or ambiguous information. They described intuition as the ability to leverage their experience, expertise, and judgment to interpret and evaluate data.

This point was further reinforced by specific examples from engineering projects. Participants shared how intuition helped them select the best analysis methods, tools, and parameters, or even detect and correct errors and outliers within their data sets. These anecdotes illustrate how intuition acts as a valuable complementary skill to technical and analytical abilities, guiding decision-making when logic alone might fall short. Rivers, a senior, perfectly encapsulated this:

> *"You must logically evaluate whether your answer makes sense. Unlike homework or other situations where you might have access to answers or people who have found the answers, you're relying solely on your own understanding and proficiency. You're using the skills and knowledge you've acquired to determine if your conclusions logically hold up."-Rivers*

This statement underscores the crucial role of intuition in verifying and validating data analysis, especially when working with uncertainty. It is about recognizing patterns, identifying potential inconsistencies, and ultimately, feeling confident in the decisions students make based on the data.

5.1.4 *Computational*

During the interview analysis, a significant limitation in the students' understanding of data proficiency emerged. While they grasped the importance of data manipulation and analysis, they often tied the concept too narrowly to experiments and computational tools. This suggests a gap in understanding the broader applicability of data proficiency across various domains. Research [13] supports the notion that data skills extend beyond hands-on settings, aiding in conceptual understanding within math, physics, and other subjects. While some students acknowledged this wider utility, many associated data proficiency primarily with experimental contexts. This limited perspective is evident in the provided quotes:

> *"Data proficiency involves running tests in a lab, obtaining measurements, and then using mathematical equations or scientific principles to transform the data into meaningful results."-Asgard*

Terminator, a senior, associated data proficiency with programming:

> *"I think of programs like Excel and C++, in terms of coding and anything that can store data."-Terminator*

However, a few students, like A1 offered a refreshing perspective. They viewed data proficiency as the ability to analyze information from any source, including everyday situations like making decisions or comparing prices. This broader understanding aligns with the reality that data is ubiquitous and constantly shapes our lives.

> *"Data proficiency involves collecting and evaluating raw data to produce useful insights. We use data every day, and most people are data proficient without realizing it because making daily decisions requires data."- A1*

Data proficiency is indeed a vital tool for students across all areas of their learning. Its omnipresence underscores the need for students to master these skills to develop robust critical thinking and creative problem-solving abilities. This translates into tangible benefits, such as the ability to confidently check their work on exams or interpret complex information presented in diverse formats.

5.2 How do MAE undergraduate students identify the opportunities to develop data proficiency in their academic trajectory?

Moving beyond definitions, our second research question explored how MAE students develop their data proficiency. We investigated the methods they use and the opportunities they actively seek to hone these skills. Additionally, we aimed to identify the primary way students perceive their curriculum fostering data proficiency.

Our analysis revealed two key themes regarding how MAE students acquire data skills. First, experiential learning, particularly through laboratory courses, emerged as their preferred method. Second, a strong emphasis on necessity appeared to drive their data skill development, suggesting students may not always actively seek out these opportunities.

5.1.1 *Experiential Learning*

The students primarily saw experiential learning as the key method for developing their data skills. They emphasized the importance of hands-on experience and iterative learning in a community-driven environment, where real-world challenges and collaborative projects serve as the foundation for developing true data proficiency. MAE students highlighted that individual practice was a significant factor in developing data proficiency. While not said explicitly, when it comes to data proficiency, MAE students put themselves in situations that allowed them to be exposed to data for long periods of time. They enjoyed environments that focused on different kinds of information and activities that helped them develop an understanding of principles.

> *"But when it comes to projects, with projects I would say that, for labs you are restrained to a certain period of time probably once or twice a week where you're learning these things. With a project, you've got long-term exposure on however long the project lasts, but it's more continuous, more frequent, and I feel like you learn more out of a project than you would have out of a lab." – Bonsu*

First-year and sophomore participants primarily associated the acquisition of data skills with projects and labs. However, upper-class students recognized that all forms of assessments played a role in becoming more data proficient, emphasizing the importance of experience in data skill development. Machu Pichu, in particular, highlighted the unique benefits of experiential learning on his intuition:

> *"I believe that intuition plays a significant role in my school experience, particularly as an engineering student who engages in practical activities. The capstone projects provided me with the opportunity to apply my skills in a tangible, real-world context. However, in most of my other classes, there is not much room for intuition. It is more about following the instructions and applying what we have been taught."- Machu Pichu*

He also stressed the unique importance of hands-on projects as a form of assessment. They provide a platform for the development and application of data skills that align with the practical demands of the engineering field. MAE students also appreciated the opportunity that experiential learning brought as collaborative assessments allowed them to work and learn from others. They enthusiastically endorsed bouncing ideas off peers, valuing how it sparked new insights and unearthed blind spots invisible to a single mind. The camaraderie and support within learning communities also served as a powerful counterweight to the pressure of demanding projects. However, most students also harbored at least one harrowing tale of participating in large group projects.

> *"From a technical perspective, it was truly a great experience, but the social aspect definitely presented its own challenges. As the project manager for my team, I had to deal with not just issues related to work or communication, but genuine behavioral issues. This experience taught me a lot about patience and understanding the people you work with, reminding me that people come from different walks of life. However, I do hope that the industry isn't like that." — Rivers*

These negative experiences, along with the wish to keep the benefits of teamwork, made them prefer lab-structured classes where groups were smaller. In these smaller settings, collaboration flourished, providing the advantages of diverse perspectives and shared responsibilities without the drawbacks of cumbersome team dynamics in data-intensive tasks.

> *"In a lab setting, such as a physics project where two people have to collaborate, everyone has their unique approach, which is perfectly fine. However, this can introduce a bit more error into the experiment. My experience with this has been generally positive so far. The notable difference I've observed is that more people seem eager to participate in the hands-on aspect of labs than in writing the paper for a classroom group project or performing calculations for a group project."* - *Tracy*

This sentiment resonated with virtually all MAE students. Their accounts suggest that labs served as the launchpad for their data skills journey, offering the crucial first steps in learning to collect, analyze, and interpret data in a meaningful engineering context.

5.1.2 *MAE Students Learn Data Skills Out of Necessity*

One of the surprising findings of this study was that MAE students learned data skills mainly out of necessity, even though they recognized the importance of data skills for their engineering learning. Most of the participants did not seek to enhance their data skills beyond their course requirements. This became evident when we asked them if they tried to improve their data skills on their own, and what kind of extracurricular activities they engaged in. This phenomenon was especially common among first and second-year MAE students, who had less exposure and motivation to develop their data skills.

However, a shift emerged amongst third and final-year students. Faced with internships, jobs, and capstone projects demanding advanced data capabilities, they manifested growing initiative and effort to acquire and sharpen their data skills. This wasn't just about ticking boxes; they recognized the detrimental consequences of lacking specific data competencies. Their motivation evolved from necessity to self-preservation, a recognition that data proficiency was no longer just optional, but essential for future professional success.

> *"I'm also teaching myself Python. I'm trying to delve into that area because it's not really offered within our degree program. I honestly think it would be extremely beneficial in future scenarios, especially considering how frequently we use our computers for virtually everything. Personally, I'm very interested in the optimization that I could potentially achieve. Knowing coding languages like Python or MATLAB can generally make longer processes easier. So, yes, I'm definitely focusing on those skills and trying to enhance them." -Lopy*

Many junior and senior-level students shared the views of Lopy. This newfound drive extended beyond individual efforts. Many upperclassmen actively engaged in extracurricular activities like research and clubs that provided opportunities to apply and hone their data skills in real-world contexts. By actively seeking out relevant experiences and acquiring targeted data skills, these students positioned themselves for success in their chosen fields.

While most students learned data skills of necessity, participants unanimously voiced their disdain for repetitive, rote homework that felt inconsequential. This was another reason why MAE students gravitated toward lab-structured courses when it came to building data proficiency as they felt the assessments given in those classes mattered and were not there just for the sake of having something to grade. A participant voices her distaste for tedious homework:

> *"It's one thing to sit and do homework for eight hours straight because you're aware of an impending deadline. You power through it and might remember it for that day. However, increasing the frequency of such sessions could potentially enhance retention. But it's important to note that retention doesn't necessarily equate to understanding. In my experience, I gain a better understanding when I'm confronted with something I don't know and am compelled to learn it."- A1*

Lab courses, in contrast, presented a different kind of challenge. Their assessments often held direct weight, simulating real-world scenarios where data analysis and interpretation were crucial for solving concrete problems. This tangible outcome – the success or failure of an experiment based on their data skills – provided a powerful motivator and a deeper sense of purpose, transforming learning from abstract concepts to concrete consequences. Metric Pounds gushed over the type of assessment that a particular professor assigned in its effectiveness to build data proficiency:

> *"I believe [Professor X's] assignments are particularly beneficial in this regard. Generally, the problem's output data varies and requires interpretation. You learn to take the output data from one problem and feed it into another problem as input. This is especially prevalent in space vehicle control. For instance, you learn to manually calculate how to orient solar panels towards the sun, then incorporate that into a simulation to see it in action."-Metric Pounds*

The experiences of the students' journey underscore the importance of fostering a proactive learning environment, where students are encouraged to see the intrinsic value of data proficiency beyond mere course requirements and connect it to their future career aspirations.

6. DISCUSSION AND IMPLICATIONS

This This study delves into the crucial question of how MAE students conceptualize and pursue data proficiency, a skill increasingly vital for their future careers. Utilizing the HPL framework as our theoretical lens, we developed key themes that shed light on this under-researched area. MAE students overwhelmingly recognize data proficiency as essential for their professional success. Through our analysis, we were able to present a rich understanding of how they define and characterize this skill. This contribution is paramount, as our study represents one of the first to explore data proficiency definitions beyond the realm of computer science and software engineering students. By expanding the discussion to MAE students, we paint a more comprehensive picture of how various disciplines perceive and approach this critical skill. By delving into the characteristics associated with someone considered data proficient, this study goes further. We uncover the qualities that MAE students value in individuals with strong data skills.

A second notable contribution of this study is the innovative application of the HPL framework. While it is typically utilized to assess and develop learner-centered environments, this study leverages the HPL framework to explore how MAE students identify opportunities to enhance their data proficiency. Our findings revealed that the primary way MAE students attained data skills were through lab-structured courses, however, very few actively pursued them beyond prescribed coursework. As the students talked about their experience acquiring and using data skills, we could see elements of the HPL framework clearly shine through, particularly, the four key dimensions: learner-centered, knowledge-centered, assessment-centered and community-centered.

MAE students' preference for experiential learning, particularly lab-structured classes, aligns directly with the HPL framework's four dimensions. This preference can be attributed to the unique learning environment created by these labs, which actively engages students and facilitates effective data skills acquisition.

As Bonsu highlights, hands-on projects in labs provide long-term exposure to diverse data forms, fostering proficiency, a key aspect of the knowledge-based environment emphasized by HPL. This environment focuses on understanding principles through activities that promote sense-making, aligning with students' desire to apply academic content in practical contexts.

Lab classes resonate deeply with the learner dimension due to their active engagement approach. Hands-on activities stimulate curiosity, encourage exploration, and cater to diverse learning styles, personalizing the experience for each student. Knowledge construction, another HPL principle, thrives in labs. Students move beyond passive information reception and actively participate in knowledge creation through experimentation, data analysis, and conclusion drawing. This solidifies theoretical concepts through practical application, leading to deeper understanding. Assessment in labs transcends traditional testing. Formative assessments like observations, discussions, and data analysis provide ongoing feedback, empowering students to self-evaluate and adapt their learning. This aligns with the HPL framework's assessment dimension. Finally, the community dimension flourishes in collaborative lab settings. Students work together, share ideas, and learn from each other's successes and challenges, fostering a sense of community that promotes communication, teamwork, and peer support, as emphasized by HPL.

While acknowledging the significance of data skills for their engineering understanding, very few actively pursued them beyond prescribed coursework. This surprising pattern validated our choice of the HPL framework as it sheds light on the critical interplay between learning environments, student agency, and data skill development. The HPL framework posits that learning thrives when three elements converge: content, context, and learners. In the context of data proficiency, our study suggests that many students lack the agency and motivational context to independently pursue these skills, relying primarily on structured course environments to drive their learning. This realization underscores the crucial role of designing learning environments that empower and motivate students to actively engage with data skills. By adopting a learner-centered approach aligned with the HPL principles, educators can equip MAE students with the autonomy and intrinsic motivation needed to flourish in this data-driven landscape.

Our study unveiled a crucial finding that many MAE students equated data proficiency primarily with manipulating and analyzing data from structured sources like experiments and computer simulations. While these skills are valuable, our analysis suggests a narrower understanding compared to a more comprehensive definition of data proficiency. It's vital for educators to acknowledge this limited perception and actively address it. Data proficiency extends far beyond computational thinking applied to experimental or computational data. By explicitly highlighting these aspects of data proficiency, educators can equip MAE students with a more versatile and relevant skillset. This expanded understanding will serve them well, not only in future engineering careers but also in navigating the increasingly data-driven world around them.

7. CONCLUSION

This study investigated how MAE students conceptualize data proficiency and how they acquire and utilize data skills throughout their academic journey. Through thematic analysis of 27 qualitative interviews, we identified four key characteristics of data proficiency as perceived by MAE students: information literacy, data interpretation and presentation, data application, and computation.

Interestingly, the study revealed that experiential learning emerged as the preferred method for developing data skills among these students. Participants emphasized the value of hands-on experience, iterative learning within a collaborative environment, and tackling real-world challenges through collaborative projects. They viewed these elements as instrumental in building true data proficiency.

These findings contribute significantly to the ongoing discussion about data proficiency in engineering education. By shedding light on student perspectives and preferred learning approaches, this research offers valuable insights that can inform the design and implementation of data science courses and curricula in undergraduate engineering programs. By incorporating experiential elements, hands-on activities, and collaborative problem-solving opportunities aligned with real-world scenarios, educators can create learning environments that effectively equip future engineers with the data skills they need to thrive in an increasingly data-driven world.

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8. References

[1] S. Miller, "Collaborative Approaches Needed to Close the Big Data Skills Gap," Journal of Organization Design, vol. 3, no. 1, p. 26, Apr. 2014, doi: 10.7146/jod.9823.

[2] D. Donoho, "50 Years of Data Science," Journal of Computational and Graphical Statistics, vol. 26, no. 4, pp. 745–766, Oct. 2017, doi: 10.1080/10618600.2017.1384734.

[3] S. L. Brunton et al., "Data-Driven Aerospace Engineering: Reframing the Industry with Machine Learning," AIAA Journal, pp. 1–26, Jul. 2021, doi: 10.2514/1.J060131.

[4] A. Godwin and A. Kirn, "Identity-based motivation: Connections between first-year students' engineering role identities and future-time perspectives," Journal of Engineering Education, vol. 109, no. 3, pp. 362–383, Jul. 2020, doi: 10.1002/jee.20324.

[5] F. Wu, W. Fan, C. Arbona, and D. de la Rosa-Pohl, "Self-efficacy and subjective task values in relation to choice, effort, persistence, and continuation in engineering: an Expectancy-value theory perspective," European Journal of Engineering Education, vol. 45, no. 1, pp. 151–163, Jan. 2020, doi: 10.1080/03043797.2019.1659231.

[6] J. P. Monat, T. F. Gannon, and M. Amissah, "The Case for Systems Thinking in Undergraduate Engineering Education," International Journal of Engineering Pedagogy (iJEP), vol. 12, no. 3, pp. 50–88, May 2022, doi: 10.3991/ijep.v12i3.25035.

[7] C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, "Engineering Design Thinking, Teaching, and Learning," Journal of Engineering Education, vol. 94, no. 1, pp. 103–120, Jan. 2005, doi: 10.1002/j.2168-9830.2005.tb00832.x.

[8] J. A. Lyon and A. J. Magana, "Computational thinking in higher education: A review of the literature," Computer Applications in Engineering Education, vol. 28, no. 5, pp. 1174–1189, Sep. 2020, doi: 10.1002/cae.22295.

[9] T. Doleck, P. Bazelais, D. J. Lemay, A. Saxena, and R. B. Basnet, "Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: exploring the relationship between computational thinking skills and academic performance," Journal of Computers in Education, vol. 4, no. 4, pp. 355–369, Dec. 2017, doi: 10.1007/s40692-017-0090-9.

[10] J. del Olmo-Muñoz, R. Cózar-Gutiérrez, and J. A. González-Calero, "Computational thinking through unplugged activities in early years of Primary Education," Computers & Education, vol. 150, p. 103832, Jun. 2020, doi: 10.1016/j.compedu.2020.103832.

[11] John Bransford, Ann Brown, and Rodney Cocking, How People Learn, vol. 11. Washington, D.C.: National Academies Press, 2000. doi: 10.17226/9853.

[12] V. Clarke and V. Braun, "Thematic analysis," The Journal of Positive Psychology, vol. 12, no. 3, pp. 297–298, May 2017, doi: 10.1080/17439760.2016.1262613.

[13] I. Vourletsis, P. Politis, and I. Karasavvidis, "The Effect of a Computational Thinking Instructional Intervention on Students' Debugging Proficiency Level and Strategy Use," in Research on E-Learning and ICT in Education, Cham: Springer International Publishing, 2021, pp. 15–34. doi: 10.1007/978-3-030-64363-8_2.