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Work in Progress: The Strategic Importance of Data Science in Civil Engineering: Encouraging Interest in the Next Generation

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Abstract

Over the last decades, the increased availability of data has significantly changed civil engineering practice. A wide range of jobs in virtually all sectors demand computing and data analysis skills to an unprecedented extent. Unfortunately, students from civil engineering often lack programming skills and the motivation to acquire competences in data analysis. The intuition driving this research is that the approach currently used to teach data science in civil engineering is failing to gain the interest of students. This study has two objectives: (1) to explore the attitudes and beliefs of civil engineering students towards data science and (2) to propose pedagogical activities aimed at integrating data science into undergraduate civil engineering courses. Toward the first objective, an instrument was developed using items adapted from the Computing Attitudes Survey (CAS) and the Engineering Professional Responsibility Assessment (EPRA). The survey was administered to civil engineering students, with responses received primarily from senior-level students. An exploratory factor analysis of the survey responses identified five factors related to computing attitudes, professional connectedness, data science value, abilities in data science, and importance of skills in engineering. The analysis of specific survey items found that students' perception of the importance of data analysis is likely lower than that of professionals and employers. These baseline survey results are promising to use the instrument after interventions that target computing and data science issues in civil engineering, tied to social issues. To address this misalignment between students' perceptions and industry needs, we propose the development of pedagogical activities integrating the capabilities of data science with the social responsibility of civil engineers in undergraduate courses. Future research is needed to gather additional student response data and to deploy and pilot the proposed pedagogical activities and evaluate their impact on students' perceptions.

Introduction

The increased availability of data has drastically impacted the practice of civil engineering in the last 20 years [1]–[5]. However, several studies have highlighted that current practice is not taking full advantage of big data because data science is not widely deployed [2], [4], [6]. Data science centers on the notion of multidisciplinary and interdisciplinary approaches to extracting knowledge or insights from large quantities of complex data for use in a broad range of applications [7]. Topics of data science span the overall pipeline of data collection, management, statistical analysis, visualization, modeling and prediction, and data-driven decision making in real-world applications. As sensors become cheaper and more data become widely available, opportunities for a better integration of data science in civil engineering becomes apparent. Familiarity and confidence working with data and data scientists are thus desirable.

A wide range of jobs in virtually all sectors demand computing and data science skills to an unprecedented extent [8]. A recent report published by the National Academies of Sciences, Engineering, and Medicine [7] urged academic institutions to provide educational pathways to prepare students for an array of data science roles in the workplace. Revisions to the ABET Civil Engineering program criteria are being developed and considering the addition of "formal science" (which is defined to include "data science") as an option to an additional area of basic science and/or requiring numerical methods [Bielefeldt personal communication; 11/6/21 ASCE PCTC meeting]. Unfortunately, students from civil engineering often lack skills in data science and the motivation to acquire these competences [9]–[12].

Previous research analyzing the performance of students in data science courses have indeed found that motivation is a powerful predictor of academic performance [13]. A meta-analysis performed by Valentine et al. [14] found that early self-beliefs correlated positively with later achievement. Similarly, studies in chemistry and mathematics [15], [16] found that students' achievement expectations and self-concept were better predictors of success than previous instruction in these fields. Student beliefs play an important role in how students learn and it is thus imperative to understand how our educational practices impact students' perceptions [17].

The intuition driving this research is that the approach currently used to teach data science in civil engineering is failing to gain the interest of students, ultimately impacting their academic performance and skills. Previous research has found that civil engineering students are particularly motivated by the impact of their work [18] and have higher views of social responsibility [19] than other engineering majors. Indeed, "improving society" is a key motivational factor for women and students from underrepresented minorities [20], [21]. Data science is often introduced in the civil engineering curriculum as specific courses focused on computer programming and data analysis (e.g., probability and statistics). We hypothesize that the current approach used to introduce data science in civil engineering is failing to connect data science with the social responsibility of civil engineers, contributing to a negative attitude of students that ultimately hinders their learning process in the data science domain.

Research Questions

This work in progress is a first step to explore the attitudes and beliefs of civil engineering students towards data science and how the design of learning experiences can enhance students' beliefs and perceptions in this domain. The research questions guiding this research are:

RQ1) What are the attitudes and beliefs of undergraduate civil engineering students towards data analysis and the societal impact of the profession?

RQ2) Can a learning experience successfully combine civil engineering concepts, data analysis, and societal impact?

RQ1. Attitudes and Beliefs of Undergraduate Civil Engineering Students

Survey Development

An instrument was developed using items adapted from the Computing Attitudes Survey (CAS) [17], [22] and the Engineering Professional Responsibility Assessment (EPRA) [23]. The most recent version of the CAS instrument [22] uses a 5-point Likert scale and consists of 40 questions that are grouped in six factors related to computing attitudes: (1) problem solving - fixed mindset, (2) gender equity, (3) importance, (4) problem solving – strategies, (5) gender bias, and (6) personal interest. EPRA, in turn, consists of 50 items evaluated using a 7-point Likert scale. ERPA is intended to assess the impact of curricular interventions aimed on students' views of social responsibility.

The instrument development included: (1) item selection and adaptation based on face validity among the team of three faculty members (two civil engineering and one computer science professor) and one civil engineering undergraduate student; and (2) interviews and survey pilot testing with four civil engineering graduate students. The final survey included 47 items measuring students' perception towards computing and computer science (CS), data science (DS), and social responsibility using a 7-point Likert scale, one embedded attention check item, a couple of questions related to CS/DS courses, and demographic items at the end.

Respondents

This pilot survey was distributed to civil engineering undergraduate students in eight courses in spring 2021 at the University of Colorado Boulder (IRB approval #21-0105). Students were invited to participate in the survey through an email sent by the course instructors on behalf of the research team. This email included a link to a survey implemented on Qualtrics. To incentivize participation, a $50 Amazon gift card was offered to a randomly selected participant.

A total of 70 valid responses were collected, representing 18.8% of the total population of civil engineering students. 18 additional responses were recorded but not included in the analysis because they failed to respond to an "attention check" question asking them to select a specific response in the survey. Student demographics are summarized in Table 1. The majority of the students who responded to the survey were seniors, had worked a summer or part time engineering internship, had taken one or more courses in computer science or data analysis, were male, and Caucasian/White.

Table 1. Demographics of survey respondents

Demographic	**Categories**	**Number responses**
College rank	First-year Sophomore Junior Senior 5th year senior	2 7 6 47 8
Previous engineering work and/or internship experience (check all that apply)	None Summer or Part Time Internship/Co-term Full time employment Research Position	28 39 3 7
Previous experience with computer science or data analysis?	None I have taken one or more classes in this topic	7 63

Demographic	Categories	Number responses
Gender	Male Female Prefer not to say	45 24 1
Race/Ethnicity (check all that apply)	Caucasian / White Asian African American or Black Hispanic / Latinx Native American / Alaskan Native Native Hawaiian or Other Pacific Islander International Prefer not to say	50 8 1 5 1 1 4 1

Survey Validation

As a first step, the survey structure and reliability was explored, to confirm that the items would fall into the constructs expected based on the survey development. An exploratory factor analysis (EFA) was conducted in IBM SPSS using principal component analysis. Putting in all 47 of the 7-point Likert-type items, a five-factor solution appeared appropriate based on the scree plot. The Bartlett's test of sphericity had a significance <0.001, indicating that the dataset is suitable for factoring. However, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was only 0.543, which is generally considered to be inadequate; in future work, a higher number of student responses will be needed to validate the survey. A summary of the EFA results based on the rotated component matrix are shown in Table 2.

Table 2. Survey Structure Results

Factor	% Variance	# Survey items	Loadings	Cronbach's Alpha
1 Computing and data analysis attitudes	18.4	16	.857 to .426	0.917
2 Professional connectedness	15.0	10	.786 to .373	0.826
3 Data science value	6.7	7	.680 to .486	0.773
4 Abilities in computing, DS, helping	6.3	8	.718 to .388	0.758
5 Importance of knowledge to engrs	5.9	6	.778 to .250	0.678

The factor that accounted for the highest percentage of the variance mapped to the computing attitudes items derived from Dorn et al. [17] and Bockmon et al. [22], and similar items modified to explore attitudes toward data science and data analysis. The clustering of computing attitudes and data analysis attitudes together is interesting. The second factor included the items from EPRA related to social responsibility, primarily the items from the professional connectedness realm. The third factor included items related to data science extrinsic value perceptions (employability). The fourth factor included professional ability items from EPRA and self-rated abilities related to computing skills. It was somewhat unexpected that students' self rating abilities across these very different areas clustered together but perhaps reflect overall self-confidence (and in some cases Duning-Kruger effect). The fifth factor included the majority of the 'importance of skills and knowledge for professional engineers' items from the beginning of the survey.

Assuming that the five factors represent the survey structure, the reliability of those scales (internal consistency of the items) was evaluated using Cronbach's Alpha. Based on the computed alpha values (Table 2), the first factor is considered excellent, factor 2 good, factors 3 and 4 acceptable, and factor 5 questionable (using rules of thumb [24]). Again, these results support the importance of gathering additional student response data in order to more rigorously validate the survey instrument.

Analysis of Survey Factors

Data analysis to compare among groups used non-parametric statistics (e.g., Kruskal Wallis tests among multiple groups; Spearman correlations), appropriate given Likert-type data that may not be normally distributed.

The average student ratings for the four primary survey factors are summarized in Table 3. Students had the strongest agreement with factor #4, related to their confidence in different skills and abilities (6.27 ~ agree). Responses to this factor did differ among students with different responses to the computing attitude question (see Table 4 below; sig. 0.024 in KW test), where students who wish there were more courses offered on CS and data analysis rated their ability lower.

Table 3. Average student survey responses across the multiple items in each construct on a 7-point scale (1 strongly disagree to 7 strongly agree)

Survey Factor	Example survey item(s)	Mean	Std Dev
1 Computing attitudes	I enjoy solving computer science problems	4.75	1.01
2 Professional connectedness	I think it is important to use my engineering to serve others	5.83	0.63
3 Data science value	Data Science skills will make me more employable	5.69	0.80
4 Abilities in CS/DS and helping	I feel I would be able to use existing computer programs to analyze data (i.e. Excel, Matlab, etc.) I can have an impact on solving problems that face my local community	6.27	0.58

Students had a generally strong desire to use engineering to help society (professional connectedness). As has been found in previous research, feelings of professional connectedness were stronger among female compared to male students (avg. 6.06 vs. 5.72, sig. 0.043). There were not statistically significant gender differences in computing attitudes, data science value, or abilities. Differences between attitudes of students in different ranks was not found (although statistical power is limited by the small number of students outside of the senior rank).

There were some statistically significant correlations among the factors. The strongest correlation was between abilities and professional connectedness. The correlation among a student's feeling that they have the ability to help others (generally and via engineering) has been previously been shown to be related to feeling motivated to help others via engineering (professional connectedness) [23]. It is interesting that in this survey where the ability factor included 3 items related to abilities in CS/DS skills, the correlation with professional connectedness was still quite strong. There was also a positive correlation between computing attitudes and data science value. The correlation between data science value and professional connectedness is somewhat unexpected, but lends support to the underlying motivation for the study that linking CS/DS skills to the ability to help others through engineering might motivate civil engineering students toward CS/DS skills.

Table 4. Spearman's rho for non-parametric correlations among the factors

Survey Factor	Comp Attitudes	Prof Con	DS Value	Abilities
Computing and DS attitudes		0.113	0.409**	-0.024
Prof connectedness	0.113		0.241*	0.412**
Data science value	0.409**	0.241*		0.129
Abilities	-0.024	0.412**	0.129	

** correlation significant at 0.01 level (2-tailed); *significant at 0.05 level (2-tailed)

Analysis of Relevant Survey Items

In addition to the analysis of survey factors, interesting results were found in specific survey items. This is the case, for example, of students' motivation and interest in data science and the perception of its impact on employability. While students slightly agreed that data science skills will make them more employable (data science value avg. 5.69), their motivation to solve data analysis/computer science problems was neutral (computing attitudes avg. 4.75). The analysis of students' individual responses (Figure 1) shows that students generally rate the importance of data science in their employability higher than their motivation towards this topic. This difference was found to be statistically significant (p-value of Wilcoxon Signed Rank test < 0.001), suggesting that students recognize the positive impact of data science on their employability, yet they do not feel particularly motivated by this topic.

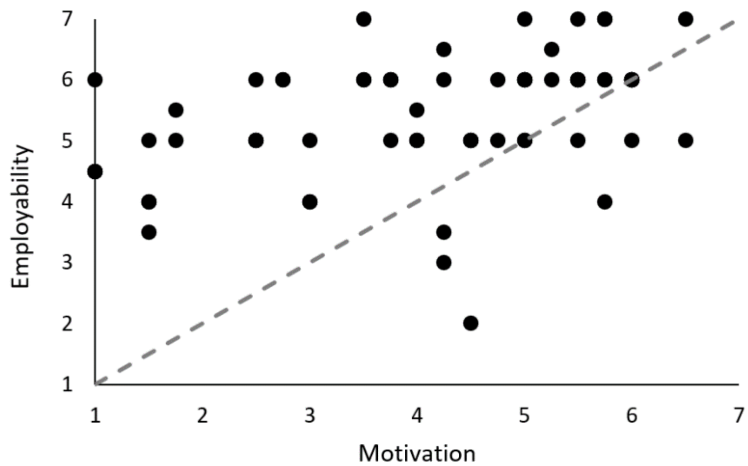

Figure 1. Students perceive the importance of data science in their professional career, yet they are not particularly motivated by this topic

A question near the end of the survey asked students to "describe their experience in CS and data analysis" and students could select among any of 3 statements they agreed with; results are summarized in Table 5. Only 27% of the students wished there were more courses offered on computer science and data analysis. This result suggests that students' perceptions on their need to expand their knowledge on data science notably differ from those of employers, who consider that civil engineering students often lack programming skills and competencies in data analysis [9]–[12]. These students who wished there were more courses offered in CS/data analysis self-rated their ability lower.

Table 5. Student responses to multi-select item regarding CS and data analysis and compared to average survey factor scores

Experience in CS and data analysis	**n**	**Computing attitudes ^**	**Data science value +**	**Abilities ***
I wish there were more courses offered in this topic	19	5.12	5.78	5.94
I didn't learn as much as I expected	31	4.63	5.75	6.36
I think I have taken enough courses offered in this topic	28	4.56	5.62	6.38

Kruskal-Wallis asymptotic significance between CS and data analysis response and the factor response: ^ 0.109, + 0.390, * 0.024

The courses that students wrote-in that they had taken in CS or data analysis included:

- Introductory level programming courses. One first-level computer science course is required in the curriculum of all civil engineering students; this single course was the most common item listed (although the specific course varied given changes in the required course over time) and 48 students listed only this single course.

- Some students listed the languages / skills they had learned, including MATLAB, C++, Python, Arduino, Java, R, Excel
- Probability / statistics (a required junior-level course in civil engineering) was listed by 4 students; given the large number of seniors in the course, the small number of students who listed this course was surprisingly low (<10% of the seniors)
- A few students listed other courses that "required the use of computer science expertise" including physics lab, differential equations / linear algebra
- Three students noted high school level courses (including AP Computer Science)

The average importance of "data analysis and computing skills" ratings by students ranked it 7 out of 9 potential skills important for a professional engineer (Table 6). Skills such as ethics, societal context, and cultural awareness were deemed more important than data analysis and computing. These results suggest that students' perception of the importance of data analysis is not aligned with professionals and employers, who identify data analysis as one of the most important competencies needed in engineering graduates [9], [19]. The importance rating of data analysis and computing skills did not differ based on demographic characteristics of the students including college rank, previous engineering work experience, previous courses in CS or data analysis, or gender. However, it was found that the highest importance ratings (on average) were among the students who indicated solely "I didn't learn as much as I expected" with respect to their experience in CS and data analysis (importance avg. 5.9, n=23).

Table 6. Students' ratings of the importance of skills for a professional engineer (7-pt scale from 1 very unimportant to 7 very important)

Skill	**Mean**	**Std Dev**	**Rank**
Fundamental skills (i.e. math and science)	6.37	0.66	4
Technical skills (i.e. conducting experiments, design, engineering tools, & problem solving)	6.50	0.68	3
Data analysis and computing skills	5.66	1.09	7
Business skills (i.e. business knowledge, management skills, & professionalism)	5.56	1.07	8
Professional skills (i.e. communication, contemporary issues, creativity, leadership, lifelong learning, & teamwork)	6.63	0.62	1
Cultural awareness / understanding (i.e. of your culture, and those of others)	5.73	1.23	6
Ethics (i.e. ensuring all of your work follows professional codes of conduct)	6.63	0.75	1
Societal context (i.e. how your work connects to society and vice versa)	6.01	1.08	5
Volunteerism (for professional and personal reasons)	5.20	1.21	9

The students' high perception of the importance of social and ethics skills support findings from previous studies that found that civil engineers are particularly motivated by the impact of their work [19] and have higher views of social responsibility [20] than other engineering majors.

These baseline survey results are promising to use the instrument after interventions that target computing and data science issues in civil engineering, tied to social issues.

RQ2. Work in progress: Development of learning experience

To address the second research question, the research team is working on the design of pedagogical activities aimed at integrating data science into two undergraduate civil engineering courses. The design of the interventions is grounded in Expectancy-Value Theory (EVT) [25], [26]. This theory has been commonly applied in engineering education settings [13], [27]–[31]. At the heart of the model is the idea that expectancy and value lead to student motivation which is a key ingredient for learning and cognition. This theory suggests that both expectancies for success and subjective task values directly influence the choice of activity, the persistence in it, and the final result (i.e., student performance). Expectancy describes one's expectation of success, often framed in terms of self-efficacy. Value represents subjective task value and includes intrinsic value (i.e., interest and enjoyment), attainment value (i.e., importance), utility value (i.e., usefulness of the task), and relative cost.

In order to catalyze changes in student's attitudes toward data science and explore the hypothesis driving this research (i.e., "creating better connections between data science and the social responsibility of civil engineering will foster positive attitudes of students towards data science"), we will incorporate multiple opportunities to expose students to data science throughout the semester. The envisioned activities include:

- Invited speakers, who will be asked to highlight the role of data science in their work and provide concrete examples of application of data science in civil engineering practice. These presentations are aimed at making clear the value of data science in the workforce (i.e., utility value in Expectancy-Value Theory).

- Case studies to showcase the capabilities of data science to improve civil engineering practice and the impact of these improvements on society. For example, a specific application that we envision in an introductory course to transportation engineering consists of a hands-on experience in which students will use cellphones to collect pavement roughness data near the university and use this information to derive insights on pavement condition and inform maintenance needs. These recommendations will be tied to the social and environmental impacts of timely pavement maintenance, fuel efficiencies, and safety. We envision this activity to impact students' interest (i.e., intrinsic value in Expectancy-Value Theory), as they will be using smartphones devices that they use in their regular activities to perform a technical evaluation of pavement condition. Besides, the connection of these assessments with maintenance needs and the social and environmental impact of timely maintenance is aimed to highlight the importance of the use of data in engineering (i.e., attainment values in Expectancy-Value Theory).

- Finally, group discussion at the end of the semester will be facilitated to have students discuss the integration of data analysis in the course during the semester.

Conclusions and next steps

The increased availability of data has significantly changed civil engineering practice and professionals perceive data analysis as one of the most important competencies needed in engineering graduates [9], [18]. Civil engineering students, however, often lack programming skills and the motivation to acquire competences in data analysis [9]–[12]. Current approaches in the undergraduate formation of civil engineering are thus failing to prepare students to enter a job market that is increasingly demanding competencies in data analysis.

This study explores this problem and provides preliminary results on the students' attitudes and beliefs towards data analysis and the societal impact of civil engineering. The results show that students' perception of the importance of data analysis is not aligned with professionals and employers. This study also found that, even though students recognize the positive impact of data science on their employability, they do not feel particularly motivated by this topic.

To address this misalignment between students' perceptions and industry needs, we propose the development of pedagogical activities integrating the capabilities of data science with the social responsibility of civil engineers in undergraduate courses. In this paper, we provide examples of activities aimed at integrating data science in civil engineering courses.

Further research is needed to expand the surveyed population and gather a more representative sample of undergraduate students in civil engineering across the nation. Also, more research is needed to deploy and pilot the proposed pedagogical activities and evaluate their impact on students' perception.

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