Data Use in the Design of Interventions to Improve Equity in Engineering Education

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***Abstract*—Introduction: This full research paper explores how data is used to design equity interventions. The percent of engineering degrees awarded to people who have historically been excluded from engineering has increased since 2010. But there is still substantial underrepresentation for women and people from racially and ethnically marginalized groups. One potentially promising practice is to harness the power of data, including big data, to design interventions to improve equity. However, there are gaps in our understanding of how higher education faculty and staff use this data in designing equity interventions.**

Objective: The purpose of this paper is to answer the question: How is data used in the process of designing efforts to improve equity in engineering programs?

Methods: We performed a content analysis on surveys completed by and artifacts generated by higher education faculty and staff who participated in a structured professional development and research experience. The experience focused on planning and executing a data-driven project designed to improve equity in engineering education.

Results: Analysis of the data suggests the following: participants articulate the core challenge that they are facing in terms of data indicating demographic disparities, make the case for addressing inequities via presentation of relevant data, and conceptualize evaluating success via gathering quantitative data about intervention outcomes. However, many projects are not, themselves, focused on the creation or use of data (e.g., mentoring programs).

Conclusion: This work shows how higher education faculty and staff who are designing interventions to promote equity in engineering education are using data in the design phase of their work. Understanding their patterns of data use is an important first step in determining how data use impacts their projects' outcomes and, based on that finding, how future cohorts can be best supported in the design of their interventions.

***Index Terms*—equity, professional development, data collection**

I. Introduction and Background

The percent of engineering degrees awarded to people who have historically been excluded from engineering has increased since 2010. But there is still substantial underrepresentation for women and people from racially and ethnically minoritized groups [1].

One potentially promising practice is to harness the power of data, including big data, to design interventions to improve equity. Data-driven decision-making has become commonplace in K-12 settings; it is less common in higher education although its use is increasing [2]. Even in K-12 contexts, the research literature generally does not focus on equity issues related to data use [3]. There has been a tendency to focus on data used by teachers to make decisions about curriculum and instruction (i.e., learning analytics). Learning analytics is increasingly pursued via educational data mining, which harnesses large data sets in the performance of learning analytics tasks.

Agasisti and Bowers propose a classification system that organizes data-driven decision-making in educational contexts into three groups: learning analytics, educational data mining, and academic analytics [4]. In their framing, *academic analytics* concerns the analysis of data to make decisions at the level of the organization in order to improve an educational system; the data in question is therefore generally institutional data, not student data. Academic analytics holds the potential to improve equity in engineering and in other disciplines by examining disparate impacts of policies, practices, and norms.

However, equity-focused academic analytics can be particularly challenging, given the difficult issues related to collecting and using data related to race, ethnicity, gender, and disability. This includes the potential for these data collection efforts to themselves further oppression if they not carefully designed to preserve the agency and recognize the full diversity of the research subjects. Data-driven efforts can, for example, present survey respondents with a set of options for their race and ethnicity that, by (over)limiting their choices, can itself constitute an act of oppression [5]. Or, data-driven approaches can present data in such a way as to encourage deficit thinking [6]. Efforts to more productively use quantitative data to address inequities include the examination of gaps in degree awards by demographic group [7], which leveraged the tendency for institutions of higher education to focus on metrics and performance indicators.

Crucial to these efforts to meld concern for equity with a data-focused culture is leadership [8], particularly in the form of leaders who are capable of combining knowledgeable use of data with a commitment to improving equity. This skill set requires training and preparation. The stEm PEER Academy is a professional development program for higher education engineering faculty and staff that focuses on developing their ability to implement data-focused interventions with the goal of improving equity. It is mostly a virtual program, consisting of an intensive summer workshop, monthly meetings, and one-on-one mentorship. The stEm PEER Academy has five goals:

- Improve understanding of the engineering education landscape,
- Enhance the ability to use data to inform intervention efforts,
- Pursue practices that are supported by research to increase degree completion by underrepresented groups,
- Enhance participants' professional networks, and
- Design and implement an equity-focused intervention.

More generally, the program is designed to equip participants to be leaders in improving equity at their institutions and in engineering education more broadly [9]–[11]. The stEm PEER Academy is part of the Engineering PLUS Alliance, a larger project designed to increase the number of women and/or BIPOC engineering students. Over its first two years, 38 higher education faculty and staff have participated in the program, with participants from 34 different institutions: 22 public, 7 private, and 5 community colleges.

This study is rooted in the theoretical framework for data-driven decision making developed by Mandinach, Honey, and Light [12]. This framework posits three major phases for data-driven decision making: the data phase (collection and organization of data), the information phase (analysis and summary of data), and, finally, the knowledge phase (synthesis and prioritization of data). These three phases lead ultimately to decisions, implementation, and impacts, which then feed back into the three main phases. While this framework was initially designed to describe data-driven decision making in K12 schools, the process of data use is similar in other contexts.

However, there are gaps in our understanding of how precisely higher education faculty and staff use data when designing equity interventions as there is, to date, minimal research in how data-driven decision making is used in higher education contexts [2]. Thus, the objective of this paper is to answer the question, How is data used in the process of designing efforts to improve equity in engineering programs? Accordingly, this paper is focused on understanding which phases of the framework for data-driven decision making are evidenced in the stEm PEER Academy participants' plans to design equity interventions.

II. Methods

Participants were recruited through the National Science Foundation (NSF) INCLUDES Alliance network, the American Society for Engineering Education's Project Kaleidoscope (PKAL) network, the Louis Stokes Alliances for Minority Participation (LSAMP), and other synergistic NSF-funded grant efforts, in addition to other engineering education networks.

Participants in the stEm PEER Academy were selected after submitting a short essay about an evidence-based practice that they might implement at their own institution that would ultimately increase the number of women and BIPOC engineering graduates. Participants were also supported by two letters of recommendation (from their unit or college leadership or from a colleague) to demonstrate institutional buy-in to their long-term participation in the the stEm PEER Academy, and their CV. Of the 38 participants, 34 consented to participate in the research process. The gender distribution of participants was 74% women, 0% non-binary, and 26% men. By race/ethnicity, participants were 26% Asian, 6% American Indian or Alaska Native, 29% Black, 9% Hispanic, and 29% White. Because the stEm PEER Academy is cohort-based, participants in this study were in either their first ($n = 19$) or their second ($n = 15$) year of participation.

Participants in the stEm PEER Academy generated artifacts related to their plan to improve equity in engineering education on their campuses. This generation phase occurred after approximately 20 hours of professional development in the program. Participants' projects can be grouped into four categories based on their intended impact:

1) Projects that impact K-12 students and their potential engineering pathways, such as a residential program for high school students.
2) Projects that impact undergraduate students, such as bridge programs.
3) Projects that impact graduate students, such as scholarships.
4) Projects that impact faculty such as DEI or growth mindset training

The authors performed a content analysis on these artifacts. First, they worked independently and tagged each reference to quantitative data in each artifact. Each reference was given two tags: one context tag and one data tag. Table II lists all of the possible tags. The context tags, which tell *why* the data was used, were generated by the authors based on the anticipated data use cases given the constraints of participants' proposed projects and the templates provided to them to describe their projects. The data tags, which tell *how* the data was used, use the categories for possible data-related activities from the taxonomy described by Shah et al. in their analysis of dozens of extant data life cycles [13]. After independent coding was complete, inter-rater reliability was negotiated to 1.00.

III. Results

There were two participants whose artifacts yielded no instances of data use.

There were five tags for describing the context of data use. There were no instances fitting the *Broader Impact* tag. Figure 2 shows the count of participants using data in each of the other contexts: *The Challenge* ($n = 23$), *Proposed Solution* ($n = 15$), and *Measuring Impact* ($n = 23$). Additionally, one item was tagged *Other*; it noted that HBCUs award a disproportionately high percentage of STEM degrees relative to their size.

Of the fourteen possible categories reflecting how the data was used, only four were identified in the participants' artifacts: *Analysis* ($n = 12$), *Collection* ($n = 22$), *Planning* ($n = 28$), and *Use* ($n = 11$). Figure 2 shows the count of participants using each category.

Figure 3 shows the count of participants using each combination of context and data tags. Not included in this heatmap is the one instance with a data tag of *Use* and a context tag of

Category	Tag	Key Question
Context	The Challenge	What is the equity-related challenge?
	Proposed Solution	What intervention does the participant propose?
	Measuring Impact	How will the impact of the intervention be assessed?
	The Broader Impact	What are the potential broader impacts of the intervention?
	Other	What other contexts are data used in?
Data	Access	How is access to the data managed?
	Analysis	How will the data by analyzed?
	Archive	How will the data be archived?
	Collection	How will the data be collected?
	End of Life	What will happen at the end of the data's life cycle?
	Governance	What rules will govern data access?
	Use	How will the data be used?
	Planning	What plans are there for using data?
	Preparation	What preparation is being conducted related to data?
	Protection	How will data privacy and security be managed?
	Quality	How will the project ensure data quality?
	Share	How will the data be shared?
	Storage	How will the data be stored?
	Visualization	How will the data be visualized?

TABLE I
OPTIONS FOR THE CONTEXT TAGS AND FOR THE DATA TAGS USED IN THE CONTENT ANALYSIS OF PARTICIPANTS' ARTIFACTS.

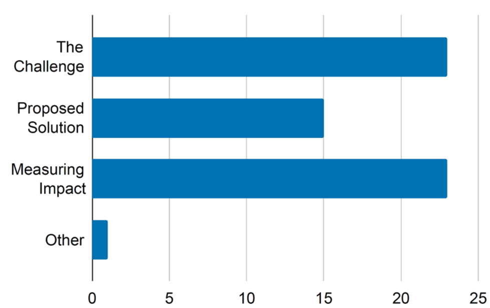

Fig. 1. Count of participants using data for each context.

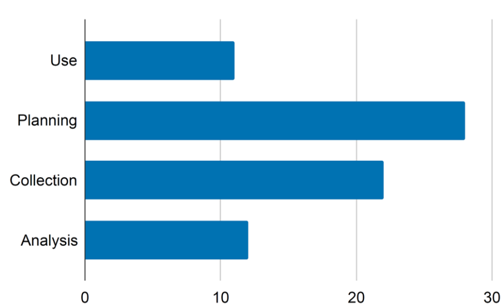

Fig. 2. Count of participants using each category of data use.

Other (described above). As the heatmap indicates, describing *The Challenge* is the most likely use of data, and describing the *Proposed Solution* is the least likely. In terms of data categories, *Planning* is the most common and *Use* the least common.

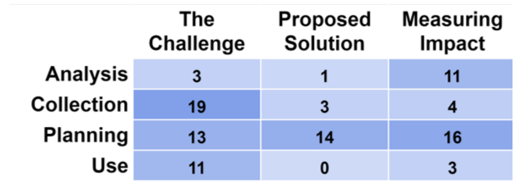

Fig. 3. Count of participants using each combination of context and data tags. Not included in this heatmap is one instance with a data tag of *Use* and a context tag of *Other*.

Figure 4 shows the distribution of data tags by context. For the *Challenge* context, data usage is predominately categorized as *Collection* (41% of instances), with smaller proportions of *Planning* (28% of instances) and *Use* (24%) and very few of *Analysis* (7%).

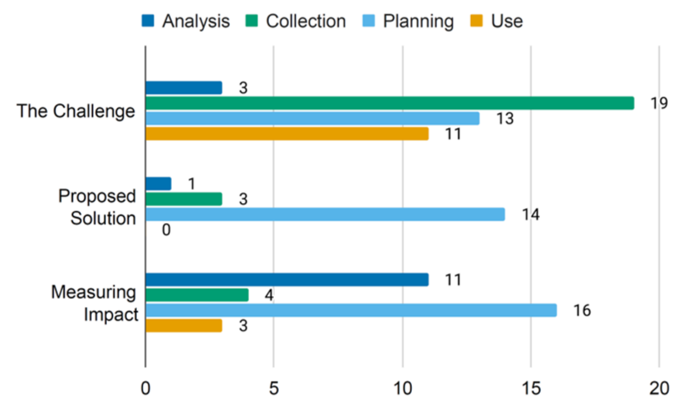

Fig. 4. Ways data is used by context.

Where the context was the proposed solution, *Planning* is by far the most common (78% of instances), with the other categories far less common: *Analysis* (5%), *Collection* (17%), and no instances of *Use*.

In the *Measuring Impact* context, *Planning* (47% of instances) is the most common, followed by *Analysis* (32%), *Collection* (12%), and *Use* (9%).

IV. Discussion

Note that two participants had no instances of data use in their artifacts. To the extent that one of the goals of the stEm PEER Academy is to enhance the participants' ability to use data to inform intervention efforts, their lack of data use may suggest an opportunity for improvement.

A. Data Context Categories

The only context tag that was not used was the *Broader Impact* tag. This is perhaps surprising since the second year participants developed plans following a template that had a section dedicated to the plan's anticipated broader impact. But interpreting whether this lacuna reflects (1) an understandable hesitancy on the part of participants to speculate on the long-term implications of their project or, contrariwise, (2) a missed opportunity to articulate the potentially positive, large-scale results of their work is not something that can be determined from the extant data. This is a question that might be worthy of exploration in future work, perhaps via interviews with participants and program mentors.

The fact that the remaining contexts (*Challenge*, *Proposed Solution*, and *Measuring Impact* occurred in about half (for *Proposed Solution*) or more (for the other categories) of [program participants'] design artifacts is noteworthy. It may suggest that, generally speaking, the project goals of augmenting participants' ability to use data to ground their intervention efforts and to pursue practices supported by research are being met by [the program] for the majority of participants.

That only one item was tagged *Other* suggests that the context categories developed by the authors before coding began were appropriate to the data set.

B. Unused Data Categories

Perhaps surprisingly, only four of the fourteen possible data use type tags were used. The unused tags were *Access*, *Archive*, *End of Life*, *Governance*, *Preparation*, *Protection*, *Quality*, *Share*, *Storage*, and *Visualization*. The lack of these tags does not necessarily speak to a problem to be addressed, but it may nonetheless be beneficial for mentors and/or participants to consider these categories in the future:

- *Access* refers to the process of acquiring and/or retrieving data. It may be the case that participants were already aware that they would be able to access the data needed for their projects, but it is also possible that they are assuming access that they may not have. Further, even if they have *permission* to access the data, there may be additional issues related to technical know-how for accessing it.
- *Archive* refers to the process of retiring data. This aspect of data use may or may not be relevant to participants' projects.
- *End of Life* refers to destroying or disposing of data. Generally speaking, participants were not gathering the type of data that would later need to be destroyed (e.g., transcripts with personal information) but rather were using institutional data (e.g., enrollment and retention counts)
- *Governance* refers to control of data. As with access, this issue may either have been settled or have been neglected for a given project.
- *Preparation* refers to processes such as selecting, extracting, classifying, pre-processing, filtering, and cleaning data. Once again, it might be a settled matter or a neglected matter.
- *Protection* refers to privacy and security issues related to data. Given that most participants were using institutional data, this may have been a non-issue. However, some of that data is related to potentially sensitive categories such as race and gender, and participants may or may not be aware of concerns related to, for example, the possibility of such data be de-anonymized [14].
- *Quality* refers to the calibre of the data. Participants may have felt sure that the data was of adequate quality, may have had some concerns but felt that the available data was adequate, or may not have considered the issue of data quality.
- *Share* refers to disseminating or publishing data. This aspect may have been intrinsically less relevant to projects which are, generally speaking, focused on implementing an intervention, not disseminating information.
- *Storage* refers to whatever retention mechanisms are deployed for the data. This aspect of data use is likely to be of limited significance to most participants' projects.
- *Visualization* Because the artifacts were text-based, it is not surprising that they did not contain data visualizations.

C. Identified Data Categories

The four categories that were found in the participants' artifacts were *Analysis*, *Collection*, *Planning*, and *Use*. As shown in Figure 4, the four identified data categories occurred in different proportions depending on the context.

1) Analysis: Analysis occurred in roughly one-third (32%) of *Measuring Impact* instances but only 7% in the context of the *Challenge* and 6% when the context was *Proposed Solution*.

Typical instances of data analysis in the context of measuring impact are found in participants' plans to analyze data related to long-term retention, number of students in a cohort (presumably by demographic group), number of mentoring activities, student experience (as indicated by a survey), and increased diversity in seminar speakers.

2) Collection: Collection was the most common in the context of describing the *Challenge* (41%) and much less so for the *Proposed Solution* (17%) and *Measuring Impact* (12%).

Representative examples of data *Collection* in the context of the *Challenge* involve instances where, concomitant with the proposed intervention, the participant plans on collecting data via surveys, observation, or grades in order to determine if the goals of the intervention are being met.

Data *Collection* for *Measuring Impact* was much less common (note that the authors classified plans to collect data to measure impact under *Planning*, not *Collection*). Where it did occur, it was usually in the context of the intervention itself; for example, one proposed intervention involved preparing students to learn to collect their own data in order to evaluate their own success.

3) Planning: Planning was the majority of data use types when the context was the *Proposed Solution* (78%); it was also 47% of *Measuring Impact* and 28% of *The Challenge*.

A typical example of data *Planning* in the context of the *Proposed Solution* involved comparing retention rates for Black students before and after an intervention was inaugurated. It is not surprising that so many instances of data use are classified as planning, since these artifacts reflect a moment in time in their participation in the program when participants were planning their interventions.

4) Use: Data *Use* was the least common, occurring in no instances of *Proposed Solution*, 9% for *Measuring Impact*, and 24% for *The Challenge*. An example of *Measuring Impact* involving data *Use* is one proposal to track students' academic performance over the course of the intervention.

D. Limitations

One limitation of this work is that the categories for data use adopted from Shah et al. [13] did not fully account for the ways that participants used data. First, many of the categories were not used at all. Second, there was one category of participants' usage that did not map neatly onto the categories: many participants used data to express a goal. For example, one participant intended to offer outreach activities with the hope that those activities would ultimately lead to increased enrollment at their institution; their description of improved enrollment numbers would perhaps best be characterized as a *goal*. Since this was not one of the pre-determined categories, the authors classified it as *Planning*.

The design of this project did not permit definitive statements as to whether some types of data use (e.g., attention to governance, end of life, and privacy and security concerns) were adequately addressed by the participants, although this likely would be a productive venue for further study.

V. Conclusion

The stEm PEER Academy is designed to be iterative in order to respond to the needs of participants. Anticipated changes that will be made to the program are to more intentionally support participants in leveraging their institutional data and, more specifically, to increase emphasis on participants' assessment and evaluation data plans when they are ready to implement their projects after the planning stage. Further, participants will be encouraged to expand their awareness of funded efforts and allies at their institution.

Recommendations for others who support systems change and learning communities in similar contexts might include incorporating home institution mentors, allies, and/or colleagues to supplement the participant's support system, as it appears to be particularly helpful when more than one participant is located at the same institution. It may even be useful to encourage future participants to apply to the program with a mentor or ally from their home institution. This approach will help address one of the limitations of the the stEm PEER Academy, which is that the mentorship provided by the program's directors cannot scale extensively due to time constraints.

As participants become more practiced at developing, implementing, and assessing interventions, they will be positioned to be leaders in future iterations of the program. A pilot leadership development program is planned to further position these participants to become change agents.

In general, we found that the program participants met the stEm PEER Academy's goal of encouraging participants to be actively engaged with data as part of their planned interventions to improve equity. This use of data spanned a variety of use cases and contexts relevant to their personal projects. This work serves a contribution to the research literature concerning data-driven decision making in higher education contexts, especially with regard to equity-focused work.

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