Using Big Data and Algorithms to Foster Equity in STEM

A Workshop on Emerging Research Themes
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Executive Summary

The ADVANCE Resource and Coordination (ARC) Network convened scholars from multiple disciplines for a two-day workshop to prioritize under-studied research questions under the general theme of **Using Big Data and Algorithms to Foster Equity in STEM**. The Research Advisory Board of the ARC Network, a National Science Foundation-funded initiative at the Women in Engineering Proactive Network (WEPAN), identified this theme as a primary area in need of further research exploration as well as policy and practical intervention in academic science, technology, engineering, and mathematics (STEM) workplaces.

This theme was selected because of the ways in which big data and algorithms often perpetuate inequity, discrimination, and violence against people from marginalized communities. For example, facial recognition software used to unlock cell phones, for airport passenger screening, in employment decisions, in ride sharing applications, and for law enforcement surveillance not only raises privacy issues, but also dangerously and consistently has the poorest accuracy when used to identify the faces of Black women (Buolamwini & Gebru, 2018; Watkins, 2021). This is a problem not only because we want the technology to work, but because marginalized individuals are disproportionately targeted. At the workshop, the planning committee sought to discuss the possibility of how big data and algorithms might instead *foster* equity, particularly in STEM fields.

Members of the workshop planning committee nominated scholars working in these areas who represent a diverse array of disciplines, research specialties, institution types, career stages, and social demographic backgrounds. Twenty scholars and practitioners convened in December 2021 and participated in a series of facilitator-led discussions designed to culminate in a research agenda of under-studied questions that will advance understanding of using big data and algorithms to foster equity in STEM.

By the end of our time together and with additional input from the larger community of researchers and practitioners, the group prioritized three research frontiers:

- **Missing data:** The problem of missing variables and/or values in big data sets
- **Mixed methods:** The need for qualitative methods to complement quantitative approaches to big data: getting to the "why" and 'how' to supplement the "what"
- **Interventions:** The desire to design interventions to correct inequities identified from analyses of big datasets

The three priority areas emerged from extensive discussion among workshop participants, and suggestions for expanded research needs are provided. In addition, other questions where research is needed include:

1. What are effective practices for dealing with **data exhaust**, or uses of data different from the intended ones at the time of data collection, especially when we are trying to promote equity?
2. How will we understand outcomes? Big data approaches can rarely tackle causation, yet these approaches can suggest interventions that need to be tied for anticipated outcomes. The most important desired outcome is an understanding of what characterizes well-being or success in STEM.
3. What measures of bias within the data are needed and how can we incentivize explicit descriptions of those biases in publications?
4. How can researchers integrate participatory methods of data analysis with big data in ways that do not jeopardize privacy?
5. How can we encourage more scholars from **marginalized backgrounds** to engage with big data approaches?
6. How can researchers influence federal funding directorates to support, fund, and engage in critical and ethical work to foster equity in STEM through big data and algorithms?
7. How can big data and algorithms help us understand the effectiveness of interventions for STEM equity from middle-school through late career? Where are the unsolved problems, and how do we ethically collect data to tackle those?

We encourage researchers to consider pursuing these topics and exploring the questions described within this report, especially in collaboration across fields and with practitioners.

Background

The ADVANCE Resource and Coordination (ARC) Network is a National Science Foundation-funded initiative at the Women in Engineering ProActive Network (HRD-1740860 and HRD-2121468). Its over-arching goal is to curate, disseminate, and support a community that shares research and promising practices for intersectional gender equity in higher education science, technology, engineering, and mathematics (STEM) departments. Through ARC's Emerging Research Workshops, it also has a mission to identify emerging research themes and directions for new research in those areas. Here we report on the latter mission.

The ARC Network is supported by several advisory committees, including the Research Advisory Board (RAB). As part of its work, the RAB is charged with identifying important topics emerging in the literature on intersectional gender equity in STEM. Subsequent goals include recruiting a diverse cohort of scholars who commit to participating in a two-day workshop on that topic. The workshop itself is designed to identify important questions for which additional research is needed, using intersectionality as a framework. In the spring of 2019, the RAB recommended that ARC host an Emerging Research Workshop on the general topic of big data and algorithms.

This theme was selected because of the ways in which big data and algorithms often perpetuate inequity, discrimination, and violence against people from marginalized communities, especially given how big data and algorithms are more commonly used now than ever before. For example, facial recognition software used to unlock cell phones, for airport passenger screening, in employment decisions, in ride sharing applications, and for law enforcement surveillance not only raises privacy issues, but also dangerously and consistently has the poorest accuracy when used to identify the faces of Black women (Buolamwini & Gebru, 2018; Watkins, 2021). Facial recognition research has yet to explore the implications for transgender and nonbinary folks and little work has included people with disabilities let alone the intersections of these social positionings with other forms of marginalization. At the workshop, the planning committee sought to discuss the possibility of how big data and algorithms might instead *foster* equity, particularly in STEM fields.

The RAB recruited a Planning Committee (see Page 2) to further define the theme, outline potential topics for discussion, identify scholars working in the area, and plan the workshop itself. The Committee started its work in autumn 2019 and suspended it in summer 2020 as the covid pandemic upended everything. We reconvened in spring 2021. Throughout its deliberations, the Planning Committee focused on recruiting scholars representing a wide range of disciplines, expertise, institutional types, career stages, and demographic backgrounds to participate, and weaving intersectionality throughout the workshop design.

The Planning Committee nominated individuals to participate in the workshop by considering a broad range of variables, including discipline, institution type, career stage, and the aspects of identity they study (gender, ethnicity, sexuality, citizenship, socio-economic status, disability, and more). The resulting group (see page 2) included scholars working in computer science, sociology, gender studies, public policy, linguistics, psychology, and economics; participants included faculty of all ranks, graduate students, postdocs, and representatives of professional societies. Participants from academic institutions came from a range of institution types including Historically Black Colleges and Universities, Hispanic-Serving Institutions, Predominantly White Institutions and public and private universities in the US and Canada. The identities of the scholars were diverse, as well, which brought added richness and deeper insights to the discussions.

Given that the COVID-19 pandemic was ongoing, we created hybrid options for participants to join the workshop remotely via Zoom as well as in person.

In 2022, we developed a draft of this report and circulated it widely among the community of research and practice. Comments and suggestions received from that audience are included in the text below.

Workshop Description

The Planning Committee designed the workshop to proceed from a general overview of big data and algorithmic bias towards prioritizing specific research questions. We began the workshop by establishing group norms and shared understandings of purpose to create a space where authentic conversations could take place over the course of two days. See Appendix I for the full agenda.

Day 1

The overall goal for the first day was **Developing a Shared Understanding for a Research Roadmap.** Participants engaged in conversations designed to examine the past, present, and future of big data and algorithms by eliciting varying perspectives, developing a shared understanding, and reaching conclusions about emerging research areas on using big data and algorithms to foster equity in STEM.

We used the technique known as the World Café: for each conversation, participants were in discussion with a new, small group of colleagues. Within each small group, a host was charged with keeping the discussion focused and ensuring that all voices were heard. Once the discussion had concluded, the facilitator asked each group to report out; in that way, everyone had a sense of the communal responses prior to moving to the subsequent group discussion.

Task 1

Our first task was to gain an appreciation for the expertise among participants, and to agree on vocabulary. Workshop organizers had prepared a first draft of definitions for the terms *big data, data bias, algorithm,* and *algorithmic bia*s (see Appendix II).

Towards that end, participants were grouped randomly and asked to speak with their partners on the following:

- What is the research/work you do?
- What are the sources of data sets you typically work with?
- What refinements do you have to the definitions of:
  - Big data?
  - Data bias?
  - Algorithms?
  - Algorithmic bias?

Each participant reported on the outcome of these conversations, which in turn sparked a lively group conversation (see Appendix II for detailed comments). Some thought that the emphasis on “bias” in the questions did not adequately cover concepts of equity, power, and social justice. Further, the word “bias” itself needs to be unpacked to distinguish statistical bias, observer bias, cognitive bias, etc. Participants agreed that it is nearly impossible to truly remove all biases; rather, we need to account for and mitigate the impacts of bias. Finally, even if we could eliminate bias, unjust uses of data/ algorithms can and are likely to persist. For example, facial recognition software is now being rewritten to include the ability to distinguish faces of different ethnic groups appropriately; yet that same software has been used to unfairly target individuals who protest injustice.

A related concept is “fairness,” which has multiple dimensions. While related, fairness, equality, and equity are not the same thing. Fairness is about impartial treatment without favoritism. With equality, the expectation is that everyone is treated the same way. Equity, however, accounts for context and means that people are treated in ways that allow for just outcomes to occur. As the above example illustrates, lack of bias does not necessarily promote equity or justice in process or outcome. These issues are exacerbated because so few large data sets and algorithms use an explicit intersectional framework required for equitable outcomes.

Another important distinction that the participants discussed was that between data bias and data noise (data that are corrupted, interpreted, or distorted in ways that do not necessarily lead to social inequity but are problematic for accuracy reasons). Those who study equity issues often use existing large data sets, which were collected for other purposes. These data may have equity issues in their collection instruments or may be cleaned in problematic ways. The related concept of “data exhaust,” how researchers use data in ways unintended by those who generated the data, emerged from this discussion. Such data sets often have missing variables, and algorithms to impute missing values are problematic, especially where identity is concerned. For example, using algorithms to determine gender from names is particularly problematic for transgender people because of the high likelihood of misgendering them.

Participants also discussed algorithmic bias which derives from humans using incomplete or biased data sets to write code and/or direct machine learning. Again, because humans construct algorithms, often in an opaque way, human bias can be perpetuated in the resulting code with adverse consequences. Because of a lack of transparency, making changes to the algorithms to address these problems as they surface is an additional challenge. Other known challenges that were discussed include repurposing models not trained on the type of data a researcher is using, not validating a trained model, overfitting for a researcher's data, training for equal rather than equitable outcomes, and inadequately handling the variance of predictions.

Overall, participants shared concerns that large datasets and complex algorithms are rarely examined for bias. Many researchers, they shared, have a positive bias towards assuming large data sets and machine learning produce accurate and representative results, due to their size. Challenging those assumptions is essential if we are to achieve equity.

Task 2a

Our second task was a visioning exercise, in which we grappled with the following questions:

- What will be different if the collection, analysis, and impact of big data and algorithms are leveraged for equity in STEM?
- How will our understanding of equity in STEM be different?

As groups worked to answer these questions, they put ideas on sticky notes. Thereafter, all participants converged to arrange the sticky notes into major categories, with these key characteristics of a visioned future wherein:

Qualitative data are valued: Big data approaches can detect patterns and uncover biases, but they have little explanatory power in themselves. Rather, to probe *why* and *how* certain patterns exist in large data sets (e.g., lower patenting rates by women, under-representation within science faculties of people with disabilities), researchers must complement quantitative data analysis with qualitative approaches such as interviews and focus groups. More information is also needed on the rationale behind how the big dataset was constructed and how data was collected.

The assumption of objectivity (of traditional methods) is questioned: Scientists are biased towards quantitative approaches and trust results when they derive from large amounts of data., due to their size. Yet, we know that algorithms and data sets can be flawed and not sufficiently representative, and ways of probing them can introduce additional errors (e.g., imputation algorithms). To achieve equity, we must forego the assumptions of primacy and carefully examine *all* research methods for unintended bias, errors, missing data, and the like. This includes qualitative approaches as well that come with its own kind of biases. Different methods need different ways of validating and accounting for bias and errors.

Transformational change is possible and can be achieved if those in positions of power heed and act in response to results of research concerning equity to create structural change. Only when leaders actively espouse a new vision of equity, and policies, procedures, and structures change can institutions be transformed.

Collection and use of data through an intersectional framework is essential to achieve true equity. Large data sets and algorithms tend to foster single-variable research approaches, but we know that many of the unmet equity challenges lie at the intersections of gender, race, ability, sexual orientation, age, and other demographic variables. Collecting and reporting data, including mining existing data sets, in ways that permit intersectional approaches that account for systemic issues is critical to achieve those goals. Being able to leverage big data and algorithms for equity in STEM might lead to enhanced and more representative distributions in STEM statistics and contribute to increased success rates for marginalized groups in these fields - both in education and the workforce. These data need to be collected and interpreted ethically and in community-centered ways.

The illusion of meritocracy is dismantled when we fully understand challenges to equity. Many scientists and engineers believe the system within which they work is a pure meritocracy, but that belief is deeply flawed and espoused by those in privileged positions, not always aware of the barriers that others must negotiate. The research enterprise is conducted by humans who have biases and make assumptions about their research subjects. Equity can only be approached when those who practice science accept that the system is a human convention, subject to human error and social systems of power, privilege, and oppression.

Task 2b

Workshop participants then engaged in small-group discussions on a series of questions:

1. In what ways have big data and algorithms been used to understand equity in STEM?
2. What are the limitations of using big data to analyze equity in STEM?
3. What research is missing in the area of using big data and algorithms to understand equity in STEM, especially considering intersectionality?

These discussions also used the World Café approach, in which small groups assembled and then broke up and re-assembled for each question. This approach allowed every individual to interact with multiple participants, and the group wisdom to arise from heterogeneous groupings. Groups reported out after each question, and the principal results are:

Question 1: *In what ways have big data and algorithms been used to understand equity in STEM? What is currently happening in this area?*

It is important to realize that current research focuses more on *documenting*, classifying, and/or predicting rather than *understanding*; big data and algorithm analysis have uncovered patterns of inequity in STEM but are not always able to explain how those patterns arose nor how to ameliorate them. Datasets are themselves limited, as we described above, and thus limit our ability to fully explore patterns.

That said, studies using a variety of data sources (e.g., administrative data, text and publication data, network data, patent records, etc.) have uncovered inequities in how STEM is practiced, including:

- Grant activities: who applies for and is awarded grants; grant size and duration; individual versus group grants
- Authorship: publication rates, types of journals, co-authorship, author rank
- Letters of recommendation: language used, length
- Student evaluations: differential language used by students and professor ratings
- Citations: who is cited, self-citations
- Computer simulations: accumulation of disadvantage across a STEM career
- Request for extensions: grant submissions, applications
- Employment: hiring, advancement, salaries, resource allocation, accessibility
- Innovation and commercialization: patenting activities
- Algorithms and machine learning: interview software, resume readers, surveillance software
- Imputation: imputing characteristics of individuals and groups
- Dashboards for decision-making: dashboards for executives; tools and technology that are made that end up in administrative buildings

Participants also shared that it seems that there are two types of uses at play in our discussion: 1. data and algorithms designed and used to understand STEM and equity issues (e.g., Project Implicit) and 2. those that have been developed for other purposes but that have revealed equity issues in their use (e.g., facial recognition software or AI-based cancer diagnosis).

Question 2: *What are the limitations of using big data to analyze equity in STEM?*

- Big data approaches can require resources (e.g., costs of buying datasets, specialized software to mine data, personnel)
- Holes exist in most big datasets (missing variables, missing values); this is related, in part, to the concept of data exhaust
- Biases exist in some datasets; for example, census data under-represent individuals from skeptical or fearful groups who are more likely to be undocumented

- Difficulties of inferring missing data: using first names to impute gender according to a binary introduces errors; variables concerning race rarely allow for multiple or accurate identifications
- Foreign nationals, who comprise the majority of graduate students and postdocs in many STEM fields, are usually omitted; when included, US-centric categories are used rather than those relevant to their contexts
- Data sets rarely allow for intersectional analysis
- Scientists overvalue large sample sizes and do not always query their representativeness or measure for variance within large datasets
- Data sets that are available are rarely collected for the purposes to which researchers what to use them
- Issues of participant privacy and safety
- Qualitative research may be marginalized, with qualitative research receiving less funding and being socially situated within the academy as less prestigious and convincing than quantitative research
- Studies using big data and algorithms are rarely replicated
- Results cannot help us understand the behavior of or impact on individuals
- Ineffective, if any, methods to detect and quantify bias in data sets
- Other more appropriate methods and approaches may exist to answer the questions posed by researchers using algorithmic and big data approaches

Question 3: *What research is missing in the area of using big data and algorithms to understand equity in STEM, especially considering intersectionality?*

- Effective practices for doing intersectional research from data sets that are designed with intersectionality in mind from the outset
  - Structuring data to address questions about systemic issues impacting those who are situated at the intersection of multiple forms of oppression (e.g., trans women of color with disabilities)
  - How can we use multiple datasets/ merge data sets to identify missing values and improve intersectional collection and analysis?
  - How good/valid are the algorithms that impute/infer missing values for variables needed to address intersectionality?
  - Intersectional bias has a higher magnitude compared to biases associated with members of a single underrepresented group; less data and more complexity is a significant limitation
- Privacy issues: even in big data sets, intersectional studies can result in small sample sizes, producing concerns for privacy. Members of very small groups might be easily identifiable.
- Attitudes and policies of funding agencies:

    - Intersectional approaches for use of big data?
    - Use of qualitative methodologies to complement large data sets
- What can big data studies tell us about:
    - Implications for policy and effectiveness of interventions?
    - Connections to policy?
    - Cultures of different disciplines?
- What analysis of big data sets can never tell us:
    - We can measure publications, citations, authorship, etc. but they are at best proxies for knowledge generation and impact
    - A lot about the what, but very little about the why and how
    - Marginalized populations will have small sample sizes, and big data falls short in enlightening us about their experiences
    - Big data sets are snapshots, with little ability to do longitudinal research (with newer datasets having to match older ones to successfully do longitudinal research, otherwise we encounter the same imputation/inference problem discussed earlier).

(End of Day 1)

Day 2

We reconvened to first recap the previous day's work and place it within the context of mapping out the most promising research agendas. After discussion, the group identified ten themes for future research. Most of the group's interest was in exploring questions about big data rather than algorithms. As such, we added an 11th area to the list for those who wish to dive deeper into this important area's research, policy, and practice. A poll of participants showed strong interest in further developing the three following themes:

Three Priority Research Areas (unranked):
- Addressing the problem of missing variables and values in big data sets
- Using qualitative methods to complement big data approaches: getting to the "why" and "how", in addition to the "what"
- Designing interventions to correct inequities identified from analysis of big datasets

Workshop participants then self-organized into three groups according to personal interest, one group per priority area above. The groups were charged with refining their research question and then developing research agendas around the following questions:

1. What research methods will be most useful for answering these questions?
2. What interdisciplinary perspectives might be helpful?

3. What new collaborations might foster research in this area?
4. How might policies, practices, and programs be influenced by research in this area?

Priority Research Area 1:
Addressing the problem of missing variables and/or values in big datasets

The central research question we considered: How can we improve the infrastructure of datasets and remedy missing variables/values/populations?

The problem: Most large datasets used by researchers were not collected with the researchers' questions in mind. These imperfect datasets suffer from problems including:

1. Missing variables (e.g., ethnicity, ability status)
2. Missing values
3. Variables with insufficient categories (e.g., limited and binary gender choices, single racial classification and US-centric approaches)
4. Insufficient sample sizes to allow for intersectional questions or analysis
5. Missing populations/biased data (e.g., foreign nationals, nonbinary individuals)

Some problems derive from decisions made by designers of the original datasets (missing variables), while others are inherent to any dataset (missing values).

There are two principal methods researchers use to fill in gaps for missing variables (1) and/or missing values (2):

- Imputation algorithms use machine learning to guess missing variables and/or values. For example, first names can be used to suggest gender and ethnicity. These algorithms are widely used but contain assumptions that are often erroneous. Critical analyses of imputation algorithms are needed to guide researchers seeking to understand the limits of their inferences.
- Merger/ synthesis of multiple datasets. Sometimes what is missing in one dataset can be found in another. By comparing and, when possible, merging such complementary datasets, researchers can ask deeper questions. In some cases, linking datasets works well whereas in other cases it can introduce new problems (such as threatening privacy). Additionally, newly introduced datasets may have different gaps leading to new issues of missing/incomplete data. A critical review of existing datasets, along with suggestions for complementarity, would be extremely valuable.

Problems (3) – (5) above can only be addressed by interacting with policymakers and those who collect the original datasets:

- Researchers can collaborate with individuals/offices that direct collection and construction of large datasets to include more nuanced options. For example, multi-racial and ethnicity options for self-identified categories is becoming more common in questionnaires.
- To probe questions concerning the intersections of identity, datasets need to have very large sample sizes and/or use stratified sampling methodology. Even so, some populations may be underrepresented or limit information shared to protect themselves from additional vulnerability. Understanding the very real risks for individuals and finding ways to mitigate those risks is key to inclusive sampling. Ethical considerations are paramount to address privacy alongside concerns about access. *This challenge requires qualitative research, covered below, to address ways of mapping out such risks and their causes.*
- Many government-collected data omit individuals who are not citizens or "resident aliens." That policy excludes many graduate students, postdocs and early-career individuals in the STEM disciplines (e.g., those on H1B visas); indeed, in some disciplines these non-counted individuals are the majority. Fully understanding some questions of equity requires collection of data representing *all* who are engaged in the scientific enterprise, not just citizens and those with green cards.
- Similarly, gender counting methods regularly used for large data sets feature binary categories, usually "male" and "female," and do not include options for transgender people. This renders transgender men, women, and non-binary folks invisible.

A related problem is that available datasets tend to be snapshots, and researchers are often interested in longitudinal data. Sometimes longitudinal trends can be captured by synthesizing multiple datasets, but those trends suffer from all the problems identified above. The well-documented loss of many groups from STEM, starting in middle school and progressing through late career, can be *demonstrated* by big-data approaches but can only be *understood* by following the same individuals through their trajectories via qualitative methods.

Solving the above problems will require collaborations between government, industry, and educational institutions. Those collaborations should be both inter- and multi-disciplinary to ensure that many ways of examination and understanding can be brought to bear.

Priority Research Area 2:
Using qualitative methods to complement big data approaches

Quantitative data analysis has proven very effective for identifying areas of inequity in STEM, including publishing, patenting, career progression, citations etc. Documenting patterns of inequity is an important step, but big data is limited in its ability to explain the origin and persistence of those patterns., the 'why' and 'how'. Experimental science has a very strong bias towards large sample sizes and quantitative analysis, and results from analyzing big datasets have been readily accepted, oversold, and under-investigated. Yet their limited explanatory power means we must use supplementary/additional research methods to understand and address inequities.

Qualitative data methods rely on in-depth understanding of individual experiences, and extrapolation from those experiences. The use of interviews, open-ended survey questions, and focus groups, for example, allows researchers to probe possible causation that could underlie larger-scale patterns. Indeed, the use of qualitative methods has allowed us to better understand why, for example, women in graduate school consider leaving computing (Crenshaw et al., 2017), why LGBT+ physicists experience hostile environments (Barthelemy et al., 2022), and how disabled women of color struggle to find accommodation and acceptance in mainstream science (Metcalf, Russell, & Hill, 2018). A clear lesson from work on equity in STEM is that multiple and mixed methodologies provide documentation, confirmation, and explanation, which together lead to needed and relevant policy changes.

Qualitative data takes many forms, including ethnographic information, answers to open- ended questionnaires, interviews, analysis of social media posts, textual analysis, etc. These data can reveal appropriate research questions for which larger datasets can be collected. When quantitative and qualitative methods are used in tandem, they can inform each other, provide richer understanding, and suggest more focused future research questions.

Of course, qualitative analysis has its own inherent difficulties, which are often addressed in qualitative research methodologies. Information gleaned from interviews and questionnaires can be biased (subjects say what they think the researchers wants to hear; subject answer in ways to protect themselves from repercussions). This issue can also occur in quantitative measures (for example, demographic questionnaires with categories participants choose from). Thus, a deeper bottom-up understanding of the causes of bias and perceived risks from the research subjects is essential. Furthermore, researchers may introduce their own biases as they interpret the data. Few STEM professionals in the experimental sciences have been trained in qualitative techniques, which supports the argument for multi-disciplinary teams to achieve reliable results (and separately, an argument for more holistic training within fields)

Furthermore, qualitative research often requires collaboration with groups who represent potential research subjects. The inclusion of people who are subjects of research can greatly improve research methodologies by suggesting fruitful avenues of inquiry and potential sources of bias and error.

Priority Research Area 3:
Designing interventions based upon results from analysis of large datasets

This group identified research problems including:

- What are the latent gatekeeping practices that keep people out of or cause them to leave STEM? How can big data be used to create accountability and transparency around such gatekeeping behaviors? How can we intervene in gatekeeping behaviors and functions?

- How much do we know about the effectiveness of interventions that seek to promote equity, and what is big data's role in those inquiries? How can we know more, prior to advancing additional interventions?
- How do we disrupt inequities in funding, publications, and career progressions? What do we know about those whose proposals are not funded, whose papers are not published, and who are not promoted? Can we acquire data (e.g., reviewer comments, paper rejections and demographic data on the authors of those papers) and construct valid datasets for such analysis?
- Is research on topics related to diversity, equity, and inclusion marginalized? Are grant proposals and manuscripts on such topics given equivalent consideration more than "normative" studies and methodologies, or do such research plans only apply for awards and grants that specifically target DEI? What interventions would best support and reward interdisciplinary work?
- How can we assess the internal distribution of resources within institutions for equity? What are the contextual factors that influence the effectiveness of interventions? For example: interventions created for predominantly white institutions (like mentoring program) may not work well at an HBCU.
- What kinds of interventions do faculty, staff, students favor? Which ones do they find problematic, and why? How do we address conflicting needs across groups?
- What networks within and between institutions are most helpful for assessments?
- How can we better detect, measure, and analyze the impact of bias on society and other processes?

To answer these questions, researchers can:

- Complement big data analysis with mixed-methods research that incorporates qualitative, ethnographic, and participatory action methods and are informed by the needs of marginalized communities and by critical quantitative methodologies
- Gather baseline data of current state and design longitudinal studies moving forward
- Study the actions and impact of individuals who are gatekeepers (either intentionally or not) with disproportionate impact (e.g., deans, department chairs), perpetuating inequities.
- Analyze networks for homophily and its impact on equity
- Design databases to have more transparency, about data collection practices, selected variables, and missing data.
- Form collaborations
    - Between interdisciplinary researchers with experience in qualitative methodologies (ethnographic and participatory action research) and quantitative methodologies (big data, survey, algorithms)

  - With communities impacted by marginalization
  - With institutional leadership/gatekeepers (i.e., Institutional data offices)
- Measure the impact of interventions through big data so empirically informed policies will be more efficient with more effective outcomes

Additional Research Area Recommendations

- What are effective practices for dealing with **data exhaust**, especially when we are trying to promote equity?
- How will we understand outcomes? Big data approaches can rarely tackle causation, yet they can suggest interventions and priority areas for qualitative research. The most important desired outcome is an understanding of what characterizes well-being or success in STEM.
- Measures of bias within the data are needed, and descriptions of those biases in publications should be explicit.
- Investigate ways to integrate community-centered categories and participatory methods of data analysis with big data in ways that do not jeopardize
- Find ways to encourage and break down barriers for more scholars from **marginalized groups** to engage with big data approaches
- The NSF budget request includes a whole new directorate for technology and innovation; how can researchers influence the way such a directorate is structured the kinds of work to be funded to foster equity?
- What is the effectiveness of interventions for STEM equity from middle-school through late career? Where are the unsolved problems, and how do we collect data to tackle those? And to design more focused interventions, based on existing data, and building on existing research (on successful and unsuccessful interventions).
- In what new ways can algorithms and machine learning contribute to social justice aims in STEM?
- How can we utilize existing datasets for intersectional analyses related to equity in STEM?

End of Workshop

Evaluation by participants

We asked participants to assess the workshop via an instrument that probed their experiences. Overall, participants gave the effort high marks for posing important questions, stimulating discussion, highlighting inter-disciplinary approaches, and converging on the most important next steps for the research community.

Conclusion

Big data approaches have proven extraordinarily successful in documenting some patterns of inequity in STEM. Yet, other kinds of inequity are difficult to study with such methods because of small sample sizes (especially for intersectional questions), missing populations (e.g., Indigenous folks), missing variables, and potential biases in the data themselves (nonrandom sampling, missing data, falsified responses). Furthermore, large data sets have relatively little explanatory power, and thus rarely suggest useful interventions. Workshop participants offered several suggestions for future research directions that offer pathways forward and identified those with the most promise for achieving equity.

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Appendix I. Agenda for the Workshop

Emerging Themes Workshop: Using Big Data and Algorithms to Foster Equity in STEM

December 3-5
Sheraton Grand at Wild Horse Pass, Phoenix, AZ

PARTICIPANT AGENDA

WORKSHOP GOAL –
Identify emerging research themes and directions for new research in the area of using big data and algorithms to foster equity in STEM.

FRIDAY, DECEMBER 3, 2021

- Participant arrival
- Registration
- Dinner at 6 p.m.
- Introductions and review of planned agenda

SATURDAY, DECEMBER 4, 2021

8:00 AM	**Breakfast**
9:00	**Workshop introduction**
9:30	**Partner introductions**
10:00	**Small group discussions to build familiarity and refine workshop definitions/language**
10:45	**Break**
11:15	**Large group discussion to coalesce definitions/language**
12:00 PM	**Lunch**
12:45	**Producing a vision for this work**
2:00	**Break**

2:30 **Developing shared understanding for a research roadmap**
Participants will engage in a series of conversations designed to elicit varying perspectives, develop shared understanding, and reach conclusion about emerging research areas on using big data and algorithms to foster equity in STEM.

6:30 **Dinner**

SUNDAY, DECEMBER 5, 2021

8:00 **Breakfast**

9:00 **Review workshop outcomes from Saturday, introduce plan for the day**

9:15 **Identify prioritized research areas/issues and self-organize into groups to begin in-depth research planning**
Each group will answer this question for its relevant area/issue: Given the research area/issue, what question or set of questions, if answered, will make the greatest contribution to equity in STEM?

12:00 **Lunch**

12:45 **Report-outs from groups to share about their research ideas and planning**

1:30 **Workshop review and next steps**

2:00 **Depart for the airport**

Appendix II. Key terms used in our discussion

Part A: Proposed definitions for discussion and refinement

Algorithm – a self-contained step-by-step set of operations that computers and other 'smart' devices carry out to perform calculations, data processing, and automated reasoning tasks.

Big Data – The Five V's:

- Volume – large amount of data.
- Velocity – the speed at which new data is being created.
- Variety – the diversity of data types.
- Variability – the way data is captured may vary from time and place.
- Value – insights from big data must be based on accurate data and lead to measurable improvements.

Data Bias:

- Data is not representative of the population or phenomenon of study.
- Data does not include variables that properly capture the phenomenon we want to predict.
- Data includes content produced by humans which may contain bias against groups of people.

Algorithmic bias: the lack of fairness that emerges from the output of a computer system. The lack of fairness described in algorithmic bias comes in various forms, but can be summarized as the discrimination of one group based on a specific categorical distinction. Algorithmic bias takes several forms, for example, racial bias, age discrimination, gender bias, and more (Bir, 2020; Johnson, 2019).

Part B: Discussion topics concerning the above definitions

- Were there any new words or phrases that needed to be defined?
  - **Equity**
    - there's a framing and focus on bias in the definitions, but that may be a narrow frame (group 4 talked about issues involving power, justice, equity)
    - there's being unbiased in a statistical sense and also what you do with that; the question becomes "now I have some statistical significant estimate, what do I do with that?"
    - even if you resolve issues of bias, there are other ethical issues to consider when looking at algorithms; bias isn't the only issue to consider

- What is the goal of equity in STEM?
- bias ends up being a wrapper for things that end up being automatic (e.g., cognitive bias); bias in data can be something in between automatic and something that someone did intentionally
- the result of intentional decisions
- ARC Network talks about how equity is different than equality; equity for them is making sure that people have the resources and receive the recognition they need for the context they're at/where they are in order to be successful in their pursuits or to have a sense of wellbeing (e.g., giving soccer players shoes that fit their individual sized feet in order make the individuals and the whole team successful)
- capabilities approach - we might think of equity in terms of equality of concrete capabilities to achieve what is desired
- the definitions were lacking the end goals; in this case the purpose was equity in STEM and we need to define that in order to get better definitions (start with the goal and the motives and work backgrounds to determine what data you need to get to those goals)
- example of debiasing but unethical in facial recognition (accurately identifies all faces but then is used to target people who attend protests)

- **Fairness**
  - there's been a push to look at accuracy as a metric of inherent bias, but this doesn't take into account variance
  - a fair algorithm is going to be determined by how fairness is defined
  - there are competing notions of fairness based on competing notions of justice and maybe it's not the right thing to do restrict us to one definition of fairness
  - if we build a system that is unbiased, but it's used to do some form of discrimination, is the algorithm then considered biased?
  - we are promoting integrity and accountability at all three levels: the design, the implementation, and analysis
  - bias is an insufficient term to describe the outcomes of a system
- **Intersectionality**
  - the framework for how systems of oppression intertwine to influence experiences and opportunities
- Parking lot
  - What is the definition of success?

Big data

- there's a difference between the statistical significance and the meaning of your data
- in the discussion of variability, we need to insert confirmability and context
- power systems - precursors and predicates, big data has dependencies in terms of who has the resources and infrastructure to collect the data and analyze it, etc.;

we're taking up big data's limitations when using it

- data exhaust - data is sometimes created for a primary role and then used for a secondary role by others; not using data for its intended purpose
- variety or different sources that the data is coming from
- For big data to be considered big data, does it need to meet all five Vs?
    - big data exceeds are capacity
- the definition of big data is missing utility and how big data is a tool that people use
- including perceived validity - conflation of truth and how large data sets are considered more valid; who is allowed to express themselves?

Data bias

- in many ways all data is produced by humans; how data is collected, stored, analyzed is all determined by humans; the bias is relatively inherent
- all data is informed by human values and is embedded with human values and it might be worthwhile to distinguish between data that we deem appropriate
- inherent frustration in the phrasing and not including the human factors; when does this bias exist?
- the process through which the data is conducted; all the processes/methodology that data passes through need to be unbiased
- wisdom of how to use data sets - just because you have an unbiased analysis that leads to equity, there's also what you do and how you analyze your data and then what people do with those findings; goes back to the intentional decisions made by humans
- data bias also includes are instrumentation bias; the way we collect data and the variability that is included in that needs to be considered
- interrelated definitions between data analysis/statistical inference and potential discrimination
- there's bias and then there's noise; we don't want either, but we need to analyze things in a careful and thoughtful way when we're unable to completely eliminate bias
- we haven't talked about hypothesis versus discovery driven analyses and how that determines your approach

Algorithm/algorithmic bias

- understanding that it's not just the operations of computers and smart devices, but a human component
- the definition of algorithmic bias was fairly limited, doesn't talk about favoring, discrimination in terms of specific groups, lacks the positive bias as well
- instead of etc. in the definition make it clear that we're talking about specific demographics and include those groups
- is it possible that we'll have a biased algorithm even if we feed in an unbiased data set?
- knowing the steps the algorithm took to make its decisions, would a human make

those same conclusions and follow those same steps to know that there is a bias in the process?

- which algorithms are we including and considering in terms of algorithmic bias? obfuscation and amplification?
- need to understand what is represented and is that what we want represented and reflected in our process?
- the language that algorithms are written by people, so people need to be included as the agents of action
- rewriting the definition of algorithmic bias to say "a human constructed step by step set of operations...tasks which are then used by society"