Executive Summary

In this literature review, we present a comprehensive search on five topics requested by the National Academy of Engineering’s (NAE) Racial Justice & Equity (RJ&E) Committee:

- Increased Awareness of Racial Injustice and Inequity
- Mentoring for Minority Engineering Students and Early-Career Minority Engineers
- Nondegree Training for High-Tech Positions
- Development of Data and Relationships to Support Machine Learning Algorithms
- Efforts to Increase the Participation of Minorities in Engineering and Technology Using Place-Based Innovation Zones

1. Increased Awareness of Racial Injustice and Inequity
One charge to the RJ&E Committee is to define activities to make NAE members and the general engineering community aware of racial injustice and inequity and what engineers and engineering can do to promote equity, justice, and inclusion in the field and society more broadly. NAE members and their professional connections are a great resource and can create systematic change by spotlighting these issues and sharing ideas for change. The literature review focuses on ways to develop effective and targeted messaging to industry, academia, and the public; effective public awareness campaigns in other disciplines; and examples of best practices and potential metrics to use in tracking the impact of this outreach. The review covers literature from the social sciences (e.g., cognitive psychology, psycholinguistics, social psychology), marketing and communications research, and other relevant evidence bases.

2. Mentoring for Minority Engineering Students and Early-Career Minority Engineers
The literature review builds on the recommendations of The Science of Effective Mentoring in STEMM¹ (NASEM 2019) to help institutions develop “intentional, inclusive, and effective mentorship in all institutional contexts” (p. 7). The review should discuss the best practices of successful engineering-specific mentoring programs and define new areas for research on mentoring. Beyond the research in the NASEM report, the review should highlight any relevant research from engineering education research, position papers from industry, corporations, or government labs, or any research in other fields that has been published since 2019.

3. Nondegree Training for High-Tech Positions

¹ STEMM = science, technology, engineering, math, medicine
Income inequality between populations of color and the population at large has grown steadily in the US, impacting quality of life, upward mobility, and access to health care, education, political power, and status (Amadeo 2021). Closing the wealth gap is fundamental to enabling equal access. Engineering or computing-related jobs are among the fastest-growing and highest-paying occupations and also have low unemployment rates and high job security. Black individuals represent 12% of the US population but are underrepresented among degree holders in college majors associated with these occupations, accounting for only 8% of general engineering, 7% of mathematics, and 5% of computer engineering majors. Because many high-paying jobs in IT do not require a bachelor’s degree in engineering or computer science, companies and other organizations, including community colleges, provide short-term training that leads to high-paying jobs. The commissioned paper will review current literature on the success and challenges of using nondegree training for transitioning to high-tech positions, highlight the best practices of programs that have been shown to help nondegree-track participants secure high-tech positions, and note any long-term evaluations of programs that describe the career trajectories of those who participate.

4. Development of Data and Relationships to Support ML Algorithms
The literature review will focus on programs looking at ways to eliminate bias in key areas that affect minority engagement and the likelihood of success for individuals from historically minoritized populations. This topic is very broad and the literature review and landscape scan will determine a potential influence point for future NAE work, which might, for example, focus on college and university admissions (at both the undergraduate and graduate levels), educational recruiting and retention programs, and hiring processes. Predictive analytics are used in multiple areas, with direct impacts on racial equity in engineering. For example, econometric modeling is commonly used in college admissions to predict likely enrollment outcomes balanced against financial obligations, but it often rewards economic status rather than ability (van Giffen et al. 2022). In addition, social media analytics using demonstrated college interest as a major predictive criterion for success skew admissions toward individuals with greater computer access—the data collected and processed by games, web tracking, and ML systems convert those qualitative inputs into predicted quantitative outcomes such as enrollment and retention. These data may help explain why Black and Hispanic students are now more underrepresented at top colleges than they were 35 years ago (Ashkenas et al. 2017). Multiple software organizations are interested in using corrected data that would eliminate bias, but identification of the data to accomplish that goal will require careful consideration before the complex but perfunctory data collection processes start. Choosing the correct data and associated relationships could revolutionize education and employment. The literature review will discuss research conducted in this area and suggest ways for the RJ&E Committee to help identify better information to use in building predictive models.
5. Efforts to Increase the Participation of Minorities in Engineering and Technology Using Place-Based Innovation Zones

The innovation sector, generally limited to certain geographic areas (e.g., Silicon Valley, Boston, Seattle), has generated significant technology gains but has also helped drive growing equity gaps. Over the past decade, innovation districts have emerged as powerful vehicles for local economic development across a range of dimensions (Ailstock 2020; Andes 2019). The innovation districts identified by the Brookings Institute focus on economic development but do not explicitly leverage them to capitalize on engineers from historically minoritized populations in developing richer innovation solutions. The review will focus on existing literature on place-based innovation zones and criteria for evaluating place-based solutions for the development of a thriving minority engineering community in innovation zones near underserved communities.

Methodology

To conduct the literature review, we closely studied the scope of work and then each independently created terms to search for literature based on the committee’s five topics using Google Scholar as an initial search engine. The search terms were used to view the top ten results (e.g., the first page results) and relevant results were saved to a joint database for each topic. We repeated this process for up to 30 results (e.g., second- and third-page results) before modifying the key terms. This process was repeated for each of the topics until a minimum of 30 articles were analyzed for the literature review. Specifics (e.g., year and field) were filtered based on our assigned scope of work.

Once all initial sources were identified and placed in the database, we removed duplicate sources. Next, we prepared an annotated bibliography of the sources in the database to ensure relevancy. This review included a wide selection of data sources such as journal articles, commissioned reports, conference papers, reviews, blogs, and dissertations. Sources in languages other than English were not included. Data sources that didn’t fall within the scope were removed from the final literature review.

Topic 1: Increased Awareness of Racial Injustice and Inequity

For Topic 1, we conducted an exhaustive search using keywords such as “racial inequity AND communication” and “racial injustice AND best practices.” We combed through over 39,000 results including journal articles, blog posts, and opinion papers. The goal of Topic 1 is to highlight ways that members of the NAE and broader engineering community can create effective messaging related to racial injustice and inequity via industry, academia, and public sectors. This section discusses best practices and possible approaches to metrics that will enhance outreach efforts from different research areas. We conclude by suggesting relevant evidence bases to search. We also
discuss inconsistencies and nuances that emerged from the review and conclude with a discussion of future research and impact opportunities.

**Key terms:**

**AAPI** - Asian American and Pacific Islander

**BIPOC** - Black, Indigenous, and/or person of color; historically marginalized people/communities

**Xenophobia** - prejudice toward an individual from a different country

**Effective Messaging**

When it came to effective messaging, various tools were used across numerous domains. Overall, studies emphasized more opportunities for conversations across different mediums and identified some of the barriers when it comes to communication. Several sources mentioned the use of a framework, tool, or theory established in organizational spaces or an item influenced by the current environment.

**Academia**

Some authors used the academic context to develop items to address racial injustice and inequities (Falter & Kerkhoff 2018; Lai et al. 2014; Love 2022). All sources described faculty members as central to addressing racial injustice in academia. The initiatives and interventions highlighted in this section note faculty as participants in research efforts to develop appropriate action items.

Love (2022) evaluates three campuswide initiatives focused on underrepresented faculty members based on a content analysis of campus initiative documents and participant observations. The initiatives are focused on (i) men (regardless of race/ethnicity) as advocates and allies, (ii) nonvoting faculty members on search committees to diminish bias, and (iii) interactive theater on microaggressions. This study aimed to determine whether and how the NSF ADVANCE program\(^2\) could achieve its goals and use an intersectional framework to increase equity on campus. Best practices suggest building a team to combat systemic injustices, with a charge to define goal keywords clearly and directly; evaluate external documents and coordinate with external leaders on

\(^2\) https://www.nsf.gov/crssprgm/advance/
workshops; create institutional support for DEI efforts; attend bystander intervention training; and combat fear and uncertainty with action.

Lai et al. (2014) looked at 17 proposed interventions of faculty members to reduce implicit racial prejudice. Eight of them reduced implicit preferences for White people compared to Black people. Among Blacks, the most successful interventions involved high self-involvement and connected Black people with positive and White people with negative traits. The eight most effective interventions were (1) group boundaries shifted through competition, (2) vivid counterstereotypic scenarios, (3) an implicit association test (IAT) with counterstereotypical exemplars, (4) priming multiculturalism, (5) evaluative conditioning with the go/no-go association task (GNAT), (6) taking the IAT, (7) shifting group affiliations under threat, and (8) using implementation intentions with the most effective intervention as the vivid counterstereotypic scenario. The counterstereotypic scenario consists of participants imagining themselves in a life-or-death situation, exposed to counterstereotypical examples, and having to provide strategies to overcome bias.

Health Care
The Covid pandemic led some authors to reevaluate their practices and operations. Everyday activities and processes were commonly noted in the medical field, as first responders gained a new sense of appreciation and attention from the world around them. Ethics and cultural competence also emerged as an area of concern, especially for those from racially underrepresented groups (Chu 2022; Nakayama & Halualani 2012; Nobis & Sodeke 2020; Zackery 2021).

Nobis & Sodeke (2020) suggested implementing science as a form of bioethical and bioethics-motivated research to be collaborative, emphasizing the cultural and cross-cultural aspects that make research happen. The authors build on principles elucidated in Coleman et al. (2019)—trust, reciprocal relationships, honesty, transparency, cultural competency, colearning, and partnerships—and emphasize cultural competence as a way to build more robust communication and deepen levels of trust. Using ethics to motivate social justice helps change the language about whether to do something.

The Public Health Critical Race Praxis (PHCRP) is a framework for researchers to be more race-conscious as they generate research questions and develop interventions to address racial
inequalities (Brown et al. 2022). PHCRP focuses on contemporary patterns of racial relations, knowledge production, conceptualization and measurement, and action. Within each of these four areas are ten principles: (1) race consciousness, (2) primacy of racialization, (3) race as a social construct, (4) ordinariness, (5) structural determinism, (6) social construction of knowledge, (7) critical approaches, (8) voice, (9) disciplinary self-critique, and (10) intersectionality. The authors suggest that this tool will help medical researchers see the impacts of race and racism on clinical outcomes and the healthcare experience for racially marginalized patients, especially those in palliative and end-of-life stages.

Vince (2020) used Noel Burch’s framework to explain a possible solution to eradicate health disparities for African Americans. Burch’s four stages of adult learning are unconscious incompetence, conscious incompetence, conscious competence, and unconscious competence. Vince encourages his fellow physicians to move from conscious incompetence to conscious competence by reviewing and understanding the history of race and racism in the US, mandating antiracism training, dissecting the incorporation of race in medical practice, developing longitudinal pipelines nationwide, and implementing widespread culturally aware mentorship training.

Instead of a formal framework or theory, Staub (2021) discusses the role of communication in his reflections and journey as a doctor during the Covid crisis. He explains the need for vastly improved communication considering the sustained systemic inequities for marginalized populations (i.e., a higher proportion of Black and Hispanic people he sees in the ICU). According to the author, clear communication, especially for patient-physician interactions, will assist when it comes to bias and provide more positive outcomes for all parties involved.

Similarly, proper training is important for encouraging conversations around race. Acosta & Ackerman-Barger (2017) emphasize that faculty should have proper intensive training on how to engage, sustain, and deepen interracial dialogue on race and racism before having these types of conversations with health professionals. The authors provide a variety of examples to encourage healthy discourse as well as strategies to boost faculty member coaching on how to facilitate conversations about race, oppression, and privilege with health professionals.

The literature indicates that patient-physician communication can promote and sustain racial disparities in health care (Shen et al. 2018). The authors found that Black patients consistently have
worse communication quality, information giving, participation, and participatory decision making than White patients. There is a need for highly trained physicians who, through patient-centered and partnership-building techniques, have higher-quality communication with Black and racially discordant patients - where the physician and patient have different racial identities.

Statistically, there is a lack of racial and ethnic diversity in pharmacy, medicine, and dentistry faculty compared to the US population: dentistry (13.9%), pharmacy (8.5%), and medicine (7.1%) (Campbell et al. 2021). The astonishing fact is that five HBCUs contribute to 32.8% of Black faculty, yet they continue to have low residency match rates (Campbell et al. 2021). The authors propose that, to create a better faculty pipeline, effort should be directed at decreasing or removing barriers, advancing training, and providing more postgraduate residency and fellowship training.

In a divergence from traditional education offerings through a workshop or seminar, researchers have developed a state-of-the-art creative way to promote learning and engagement that is person-centric with positive results. Roswell et al. (2020) used a virtual reality (VR) racism simulation to increase empathy for medical school leaders, staff, and faculty. In addition to a 20-minute VR racism module, the workshop included a 60-minute interactive session on microaggressions and a 60-minute debrief session. The authors found that the simulation increased the participants’ empathy for racial minorities and heightened engagement and their desire to change their communication approaches.

**Industry/Corporate Sector**

Logan (2021) emphasizes the theory of corporate responsibility to race (CRR), suggesting that corporations should advocate for racial justice, improve race relations, and create an equitable society. CRR is a tool that can help corporations expand their conversations to include aspects of contextualizing and analyzing race in the workplace. CRR can be used to examine and improve public relations campaigns, corporate crises, and advertising campaigns and analyze leadership communication. Applied to race and social justice matters, this approach makes race the pivot point and focuses on race, the corporation, and corporate social responsibility. By illustration, CRR calls for corporations, especially those created and built on racism and racialization, to communicate how they improve race relations. Thus a corporation, directly and indirectly, acknowledges that it
has benefited from racial discrimination and oppression, which yields their company’s success and adds to racial contention.

Corporations have grown more aware of the need for racial diversity as a means of organizational growth and continuous innovation. They are discovering the necessity of developing HR policies and practices that are antiracist rather than “not racist.” These entities should seek to expand worker power and voices, design products and services centered around equitable outcomes, and consider a racially diverse consumer base when developing products and services. One study saw an organization create a blueprint to assist companies as they evaluate and assess the consequences of their products and practices on people of color (Hills et al. 2020). This study focused on internal company structure, the community impacted by the company, and the broad societal impact of the business practice.

In the community, leaders and officials can redesign corporate philanthropy to address structural problems, advocate for local and state-level policies that address structural inequities, and support environmental justice. These individuals can provide national-level public policy, lobbying, advocacy, investments, and communications that advance racial equity at the societal level. Corporate equity, particularly a corporation’s responsibility to exhibit antiracist practices as it conducts its business, has garnered international attention in recent decades.

Ananthavinavagan (2019) weighs in on what the United Nations can do to enhance African American rights in the United States and argues that the UN Human Rights Office needs to focus on decreasing racist practices that have persisted over time. The author noted areas in America’s history that have significantly prolonged racial injustices: the Civil War, Reconstruction, and the Civil Rights Movement. During these periods, people of color were physically, mentally, and socially displaced from housing, education, and community. Urban displacement is the structural exclusion and involuntary departure of BIPOC people from places of employment and upward mobility.

Following a similar idea for a paradigm shift, Lin et al. (2017) elaborate on ways to analyze the urban displacement and racial injustice crisis. They present three main arguments: (1) there is a collective self-interest in solving the displacement crisis; (2) the prevalent “build more” strategy does not sufficiently address the housing crisis, which requires specific antidisplacement measures; and (3) it is time for a paradigm shift based on an understanding that housing is an essential public
good like clean air and water and K-12 education. The increase of high-paying jobs in certain white collar industries, zoning and other measures that force people of color from their homes, lack of healthcare access, and inequitable educational resources compound this displacement. These factors push lower-income residents out of traditional neighborhoods. Lower-income neighborhoods tend to feel larger impacts of climate change and increased gas emissions. Building more is ineffective because it does not consider a long-time resident’s income level, basic living costs, unaffordable market rates, and construction costs. Lin et al. suggest steps that a state can take to shift to the mindset that housing is an essential public good, like clean air to breathe. Such a responsibility is indispensable in the fight to increase awareness of racial injustice and inequity.

**Interdisciplinary**

The topic of advancing awareness of racial injustice and inequalities endures the course of American history and traverses the ambit of all disciplines; it yields literature applicable across many domains. The articles grouped in this section were chosen because they do not emphasize one specific domain. Although some articles might specify or focus on a particular racial group, the general nature of their results is not limited to a sole domain.

As recently as 2021, research suggests that, beyond interpersonal, structural, and institutional racism, more efforts are needed to address the *intrapersonal* impacts of internalized racism (Fraser 2021). The author suggests that developing resilience to maintain a positive sense of self during a negative experience can create healthy outlets for emotions rather than suppressing them. Intergroup dialogues can create channels to work through difficult emotions. The difficulty faced extends beyond emotional spaces and requires addressing the complexity of racism for racial and ethnic groups (Acosta & Ackerman-Barger 2017; Brown et al. 2022; Jun et al. 2021; Shen et al. 2018; Vince 2020).

Girolamo et al. (2022) encourage an equitable peer review practice, noting that BIPOC authors in the communication sciences and disorders field are often systematically targeted. Journals can take an active role and lead conversations on racism and health by diversifying and supporting reviewers and editorial board members, encouraging and supporting submissions from underrepresented authors, setting internal guidelines for editorial board members and reviewers’
behavior, and prioritizing BIPOC content. The authors suggest a framework for equitable peer review. Below is a table that includes examples of actionable steps to achieve effective equity-based messaging and implementation for research journals and other communication sources.

Table 1. Adapted equitable peer review framework from Girolamo et al. (2022).

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<th>Stage of peer review</th>
<th>Description</th>
<th>Examples of actionable steps</th>
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| Process              | ● Equity-driven peer review process  
● Proactive policies and procedures  
● Accountability       | ● Include clinical, patient, and self-advocate reviewers  
● Provide coaching on equity in peer review  
● Create internal and external accountability mechanisms for bias |
| Editorial board      | ● Equity-driven selection process  
● Composition consistent with ASHA’s Strategic Vision  
● Accountability       | ● Build equity standards into EIC/editor contracts  
● Create equitable pathways to serving on editorial boards  
● Develop accountability goals for and publish data on editorial board composition |
| Content              | ● full representation of BIPOC communities  
● Representation of BIPOC authors  
● Equitable language     | ● Prioritize research from BIPOC authors  
● Prioritize research with BIPOC communities, anti-racist research, and diversity science  
● Develop accountability guidelines for equitable language |

Some researchers have discussed the value of intergroup dialogues, conversations, and theories when addressing race (Fraser 2021; Lambe et al. 2021; Laura 2022). Laura (2022) identified numerous ways to improve the connection of mindfulness with racial justice via intergroup practices. The author emphasizes an interconnectedness between intergroup research, racial
healing studies, and studies that incorporate and protect Black participants and other minoritized
groups. To use mindfulness for racial justice, there needs to be acknowledgment of the current
work on the subject, an increase in the number and quality of intergroup studies focused on using
mindfulness to address bias and discriminatory behavior, and an increase in the number and quality
of studies that have Black participants.

In the advertising literature, specifically, the marginalized consumers’ response to brand
activism, Chu (2022) suggests six areas to focus on: gender roles and minority women, racial
representation and advertising effectiveness, marginalized group–targeted advertising, media
behavior among multicultural consumers, education and industry diversity, and LGBTQ consumers.
The author also identifies areas to advance advertising research that includes (1) marginalized
consumers’ response to brand activism; (2) targeting marginalized consumers through artificial
intelligence and computational advertising; (3) diverse and ethnic influencers in social media; (4)
inclusive multicultural research, and (5) brands, advertising agencies, and scholars’ responsibilities
to consumers and society.

While there have been different mechanisms to address how communication should occur,
some scholars have looked at the flow of communication. García (2021) states that the poor flow of
information encourages the misalignment of what dominant groups believe compared to
nondominant groups. The author encourages community-based information flow, from a
speaker/institution/group to people who lack getting it otherwise. However, due to elements of
racial prejudice from community members, the flow of information and reliability can fluctuate.

Thinking further about how communication occurs, some sources cited research journals’ role
in addressing effective messaging techniques (Girolamo et al. 2022; Viswanath et al. 2022).
Viswanath et al. (2022) focus on reducing data absenteeism, which is when there are few or no
aspects of data on socially vulnerable groups. Often groups included under data absenteeism are
people from BIPOC and LGBTQ populations. Data absenteeism can be reduced by engaging key
community stakeholders and residents throughout the entire research process to ensure
appropriate questions and research designs.

One way to engage community members/stakeholders in the research design process is
community-based participatory research (CBPR). CBPR aims to build community-academic
partnerships that define the problem and partner with the community to solve a problem. The
tenets of CBPR are (1) an explicit understanding that the partnership will engage in the
coproduction of knowledge, including a shared understanding of the “problem” to be defined and
studied; (2) expertise is of different kinds and lies with both researchers and the community, and
better science emerges when both are in the alliance; (3) the kind of data and the process of data
collection are products of negotiation between the community and the researchers; and (4) the
partnership will determine how the data, once collected, will be used and how results will be
communicated back to the community. Building these partnerships requires not only that people be
treated as participants rather than subjects in research but also careful, explicit attention to the
question: Does science benefit all groups equally?

Effective Public Awareness Campaigns
Li (2022) looked at Asian Americans and explored the Covid-19 Hate Crimes Act and its
effectiveness. Much work is still needed, and inadequate progress has been made against
xenophobia. Examples of interventions include education-based approaches, community-involved
decision making, and civil rights enforcement to reduce hate crime occurrences. The inclusion of
more race-/ethnic-based education will encourage improved dialogues regarding racial empathy
toward others. Community-based solutions will help respond to harm and promote acts of
solidarity to help with suffering and promote compassion.

While there has been an emphasis on work related to African Americans or Black Americans,
the Covid pandemic brought attention to the experiences faced by Asian Americans. Researchers
have started to take a greater sense of urgency to understand their journeys (Jeung et al. 2021; Jun
et al. 2021; Lambe et al. 2021; Li 2022). Jun et al. (2021) used the situational theory of
problem-solving (STOPS) to analyze how some Asian Americans have used activism to combat Asian
biases reinforced due to Covid-19. STOPS is a predictive framework that involves a person’s
proactive and reactive responses to problematic situations through the interactions of the person’s
problem recognition, involvement recognition, constraint recognition, and situational motivation.
Activism in this context includes social media, political, and advocacy actions. The authors
emphasize that multiple racism experiences can increase critical awareness of racism, and the
actions of others, such as creating resources or toolkits to address anti-Asian racism, are beneficial. Coping resources should also be provided for people to encourage positive health and wellness.

Jeung et al. (2021) provide examples of participatory research efforts that affect social change through public policy for Asian Americans and Pacific Islanders (AAPI). Stop AAPI Hate followed the public policy process of agenda setting, policy formation, and policy advocacy. First, language was categorized, which helped include anti-Asian racism as a topic for policymakers, social media helped gather stories of victims, and policy recommendations were formed. Specific policy recommendations are (Jeung et al. 2021) “1. Implement Ethnic Studies throughout secondary school curricula to center on histories of communities of color, analyze the sources of systemic racism, and learn from movements that advocate for equity for people of color. 2. Provide anti-bullying training for teachers and administrators that would include practices of social-emotional learning. 3. Train students and adults in restorative justice practices, which can replace zero-tolerance approaches that have proven ineffective. 4. For online harassment and bullying, provide accessible and anonymous reporting sites on social media platforms. 5. Support AAPI student affinity groups and their school safety and anti-racism campaigns.”

Lambe et al. (2021) used intergroup threat theory (ITT) to counteract anti-Asian attitudes and behaviors. ITT is based on the perceptions of a realistic or symbolic threat that an individual faces from a group. Using survey data, the authors identified predictors of anti-Asian xenophobia. They found that men, especially those with lower educational levels and people with low levels of acceptance of ambiguity are more likely to act on anti-Asian bias.

Reeducation can be circumvented through preventive education that extends to all populations. Intergroup threat theory emphasizes the utility of focus groups and targeted messages that gave Asian Americans a voice throughout the pandemic. Also, the authors encouraged White women to use their privilege to change the narrative, given their varying power sources.

In education, Falter & Kerkhoff (2018) examined how teachers used a young adult novel, *All American Boys*, to discuss race and police/community relations. They report that, although several English teachers felt that the book did not allow neutrality and was too political, it did encourage students to think about racism beyond monolithic extremes. In sports, Rockhill et al. (2021) looked at the mission, vision, diversity, equity, and inclusion statements of Power 5 athletic departments.
and their universities. The institutions lack commitment to racial diversity in their mission statements and institutional culture.

**Effective Tracking**

Given the need for effective messaging and marketing, some researchers have discussed ways to track outreach efforts. Afego & Alagidede (2021) explored how US shareholders understood companies and their CEOs’ stance on racial injustice following the murder of George Floyd. The researchers determined that CEOs mostly use emotive (i.e., justice, healing, hope, equality) and empathic (i.e., pain, anger, hurt, sadness, fatigue) language—and that shareholders can earn a 2.13% return on average in three days following a statement’s distribution.

A Google search for corporate announcements that referred to George Floyd yielded 34 statements (including blog posts, video tweets, Instagram posts, and letters). Statements referencing organizational moral responsibility, philanthropic responsibility, and empathic solidarity were coded.

Another outreach effort that focused on racial disparities looked at oral cancer disparities. Watson et al. (2009) used a theory-driven media campaign to increase awareness of oral cancer among residents in Jacksonville, Florida. A series of taglines were distributed via direct mailings, billboards, bus posters, bus wrappings, and radio spots. The areas were selected based on focus group interviews with local African Americans, which proved beneficial in encouraging visibility for the targeted groups. A social media marketing model that encourages campaigns to be consumer driven was helpful in the creation of message and placement.

**Inconsistencies and Nuances**

In the literature review on Topic 1, a few concerns emerged from the data. Across the literature, there was a significant priority on finding ways to decrease the number of racial inequities.

But it is helpful to explicitly acknowledge which racial group the messaging is for. Most of the sources used for the literature review focused on African American/Black injustices compared to any other racial group. However, the few sources that focused on Asian Americans had a more comprehensive approach to addressing those racial inequities, that even went into policy
implications. This could be due to the timing and recent events related to Asian American and Pacific Islander rights. It could speak to the movement of research focused on other racial groups. Few sources acknowledged any aspect of intersectionality or further explored dimensions of ethnicity or citizenship status.

The healthcare field appears to have a greater awareness of and preventive action plans for racial injustices. We noted that several of the mechanisms described call for some form of intergroup dialogue among people with different social identities to engage in a stimulating, thought-provoking conversation. However, building a good intergroup dialogue experience without formal training can be detrimental, inflict more harm, and further solidify racial divisions.

**Suggestions**

Similar to statements expressed by Lambe et al. (2021), there is a need to encourage those with privilege to continually use their voice in avenues where marginalized populations are not involved. There also needs to be more acknowledgment of representation in these spaces. For example, Vince (2020), a Black male physician, provides examples of how he could bring his White male physician colleagues into the conversation.

We encourage further exploration of evidence surrounding intercultural and international development as well as the healthcare system. Our literature review was from a mostly Westernized viewpoint; we posit that some of the racial dynamics expressed could also be experienced by those of varying cultures outside of the United States. Thus, a more thorough search from an international standpoint would enhance understanding of the experiences of multiple races.

**Bibliography**


Topic 2: Mentoring for Minority Engineering Students and Early-Career Minority Engineers

This portion of the review builds on the recommendations of *The Science of Effective Mentoring in STEMM* (NASEM 2020, p. 7) to help institutions develop “intentional, inclusive, and effective mentorship in all institutional contexts.” We present recent examples of the best practices of successful STEMM/engineering-specific mentoring programs and define new areas for research on mentoring.

Mentorship is a professional, working alliance in which individuals work together over time to support the personal and professional growth, development, and success of the relational partners through the provision of career and psychosocial support.

(NASEM 2020, p.7)

The excerpt above provides a clear definition of mentorship and guides how we define and operationalize mentorship in this section. Where possible, we indicate when literature and new research specifically address recommendations in NASEM (2019/2020) or where studies present evidence that supports or adds nuance to findings on effective mentorship.

We highlight the most recent engineering-specific scholarship on mentoring minority students and early-career engineers. Keywords used for locating relevant material from these databases and search engines were *mentoring* (with variations; e.g., mentor, mentee, protégé), *engineer, minority, early-career, outcomes, retention, virtual*, and *STEM*. Over 249,000 results were subsequently scoped to fit the topic. The remainder of this topic is organized around the studies we reviewed that explicate or build on the findings and recommendations for effective mentoring of minorities in STEMM (NASEM 2020) or that implement and evaluate best practices for mentoring.

The results are primarily grouped into the following categories: mentoring configurations, new research areas, engineering and STEM-specific best practices, and suggestions for the committee.

**Mentoring Configurations**

Building on the NASEM (2019/2020) finding 3.5 on mentoring configurations, several works support effective mentoring across a range of structures (Hagness 2022). The blog “Mentoring Matters” explains six mentoring relationships designed to support the passage of skills, experience, and
wisdom from one person to another—one-to-one, group, peer, constellations, teams, and online—and expounds on different modes (e.g., formal, informal, and online). These mentoring configurations are described for an industry audience and purported to aid organizational leaders in building the capacity of their constituents (e.g., staff) to bolster their professional development strategically. By no means is this an exhaustive list of the different mentoring configurations, but they do demonstrate the most commonly used configurations in workplace settings.

Networks and Constellations

In more specific mentoring configurations, Hagness (2022) suggests that early-career professionals diversify their mentoring portfolio and invite professional society members to serve as mentors to minority (e.g., women) engineers. Using personal narrative, the author describes how to “create a constellation of mentors” who can provide complementary perspectives and serve in complementary mentoring roles. Briefly, a constellation of mentors includes multiple mentors selected based on categories (e.g., affinity, gender, formality, career stage). The constellation of mentors is a critical element of NASEM (2019/2020) recommendation 5.3: to support multiple mentorship structures and that mentees should develop a constellation of mentoring relationships with numerous individuals as needed. The work by Hagness (2022) addresses the need for early-career faculty to expand their professional networks and complements the findings of (Mendez et al. 2020b), who used a phenomenological study to show differences in mentoring needs of early- and mid-career BIPOC engineering faculty. While BIPOC engineering faculty at all levels sought mentorship related to tenure and promotion, the mid-career faculty were more aware of the importance of multiple mentors and mentoring networks than the early-career faculty (Mendez 2021).

Online Programs

When in-person relationships are not possible due to geographic distance or other factors such as individual disability, or natural disasters (e.g., the global Covid-19 pandemic), online mentoring models help build large numbers of STEM relationships or provide access to a wide variety of role

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3 “Types of Mentoring,” https://mentoring-matters.org/types-of-mentoring/
models and perspectives (Alhadlaq et al. 2019; Wendt et al. 2019). We present research for building and sustaining online mentoring configurations for women and ethnic minorities in STEM.

Huderson et al. (2021) describe the emergence of seven online mentoring programs in response to the disruptions in traditional methods of STEM professional engagement for Black women (we expound on these seven programs in the landscape scan). Huderson et al. identify advantages of online mentoring over in-person, including increased flexibility and management, and coordination of mentoring interactions is easier without reliance on travel or meetings. Like Munir (2020), Huderson et al. also discuss the benefits of mentoring for both mentees and Black women as mentors, reporting on psychological gains acquired through mentoring relationships.

Similarly, when in-person relationships are not possible due to underrepresentation, Wendt et al. (2019) argue for online mentoring to broaden the participation of minority women faculty in STEM. Based on evidence that race-matched connections validate and increase the success of Blacks in academia (Huderson et al. 2021), virtual or e-mentoring poses a solution to this problem.

In an in-person example, a mentoring workshop for African American women in engineering reported participants’ positive perspectives related to connecting with others, having a safe space to talk with other African American women, sharing information, brainstorming, and networking (Jackson et al. 2020). We also found examples of responsive mentoring programs and call attention to programs like the one Drankoff et al. (2021) evaluated and adopted online mentoring for their Women in Science and Engineering mentoring program in response to the Covid-19 pandemic. Responsive mentoring is person-centric and encourages numerous points of self-reflection. Not only does responsive mentoring result in success as measured by surveys and interviews with mentees, but enrollment in the program grew by 14% during the switch to an online format. These studies are direct evidence of how NASEM (2019/2020) recommendations 4 and 5, recognizing and responding to identities in mentorship and supporting multiple mentorship structures, can contribute to the successful retention of underrepresented minorities in engineering during highly stressful times.

While most of the scholarship on mentoring included in this review references formal mentoring relationships, Tuladhar et al. (2021) focus on using informal community spaces to foster mentor-mentee matching. Looking at the initiation stage of mentoring, Tuladhar et al. (2021)
recommend that race- and/or gender-based matching happen organically. Mentoring programs should consider dedicating funding and space for students and faculty of shared racial backgrounds and lived experiences to meet informally where interpersonal relationships can be fostered more naturally.

**Hybrid Programs**

Some scholars argue for hybrid or blended peer mentoring program models, which consist of coconstructed activity promoting cocurricular engagement (Alhadlaq et al. 2019; Rockinson-Szapkiw & Wendt 2020; Washington & Mondisa 2021). There is evidence that hybrid peer mentoring models enhance the experience of minority women in STEM (Alhadlaq et al. 2019; Rockinson-Szapkiw & Wendt 2020; Washington & Mondisa 2021). In alignment with NASEM (2019/2020) finding 3.4, that effective mentorship is personalized and responsive, the development of hybrid mentoring models like that of Alhadlaq et al. (2019) explores how the codesign of mentoring programs improves the effectiveness of e-mentoring as measured by participant engagement and satisfaction, in a Saudi Arabian context for women participants. Alhadlaq et al. (2019) highlight that generational factors (e.g., familiarization with technology platforms like Facebook) superseded the cultural influences of mentoring and suggest that for youths, the online model or incorporation of commonly used social/tech (i.e., social media apps) may help to facilitate and promote widespread engagement with e-mentoring. Also, Washington & Mondisa (2021) advocate for engaging activities like service learning and engineering-specific mentoring programs to increase diversity. The service learning component acted as an avenue of engagement and personal connections.

In STEM more broadly, Rockinson-Szapkiw & Wendt (2020) argue for blended peer mentoring program models (e.g., inclusive of training to increase competencies and skills, opportunities for self-reflection, and components of faculty support) for women who identify as racial or ethnic minorities in STEM. This article provides qualitative insights into effective peer mentoring across two HBCUs and explains the direct benefits of being a mentor in a peer-mentor relationship. The authors support their argument by analyzing interviews and open-ended survey responses that demonstrate the influence of peer mentoring on the mentor’s self-efficacy, career interest,
leadership and professional skills, and persistence. Specific influential elements (e.g., having influenced mentors’ beliefs, interests, skills, and behaviors) included recognition, functioning as a mentor, developing another’s orientation, engaging in sisterhood, and developing competencies. This article compares to the article from Cruz et al. (2021), who developed and examined a framework for peer-to-peer coaching for Latina/o students at an HSI; the program as described is similar to peer mentoring, but participants are matched and supported by culturally similar upperclassmen peer coaches.

In another STEM example (e.g., pharmacy) of a hybrid mentoring model, Belcher et al. (2019) describe innovative research mentoring programs that integrate one-to-one mentoring and small group learning experiences. The findings provide statistical evidence to suggest that this hybrid style of the program may result in improved recruitment and retention as measured by significant improvement in transformational leadership characteristics and research productivity among graduate school scholars from underrepresented populations who participated in the program (Belcher et al. 2019). The authors aim to inform other practitioners/organizations on practical components supporting underrepresented scientists’ participation in the profession.

These articles compare in that they combine mentoring with a cocurricular activity that requires engagement for a hybrid mentoring model. In the discussion of hybrid models, these articles also reflect additional metrics to evaluate mentoring effectiveness (e.g., improved transformational leadership characteristics and research productivity) (Belcher et al. 2019). Although not specific to engineering, the combination of mentoring and cocurricular engagement seems to be a symbiotic pairing that yields an effective mentoring configuration to address multiple aspects that contribute to broadly excluding and marginalizing underrepresented groups in STEM.

**New Research Areas**

Concerning the request for defining new areas of research on mentoring, we examined three other contemporary literature reviews on mentoring: by Mullen and Klimaitis (2021), defining mentorship across global applications; by Manesh et al. (2020), providing a critical review of women and minorities in construction and civil engineering education and industry; and (3) by Beck et al. (2021), a critical feminist meta-analysis of STEM mentoring programs. Below we briefly highlight
and describe some relevant findings that call attention to the study of mentoring quality and the role of culture in mentoring relationships.

**Culture**

Building off NASEM’s (2019/2020) effective mentoring recommendation 4: to recognize and respond to mentors’ identities, we present articles that address or investigate the influence of culture on mentoring relationships and experiences. Mullen and Klimaitis (2021) review mentoring practices globally to differentiate mentoring from other developmental relationships. Most of the work included in this review ranged from 1995 to 2019. While the scope of this review was not engineering specific, several STEM educational examples were used to illustrate different mentoring contexts for personal-professional development. The shared experience of cultural challenges in global mentoring programs provided valuable insights.

Corley et al. (2019) argue that most cultural dimensions for minority engineers are treated as demographic variables but that they represent the context for their experiences. They use conceptual research to expand the scientific and technical human capital model to more readily address various cultural dimensions (e.g., issues related to gender, race, socioeconomic status, nationality, and disciplinary culture). The research team then uses the added cultural dimension to explain issues related to science and engineering careers for underrepresented groups and to understand the career barriers of scientists and graduate students. This paper stresses that the interactions among cultural attributes are essential for minority experiences, and various cultural exchanges are necessary for the socialization and ultimate career success of scientists and engineers in this generation.

Collins et al. (2020) investigate “the personal journey from STEM-Practitioner to STEM-educator” of four women of color and mention new approaches for establishing culturally responsive aspects to mentoring (e.g., vertical style mentoring with service learning) that stymie stereotype threat and imposter syndrome among minority women in STEM. The study calls for more research into identifying which activities reduce the consequences of “the chilly climate.” This is another example of how mentoring programs can use hybrid models, where extracurricular activities are used to promote engagement in the mentoring process.
Culturally relevant mentoring is also evident at the K-12 level. Kier and Johnson (2021) describe some university K-12 outreach that promotes collaboration of middle school teachers and undergraduate minority STEM mentors to bring culturally relevant STEM education to middle school students.

**Quality**

In their review of global mentoring practices, Mullen and Klimaitis (2021) note a trend in research on mentoring quality, which refers to the relationship quality for mentees and whether they find it affirming. The emphasis on quality arises from mentoring theorists who identify interaction quality as the primary factor for mentoring effectiveness.

In response to NASEM (2019/2020) recommendation 7, to mitigate negative mentorship experiences, we review the latest work investigating mentoring relationship quality from multiple perspectives (e.g., undergraduate, graduate, faculty) and present best practices to evaluate negative mentoring experiences. Given the purported mutually beneficial dynamic that is part of the operational definition for mentorship, negative experiences are considered “ineffective” or constitute inadequate mentoring. The negative consequences of bad mentoring, most notably for the mentee, are to their self-esteem and mediates their work satisfaction, initiative (agency), and physical withdrawal from work (Bozeman & Jung 2020; Tuma et al. 2021). A mentor’s lack of technical and/or interpersonal expertise, lack of interest, or behavior that conveys ill intent are other factors that make for a bad mentor-mentee relationship.

**Undergraduate.** At the undergraduate level, we found research on engineering-specific mentoring that includes the voices of underrepresented students and their thoughts on what makes a mentoring relationship successful (Armendariz 2022). The researcher team uses phenomenological methods to understand what underrepresented engineering students consider their ideal mentors. The purpose of this work is to enable the design of mentoring programs where minorities’ feedback is taken into consideration. The author suggests that for minority students, factors important for mentoring relationships include the value of autonomy, occupational
experience, and consistent communication. For minority students, mentors are less sought after based solely on gender/ethnic homogeneity in mentorship.

Zackery (2021) investigates whether same-race or culturally competent mentors make for better mentor experiences for racial and ethnic minority STEM students. Effects of different mentor-mentee matching criteria were measured using mentee self-concept scales, cultural congruity scales, and the diversity subscale of mentoring competency. While mentees with same-race mentors reported higher self-efficacy, minority STEM students can also have similarly positive mentoring experiences when their mentor is competent in handling diversity (Zackery 2021).

**Graduate Students.** Bouhrira & Cruz (2021) conducted a literature review to unveil four factors that impact the successful experience of BIPOC students in engineering PhD programs. They employed a systems framework to identify four themes: the advisor-advisee relationship, student’s experience, academic support, and faculty-student interaction. Peer mentoring appeared in relation to academic support, and faculty-student mentoring also appeared in relation to faculty-student interaction, where research mentoring and mentorship for the academic career trajectory were explicitly highlighted. For BIPOC students, mentors from marginalized backgrounds were necessary for their motivation and catalyzed their success.

Chakraverty (2019) researched the imposter phenomenon, primarily as it manifests during the STEM doctoral education pursuit for minority students. Using 120 open-ended questions, survey participants described an occasion when they felt like an imposter to provide a one-time snapshot of a memory related to imposter feelings. Because the imposter syndrome phenomenon in STEM is shaped by race and gender (Chakraverty 2019), mentoring scholarship should identify what role mentoring can play in mediating the imposter phenomenon among underrepresented minority STEM students and practitioners. This article relates to Bourhrira & Cruz (2021) in that they both suggest that positive mentoring is an effective practice for mitigating the chilly climate.

**Professional.** At the professional level, Olson and Nayar-Bhalerao (2021) interrogate STEM faculty members and their perceptions of mentoring. They suggest perceptions of being a mentor shape the mentoring relationship (e.g., quality of experience) and impact mentoring-related outcomes for students. Using an exploratory case study and semistructured interviews, math and
computer science faculty discussed their views on mentoring to describe four dimensions of mentoring: settings where it occurs, the tasks of mentoring, skills for mentoring others, and what’s involved in inhabiting the identity of a mentor. This article aimed to explore STEM faculty perceptions of mentoring undergraduate STEM students. Although not exclusive to engineering, this STEM-focused study was included because it provided an exploration into the subjective view of faculty as mentor. Because mentoring is operationalized as a mutually beneficial relationship, more research should investigate how faculty perceptions of being a mentor impact the purported benefits of being a mentor.

Typically the consequences of mentoring are examined from the perspective of the mentee. Carson et al. (2019) provide a glimpse into the effects of mentoring for mentors from underrepresented groups. They assert that diversity and inclusion initiatives (e.g., mentoring) often place an additional service burden on minoritized faculty. Institutional service is problematic when it is disproportionate to the scholarly output required to advance in one’s career and obtain objective career success (e.g., tenure, promotion) (Carson et al. 2019). Often called a “minority tax,” the expectation is to be available to serve as role models and mentors for BIPOC students above and beyond their White peers. Early-career faculty from underrepresented minority groups are particularly vulnerable due to a supply-demand mismatch (Carson et al. 2019). They offer practical advice to other minoritized faculty on evaluating the appropriateness of service requests and declining those deemed not a good fit. The secondary aim of this article is to provide recommendations to institutional leaders to prevent early-career faculty from becoming overburdened with service.

With respect to the quality of mentorship experiences, there is disagreement on what makes for the most effective mentor-mentee pairing strategies. Work shows that mentoring relationships are more effective with alignment across work styles (predominantly), as well as personality and values (Bozeman & Jung 2020; King & Upadhyay 2022). However, much of the mentoring of minorities in engineering is based on the alignment of any combination of race, gender, or disciplinary specialty. One study looked at a South African context to see how examples of engineering-specific mentoring play out internationally when mentor-mentee matches are based on race and gender. Samuel et al. (2019) investigate the strategic career development of Black engineering graduates from a
An engineering mentoring program included partnerships with two companies, and each used different criteria for pair matching mentor-mentees (Samuel et al. 2019). One company had a separate committee responsible for assigning mentors based on an engineering specialty, while the other assigned mentor-mentee pairings based on race and gender. The company that assigned mentor-mentees based on race and gender experienced challenges with mentors showing reluctance to mentor gay mentees on the grounds of religious and moral conviction, as well as allegations from Black mentors that White mentor counterparts were sabotaging the graduate development program by not engaging with the mentees at work, thus jeopardizing their practical skills transfer.

Last, for the studies that focus on the quality of mentoring at the professional level, we return to the study by Collins et al. (2020), which examined the consequences of stereotype threat and imposter syndrome for STEM professionals. Collins et al. (2020) call for deliberate STEM identity development and STEM mentoring to reduce the harmful effects of the “chilly environment” for minority women. The authors support their argument with four ethnographic narratives about the STEM journey of women of color and share the results of a pilot intervention (i.e., vertical mentoring and service-learning best practices) designed to address the negative consequences experienced by women in male-dominated STEM fields. The authors’ purpose is to both point out the barriers to participation for women of color in the engineering workforce while also offering solutions to reduce the impact of these barriers so that broadening participation efforts can be more effective; it is another example of hybrid mentoring models (Collins et al. 2020).

**Conceptualizing Negative Mentoring**

As mentioned earlier, the idea of mentorship quality and negative versus positive mentoring is a newer concept in mentoring research. There are nuanced areas related to quality that need further investigation. While mentoring is typically seen as a method to reinforce STEM identity
development, for graduate students the wrong mentor can perpetuate imposter feelings (Chakraverty 2019).

Researchers leveraged an ecological systems framework to characterize the negative experiences of doctoral engineering students (Tuma et al. 2021). This article provides a direct application of recommendations 7 and 9 from the NASEM (2019/2020) report, which state that effective mentoring should mitigate negative mentoring experiences as well as advance theories of mentorship in STEMM. Tuma et al. (2021) argue that there is a knowledge gap regarding factors/elements of problematic mentoring experiences and their detrimental impacts on graduate student outcomes. The authors use exploratory interviews of 40 life science doctoral students to define and characterize negative mentoring experiences linked to challenges they faced. Using an ecological systems conceptual model, authors interpreted the variables influencing students’ negative mentoring experiences at multiple levels (e.g., ontogenic - stemming from a problematic mentor, dyadic- emanating from a dysfunctional relationship, micro - stemming from the research environment, and macro - stemming from values, norms, and beliefs that impact mentoring) that shape their overall development. Similarly to Carson et al. (2019), this study touches on the demands and consequences of mentoring when the mentor-mentee relationship is not well aligned in either a complementary or supplementary way. Figure 1, adapted from Tuma et al. (2021), illustrates the framework of the ecosystem that several scholars have referenced when examining the impacts of mentoring quality holistically (Bouhrira & Cruz 2021; Mendez 2021; Mondisa et al. 2021; Tuma et al. 2021).
In another study that sought to evaluate the impacts of negative mentoring, Bozeman & Jung (2020) argue that scholarship on the quality of mentoring as it relates to career outcomes is scant. The authors provide a comparison among three groups: employees with a good mentor, a lousy mentor, and no mentor. Although not engineering specific, this study finds that for more than 3,000 respondents, those with a mentor, even a bad one, enjoy the benefits of mentorship. Specific findings by Bozeman & Jung (2020) show that the quality of the mentoring experience influences job satisfaction more, while the mere presence of a mentor is important for mentees’ salary satisfaction. These findings help to contextualize what a mentee might evaluate as a “bad” mentoring experience. This article supports the notion that mentoring tends to have a net benefit for mentees as it relates to career outcomes. A key finding of interest is that the influence of the sector on differences in mentoring affects career outcomes: Mentoring in the public sector was beneficial for mentee job satisfaction, and in the private sector was related to career advancement benefits. The sector’s impact on mentoring effectiveness is exciting and should be considered for future workplace studies examining mentoring in engineering contexts.
Best Practices

In this section, we present studies on mentorship in engineering that reveal best practices and support the benefits of mentoring for various personal and professional outcomes. These studies are examples of developing and sustaining intentional, inclusive, and effective mentoring programs for minorities in engineering education and early-career workers. Among the engineering-specific models, there appears to be a trend toward using ecosystems when framing and characterizing the unmet educational and professional development needs of historically underrepresented engineers.

Not only has the ecosystem framing been used to investigate sources of negative mentoring experiences (Tuma et al. 2021), other researchers suggest that engineering adopt mentoring using an ecosystem approach for mentoring African American women in academic engineering (Jackson et al. 2020). Best practices also suggest that the engineering programs should foster the development of more mentoring communities for African American women and more evidence of the benefits of mentoring to the mentor (Jackson et al. 2020). Jackson et al. (2020) support the claim that mentoring should be factored into tenure and promotion decisions.

Undergraduate Mentoring

Best practices for undergraduate engineering students focus on applying frameworks and theories to explore the unknown benefits of mentoring for minority engineering students.

Mondisa & Adams (2022) adopted a learning partnerships perspective to examine how mentors help their mentees develop self-authorship. They suggest a new way to frame the mentoring practice using the learning partnerships model to understand the role of mentorship in the development of African American STEM undergraduates. Using thematic analysis of semistructured interviews according to the learning partnerships model, the authors revealed four major themes to describe the techniques mentors use to support mentee development: (1) coconstruct self-authorship strategies with mentees; (2) work with mentees to help them learn how to build persistence; (3) want mentees to recognize their strengths to exude confidence; and (4) learn about their African American mentees’ experiences. This article is related to Collins et al. (2022) in that the mentoring relationship is a mediator for influencing mentee self-concept more positively. Ogle
et al. (2020) contribute to the development of inclusive engineers by incorporating principles of equity and including them with their BIPOC peer mentor training.

Given that peer mentoring can positively impact students’ perceptions of their future professional selves, instilling principles of equity at the outset of engineering education can promote the development of professional engineers who value inclusivity. Ogle et al. (2020) evaluate how mentoring affects students’ satisfaction with the program experience (i.e., transition, belonging, and academic success) and their intent to stay in their major. An effective program supports students through a key transition point, from general engineering to their engineering major; peer mentoring offers one-on-one guidance and contributes to the engineering community. These findings shed light on the benefits (e.g., identity affirming and impact having) of peer-to-peer mentoring.

McGee et al. (2022) explore the narratives of 39 Black faculty members in engineering and computing, guided by the equity ethic framework to understand their motivations to reduce racial inequities in their fields. Findings indicate that Black faculty help broaden participation by offering supportive antideficit teaching and mentoring to Black students during critical academic junctures, fortifying and enriching the mentee’s engineering experience (McGee et al. 2022).

Our review included scholarship on STEM-specific mentoring as well. Atkins et al. (2020) explore identity development through mentoring, a concept that is critical to long-term retention in the engineering field. A qualitative analysis of 24 interviews shows that having a research mentor bolstered students’ science identity. Research-mentored students described mentors as colleagues who gave them opportunities to grow and as examples to look up to. Students valued mentors with whom they identified based on demographic similarity or shared values, as well as those who challenged them in their academic and research endeavors. Other examples of alternative theories or frameworks to design and assess STEM-specific mentoring programs can be further explored in the work of Cruz et al. (2021), who use a peer coaching framework for the development of first-year Latina/o student persistence in pursuing STEM pathways at a Hispanic Serving Institution. Additionally, Kloos & Furterer (2019) and Hart et al. (2020) apply lean six sigma methods and tools to design an undergraduate engineering mentoring program to enhance gender diversity. Each of
these frameworks provides another example of how to design intentional mentoring practices based on specific program goals.

**Faculty Mentoring**

There are two distinct categories concerning the mentoring literature at the faculty level. One stream of research investigates mentoring best practices for faculty development (i.e., faculty as mentee), and the other centers around examples and evaluations of effective mentoring (i.e., faculty as mentor). We present examples of best practices from both streams of research.

In faculty development, several studies leverage mentoring programs for early-career minorities in engineering. For example, Cutright et al. (2020) present an evaluation of a 3-year cohort model for professional development to support BIPOC faculty development to tenure track positions. Mentoring relationships were assessed qualitatively based on reflective journaling of mentees and mentor logs about meeting dates and topics. During the job search process, the mentoring activity was instrumental in helping fellows secure academic positions through specific feedback on application packages, negotiation strategies, start-up packages, and deciding between multiple offers. After program completion, fellows continue to participate in the mentoring; this finding warrants more studies on the final stage in the mentoring process, when the mentoring relationship shifts to form mentoring networks (Jackson et al. 2020).

Bhopal (2020) examines the effects of a mentoring program on the career progression of Black and minority ethnics in academia in the United Kingdom, based on 37 interviews with minority academics. This study aims to see how minorities experience career progression in the UK to see whether their policies and procedures similarly follow equality and diversity. This paper is one of the only ones discussing how policy mandates alone do not beget broad, sweeping changes in adopting intentional mentoring practices for minorities.

Recent scholarship on faculty mentoring for engineering and STEM student development adopts a systems approach. Looking broadly, Mondisa et al. (2021) have developed an ecosystem framework to support the implementation and evaluation of mentoring in STEM to address racial and gender disparities in engineering systemically. They specifically use the framework to examine and critique the first stage of mentoring, the preparation phase pertaining to the qualifications of faculty, students, and administrators as mentors. The framework is also helpful in identifying who
and where the ecological stewards are and the implications for systems change (Mondisa et al. 2021).

Mendez et al. (2020a) investigate the use of chatbots as a tool for faculty to supplement their mentoring of doctoral engineering students. Chatbots can, for example, provide career advice with responses from a programmed database populated by renowned emeriti engineering faculty. These chatbot tools were developed under the National Science Foundation INCLUDES Design and Developments Launch Pilot award (17-4458) and are intended to fulfill a myriad of roles, such as undergraduate student advising (Mendez et al. 2020a). Using a qualitative phenomenological approach, this study considers novel ways to leverage technology to offer supplemental mentoring for underrepresented minority doctoral engineering students.

Mirabelli et al. (2020) claim that mentoring relationships formed among experts from different disciplinary domains present a different mentoring context and require unique training when compared to graduate student training or peer mentorship in the same discipline. This work aims to identify salient factors related to successful outcomes of mentoring relationships among traditional engineering faculty (mentees in this context) and engineering education faculty (mentors in this context) to understand the challenges participants encountered when doing engineering education research on the formation of engineers. The findings indicate that mentoring structure and configuration discrepancies across participants created the most challenges. Key factors were identified and included the proximity of researchers (e.g., same or different institution), the style of mentorship preferred by mentor and mentee, the ability of mentees to network, and the academic rank of the mentor and mentee.

**Industry Mentoring**

Looking at international examples of engineering mentoring in the workplace, Munir (2020) suggests a culturally relevant framing for the widespread adoption of intentional mentoring. The author argues for the cultivation of an ethos for mentor engineers rooted in the shared cultural concept of *ubuntu*, an African philosophy that acknowledges that one's humanity is interlinked with the dignity and humanity of others. Ubuntu might be illustrated by forgoing one's interests for the benefit of people around you while growing together as a community. The development of joint ethos may be a unifying first step.
An international, STEM-specific industry example of mentoring is reported by Blaique et al. (2022), where mentoring and coping self-efficacy predict occupational commitment for women. The population for this study was women working in STEM in the Middle East and northern Africa. Occupational commitment and engineering turnover are suitable variables for persistence in engineering careers. This article links mentoring with occupational commitment (indirectly), but mentoring still influences key variables that predict persistence in women engineers.

Inconsistencies and Nuances

The review of scholarship on engineering and STEM-specific mentoring reveals that measuring the impact of mentoring is complicated because the multitude of purported “benefits” each require different assessments. Mentoring has been shown to contribute positively to new skills, career advancement, work commitment, job satisfaction, salary gains, self-efficacy, and/or social self-concept. It can also mediate the negative (e.g., marginalizing) educational and personal experiences that BIPOC students and early-career engineers typically encounter along the engineering education to workforce continuum. While there is consensus that mentoring is generally a beneficial intervention, more work is needed to provide nuance into what elements make for positive end result versus a positive experiences.

Another inconsistency we noted was that mentoring is purported to have four stages. However, none of the anecdotal or empirical evidence points to the process involved with closure or redirection of mentoring relations at program culmination or student graduation. Work by Jackson et al. (2020) implies that mentees begin establishing or growing their mentor networks at the end of mentoring programs.

Suggestions for the Committee

Based on our synthesis of the reviews and research on mentoring, we offer suggestions for future areas of research related to mentoring for BIPOC engineers.

The recent scholarship trend to investigate mentoring quality helps to characterize the components of a dysfunctional mentoring relationship (Bozeman & Jung 2020; Tuma et al. 2021). We suggest more research to investigate factors related to negative perceptions of being a mentor.
Are faculty with negative perceptions about mentoring more junior or preoccupied with tenure? Are these faculty less satisfied in their objective or subjective careers? Which factors positively contribute to developing a mentor identity for faculty? Is being a mentor an effective practice for combating/reversing imposter syndrome in minority engineering professionals?

More research should be conducted on the latent stages of the mentoring process so that the long-term effects of mentoring are appropriately contextualized. Finding 3.3 in the 2019/2020 NASEM report states that mentoring evolves through different stages: initiation, cultivation, separation, and redefinition. As we showed in this review, only the first stage, initiation, is covered in the literature (i.e., methods for mentor-mentee pair matching). We suggest examining all stages to determine if there is an ideal temporal component to any of the phases that mediate mentoring outcomes. Specifically, is there an ideal length of time a mentee should spend in the first or second phase (e.g., initiation, cultivation), when selecting a mentor and building that relationship, to achieve maximum effectiveness?

Concerning stages of the mentoring relationship, we noted a lack of discussion on the final phase of mentoring from almost all literature sources. There is no formal recognition of the mentorship relationship ending; it is presumed to end at the end of a program. However, research on mentoring among African American women in engineering suggests that they are eager and willing to form long-term relationships with mentors, as in mentoring networks, at the culmination of their formal mentoring program (Jackson et al. 2020).

References


Given the exponential rise in engineering and tech-related jobs and the added benefits of high pay and job security, there has been a surge of people interested in pursuing these careers. However, since most of these careers do not require a bachelor’s degree, people have started using other means to educate themselves on related topics. This section focuses on nondegree training for those transitioning to high-tech positions, including their motivations and challenges. We also discuss inconsistencies and nuances that emerged from our review and end with a discussion of future research and impact opportunities.

An extensive search yielded over 1,060,000 results using search terms that included “tech bootcamps AND outcomes,” “non-degree AND high-tech,” “coding bootcamps job placement success,” “non-tech jobs in tech,” “minorities participation tech engineering,” “non-degree training and job positions,” and “non-degree training and high pay jobs.”

Because quite a few terms are used interchangeably concerning nondegree training options we use the first portion of this section to define commonly used words. Lee & Rodríguez-Pose (2016, p.
9) observe that, although there is no single agreed-upon definition for high-tech, the following characteristics are suggested by the US Bureau of Labor and Statistics: (1) sectors with a high share of scientists, engineers, and technicians in the workforce; (2) high employment in research and development; (3) sectors that produce high-tech products; or (4) those using high-tech production methods.

We also included literature that refers to nondegree training as noncredential. According to Albert (2019), there are five key types of training or noncredential training: certificates, certifications, licenses, apprenticeships, and bootcamps.

We present nondegree training terms and examples before going into the successes and challenges of using nondegree training, including best practices.

**Key Terms**

**Badges (or learning badges):** Certificates or indicators of an accomplishment, skill, or quality learned through a digital learning environment that an educational institution has endorsed (Rosendale 2016)

**Bootcamp (generic):** intensive, short-term training programs designed to equip participants with employment-ready skills for entry-level tech positions (Kwon et al. 2020)

**Bootcamp +:** An extended training approach (1-2 years) that equips participants with a broad range of sustainable income-generating skills in addition to coding competency (Kwon et al. 2020)

**Coding bootcamp:** traditional approach, intensive 12-24 weeks full- or part-time skills training to prepare people for employment (Kwon et al. 2020)

**Credential:** a formal document such as a degree, diploma, or technical certificate conferred by an educational institution indicating completion of a particular course or study and examination (Rosendale 2016)

**Early education:** includes workshops, hackathons, and online platforms not necessarily focused on employability in the short term (Kwon et al. 2020)

**High-tech:** describes positions that use technology or skills that must be constantly updated or are considered the standard for only a few years
Massive open online course (MOOC): a course of study with fixed start and end dates taken by large numbers of people (usually tens of thousands per course) via the internet using free or low-cost educational resources provided by an instructor with affiliation to a college or university (Rosendale 2016)

Microcredential: sometimes referred to as a nanodegree; an online educational program of 6-12 months, combining both individual courses and skill-based projects that focus on skills for a specific job or competency (Kwon et al. 2020)

Mini-bootcamp: very short-term training programs ranging from days to 1 month, designed to spark interest in learning the basics of programming, recruit talent, or update professional skills (Kwon et al. 2020)

Nondegree program: postsecondary training and education program that is most often shorter in duration than a bachelor’s or associate’s degree program; it generally provides work-based learning or educational instruction to individuals beyond the typical age for secondary education to prepare them for a particular occupation (Dortch et al. 2020)

Success of Nondegree Training Programs

Several recent studies highlighted the benefits of women-tailored nondegree training, which created inclusive and positive environments for women (Albert 2019; Schnell 2019). For bootcamps that enroll only women, there tends to be a decrease in gender stereotypes and an increase in more sustained engagement through interactions among the participants and instructors (Albert 2019). And the women who participated had higher job placements despite pandemic disruptions in the workplace. Schnell (2019) looked further into the experiences of women who participated in computing bootcamps and found three stages of their experience: from “I can’t code” to “I may code”; from “I’m on another path” to “I want to code”; and from “I can code” to “I do code.”

Work by Lyon & Green (2020, 2021) suggests that bootcamps are an alternative pathway into computing professions for women who have a college degree and have developed an interest in coding. These nontraditional training grounds are said to attract a higher proportion of women. However, researchers continue to investigate why women choose bootcamps and their pathways to the workforce. The authors report that women who develop a later interest are “career changers
that create an interest in software development too late to major in CS, discovering a post-college enjoyment of programming undertaken to support work goals at a current job or an aspirational job” (Lyon & Greene 2020, p. 26).

High-tech industries offer higher wages, compared to other types of jobs, for nondegreed workers (Lee & Rodríguez-Pose 2016), but this potentially increases inequality in the surrounding community and does little to reduce poverty. The relationship between high-tech industries and the community is a delicate balance. Wage increases are intended to support the use of nondegree programs to close the racial income gap. However, increased wages are out of reach for those experiencing varying poverty levels, given the few job opportunities available for an entry-level position with limited experience. Other elements of Lee and Rodríguez-Pose’s (2016) discussion of the implications of wages on the local community are expressed in our research on the fifth topic of this literature review, place-based innovation zones.

Bootcamps appeared to be among the most successful types of nondegree training for job placement. They present an opportunity to close the wage gap, although there are differences based on program intensity, duration, and delivery method (Joshi 2019; Williams et al. 2021). While most focus on the potential salary outcomes of participating in a bootcamp, the way material is delivered is important to ensure learning and retention. Williams et al. (2021) present five evaluation activities for bootcamps: analysis of management information collected by providers, to track individuals from application through enrollment and outcomes (e.g., employment and salary); qualitative case studies; survey of learners; qualitative interviews with learners; and feasibility studies (e.g., a randomized controlled trial to evaluate the impact of bootcamps). While these nondegree programs were not exclusively focused on upskilling workers for high-tech positions, they provide a model for delivery and evaluation that could be useful.

Bootcamps also have varying salary implications. Of program graduates, 80% have jobs requiring technical skills learned in the bootcamp (Eggleston 2018). The most common job title of bootcampers (31%) is software engineer; other titles contain the term developer. When bootcamp graduates move to their second and third jobs, their salary typically increases by 18% for each new job (Eggleston 2018, 2020). The demographics of average bootcamp goers are a bachelor’s degree and career experience in nontechnical fields. While evidence points to bootcamps as a fast-track
vehicle to higher income in a high-tech position, bootcamps may not be as reliable for participants with less than a four-year degree (Eggleston 2018, 2020). However, bachelor’s degrees importance for high-paying, high-tech positions is showing signs of decreasing. Before 2017, most (78%) bootcampers had at least a bachelor’s degree; this number dropped to 74% in 2020. Participants with no college degree earn an average of $62,000 after completing nondegree training and can expect a 77% salary increase.

Joshi (2019) used regression analysis and LinkedIn to evaluate bootcamp graduates’ technical job placement. Chances of success in obtaining a future tech role significantly and positively increased, but the experience was unhelpful for participants with a technical 4-year degree.

Eggleston (2018, 2020), in the annual Course Report for coding bootcamps, provides comparisons among graduate outcomes and demographics across schools in the coding bootcamp industry. There are steady salary increases when comparing the prepandemic results (2018) with the most recent nondegree program outcomes (2020). Where alumni reported an increase in a median salary of $12,000 in 2018 (e.g., a 49% salary raise after completing bootcamp), that number rose to $25,000—an overall 56% increase in salary for bootcamp graduates. The demographic makeup of graduates in 2018 showed an upward trend in the percentage of African American boot campers (Eggleston 2018, 2020).

Before the pandemic, 41 coding bootcamps were included in Course Report’s annual evaluation. Graduates working in California earned the highest average salaries ($101,649), but those in Utah were most likely to be employed (92%). Additionally, graduates who learned Ruby on Rails reported the highest salaries ($76,150). With the advent of the work-from-home culture shift, the 2020 coding bootcamp outcomes and demographics provide a good comparison of how the landscape has changed. The report includes alumni responses from 101 coding schools.

A valuable organization for providing evaluations is the National Skills Coalition (NSC), which regularly scans and posts blog updates about states’ workforce development policies. The NSC “fights for a National Commitment to inclusive, high-quality skills training so that more people have access to a better life.”4 To better understand how states measure the attainment of nondegree credentials, the NSC conducted the first-ever 50-state scan of states. It surveyed representatives of

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4 https://nationalskilliscoalition.org/about/
postsecondary agencies, workforce agencies, higher education systems, or longitudinal data systems in all 50 states and the District of Columbia (Vilsack 2021).

**Career Trajectories of Participants**

Limited studies have looked at the longitudinal career outcomes of nondegree program graduates. Schnell (2019) argues that bootcamps often serve as a reentry point for women who felt pushed out of computing in their youth but decided to “come back.” This qualitative study used interview data with women graduates of coding bootcamps or accelerated programs that teach beginner to intermediate levels of digital skills. The work explores how and why women enter computing later in life, with most having nontechnical degrees and careers. Aramburu et al. (2021) analyzed a women-focused computer programming bootcamp in Latin countries. The authors posit that bootcamps are extremely useful as they provide coding skills training in a world where coding is often sought by the IT sector. Focusing the training on women can increase access opportunities for them. The women who participated in the bootcamps were better positioned to have a job post-Covid (Aramburu et al. 2021).

Bootcamp program outcomes are based on graduates in full-time positions as well as those who are doing freelance work or self-employed (Eggleston 2018, 2020). It takes program participants 1-6 months to find jobs after graduating, and they are more likely to work full-time. Some 13% of bootcampers are placed in a position before graduation, and 8% within six months.

**Challenges of Using Nondegree Training**

There are particular challenges associated with nondegree training, especially for marginalized populations. Racial and gender inequity is a prominent concern for access and outcomes (Albert 2019). For example, some public sectors cannot support certifications and licenses, and some certification agencies do not have need- or merit-based financial assistance for applicants. The value of credentials and the ability to collect data is useful for long-term assessments and linking credentials with other credentials. Also, since the government does not require a certification agency to register under any domain, there is minimal tracking nationally.
An NSC report, prepared with input from its Racial Equity National Advisory Panel, advocates for disaggregated demographic characteristics of state workforce data to include both degree and nondegree credential attainment, including industry certifications, badges, and certificates resulting from for-credit and noncredit programs, licenses, and registered and nonregistered apprenticeship certificates (Johnson et al. 2019). The report encourages stakeholders to identify which nondegree credentials are of most value regarding racial inequities. Compared with other research, Johnson et al. (2019) call on the federal government to have a more significant role from a policy perspective in ensuring quality for short-term credentials.

Lee and Rodríguez-Pose (2016) argue that high-tech industries help urban economies thrive even as they promote poverty and social exclusion. Their study, using data collected in 2005–11, investigated relationships between employment in high-tech sectors, poverty, and the labor market for nondegree-educated workers. The results showed no discernible impact of the presence of high-technology industries on poverty (Lee and Rodríguez-Pose 2016).

Funding poses a challenge for many as nondegree training often lends itself only to participants who have enough funds to pay for access to such training. Some companies pay, partially or entirely, for an employee to participate in nondegree training, but this is often on a case-by-case basis. Funding remains a significant barrier to AI workforce training for underrepresented students (Gehlhaus & Koslosky 2022).

There is a push to encourage antideficit perspectives on the value of nondegree training resources. Columbus (2019) argues that (i) regular measures of educational attainment are not a reliable measure of credential and skill attainment; (ii) over a third of working-class adults, or wage earners, aged 25-64 have a high school degree, but no bachelor’s degree and hold a nondegree credential; and (iii) nondegree credential programs can be a valuable supplement to postsecondary degrees instead of being viewed solely as an alternative to such degrees.

To help change the narrative, states need accurate data about nondegree credential attainment (Leventoff 2018; Vilsack 2021). In 2018 some 30 states began developing lists of “credentials of value” to measure progress in educational attainment to improve the accuracy of workforce data and analysis. These lists can help states identify quality credentials to administer financial aid, workforce development, or other programs.
To encourage the sustainability of nondegree credential training, Kwon et al. (2020) argue the need for policies that catalyze and use coding boot camps to address the shortage of skilled labor in high-tech industries in Israel. The authors summarize the four main conceptualized models for bootcamps (or nondegree programs) that dominate the market (in Africa, Asia, Latin America, the US, and Europe) as reviewed by the International Telecommunications Union: ready-to-work, bootcamp +, “minibootcamp,” and early education.

**Stakeholder Buy-in**

As briefly explained above, there are many challenges with utilizing nondegree credential training. Some scholars have pointed out the misalignment between the values of the nondegree training participants and their employers. Anyidoho (2020) examines the relative strengths of human capital theory and credentialism in explaining the importance that young people continue to place on higher education in light of diminishing employment opportunities for graduates. Students value the credentials, and employers value the skills obtained from the training. Yet findings reveal that students lack practical knowledge or struggle with how to apply their knowledge once in the labor market.

Similarly, there have been reports of a misalignment of perceptions of MOOCs. Rosendale (2016) observes that most hiring managers prefer to see candidates who have received traditional postsecondary education and credentialing forms (this article also provides useful definitions and terms). The managers are suspicious of professional skills (e.g., communication skills) learned through the MOOCs learning environment, which relies on connectivism and peer-to-peer engagement. Unfortunately, these courses can be rampant with plagiarism and poor peer-to-peer learning and engagement support. Despite the benefits offered through participation in nondegree credential training, there is a growing body of evidence that the skills learned are not universal.

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5 “Connectivism is a relatively new learning theory that suggests students should combine thoughts, theories, and general information in a useful manner. It accepts that technology is a major part of the learning process and that our constant connectedness gives us opportunities to make choices about our learning” (https://www.wgu.edu/blog/connectivism-learning-theory2105.html).
Inconsistencies and Nuances

While this topical literature search was not exhaustive, a number of articles emphasized the benefits of nondegree training (especially bootcamp) outcomes for women (Cheryan et al. 2013; Kwon et al. 2020; Lyon & Green 2020, 2021; Schnell 2019; Skrentny & Lewis 2022; Weidman et al. 1988; Weidman & White 1985). In 2018 Course Report found across the bootcamp industry that women experienced more dramatic salary growth after graduating and reported higher average salaries than men who did not have such nondegree training (Eggleston 2018). Outcomes were also stratified across demographic variables for lower socioeconomic status and race/ethnicity, but in term of gains or other positive changes in workforce participation, women generally benefit most. While low-income students see a lower average postbootcamp salary than middle- and high-income students, they see a considerable boost in salary after graduation (128%) (Eggleston 2018).

Regarding gender and career, the literature showed an inconsistency regarding women’s entry into the high-tech/engineering professions. Schnell (2019) found contrasting evidence of women entering the computing workforce for better pay and work-life balance through coding bootcamps, in contrast to the literature on why women leave computing fields. We identify a possible discrepancy in women’s temporal or developmental career stage. Schnell (2019) highlights how and why women enter computing and overcome the odds against them. Generally speaking, early-career women who leave computing and tech fields because of concerns about work-life balance and low salary have different reasons for leaving the industry at later career development stages. Women in their mid- to late career tend to leave the field because of changing family dynamics (e.g., having a child) or difficulties with salary negotiations. Concerning success criteria for coding bootcamps compared to graduate education, bootcamps graduate higher rates for women entering computing for the first time later in life (Eggleston 2018).

Another inconsistency is that despite being marketed as alternatives to postsecondary education, nondegree programs more often supplement college degrees for higher-educated adults than credentials for less-educated adults (Columbus 2019). In particular, nondegree programs for high tech are ideal for non-STEM baccalaureate holders in terms of impacting salary before and after program completion (Eggleston 2018).
Last, we highlight nuances concerning the racial pay gap in STEM and the comparison of salary for minorities in STEM compared to non-STEM. As noted, nondegree programs provide a pathway into the high-tech field for non-STEM college graduates; this demographic observes the most significant wage increase compared to nondegree and 4-year STEM degree counterparts. Because STEM careers, on average, have higher salaries than non-STEM careers, nondegree programs geared toward high-tech positions do present an opportunity to close the racial wealth gap writ large; however, in high-tech positions, racial/ethnic minorities still report earning less than their majority high-tech colleagues who also completed bootcamp (Columbus 2019). As outcome reports on bootcamp graduates are in their nacency, future research warrants further study on income disparities among salaries for workers in high-tech fields disaggregated by race and gender.

**Best Practices**

When it comes to best practices, the majority of the articles focused on bootcamps over any other type of nondegree training. The ready-to-work model is widely used globally and quickly becoming the industry standard for coding bootcamp models (Kwon et al. 2020). A hybrid offering is characterized by traditional vocational training with socioemotional and tech skills learning in an accelerated manner (Kwon et al. 2020).

**Higher Education**

Price & Dunagan (2019), in their report *Betting on Bootcamps: How short-course training programs could change the landscape of higher ed*, argue that bootcamps differ from traditional higher education in the underlying business models that support the value proposition that these organizations offer students and employers. They note that the nimble and workforce-driven model of bootcamps, in addition to whom they target and how they teach them, makes them “disruptors” of traditional higher education. The speed with which bootcamps bring new in-demand offerings makes them attractive. The authors offer five scenarios related to the future of bootcamps as well as recommendations on how higher education could respond. For example, for higher ed to address disruptive behavior, they recommend investing in new business models through autonomous units (e.g., a university that builds its own bootcamp). In addition, AI careers do not require a four-year
college credential. Community colleges offer enormous potential to grow, sustain, and diversify the AI talent pipeline through AI-related certifications (e.g., computer and information sciences and engineering technology) (Gehlhaus & Koslosky 2022).

Although the topic of interest is nondegree training for high-tech positions, it should be noted that the study by Columbus (2019) found that credentials in the trades were associated with adults in the upper-income credential group among nonbaccalaureate workers, suggesting that certificates in trades may present viable pathways to higher earnings. It is noteworthy that ten years ago, there were no clear pathways to high-tech positions from a nondegree program, yet there were clear pathways to many engineering and engineering-related career fields. One study of vocational schooling reported high wages after high school without a bachelor’s degree (Torpey 2012). The author writes with an informative and casually persuasive tone for young adults looking to enter a high-paying career without pursuing a four-year degree, outlining alternatives to high-paying jobs starting from postsecondary nondegree awards and high school diploma with relevant work experience.

**Policy: Federal and State Support**

A Congressional Research Service report outlines measures and priorities to address the upskilling of the US labor force. There appears to be consistent support for increasing federal assistance for programs aimed at short-term or postsecondary nondegree programs (Dortch et al. 2020). This report defines nondegree programs from a national operational perspective and calls for prioritization to help influence federal policy to fund or support nondegree training programs for historically disadvantaged groups.

**Funding Support**

Of interest is the financial cost or affordability of these nondegree training and funding options. Eggleston (2018, 2020) reports that in addition to loans, income-sharing agreements and deferred tuition are two trends growing in popularity in the bootcamp industry. In 2018 almost 43% of bootcamps offered an income-sharing agreement (ISA), and more than 1 in 5 (22%) graduates use one of these options. Those who graduated in January-May of 2018 are more likely to be employed.
In 2020, students who used an ISA or deferred tuition earned higher salaries after graduation; where some 19% of students opted into an ISA or deferred tuition (Eggleston 2020).

**Suggestions for the Committee**

Future research should look into the impact of bootcamps and other types of nondegree training on the participation of racial minorities and whether access to nondegree training is inconsistently available in geographical areas that are disadvantaged in terms of access to high-tech training and jobs (Lyon & Green 2020). Similar access concerns for marginalized groups were mentioned in Topic 5 related to innovation zones. Additional research should be conducted to elaborate on the racial income disparity of bootcamp graduates employed in high-tech fields, to elaborate whether discrimination or salary negotiation skills are key factors in earnings discrepancy in the bootcamp outcomes report by Columbus (2019). There should also be more work to understand career services’ resources for nondegree training participants. For example, a career services program in a nondegree training program could help with job placement for participants. In addition, more pathways into tech would be formalized through these various types of programs.

**References**


For this topic, our search used the following phrases and terms: “machine learning algorithms data race bias,” “data augmentation,” “machine learning algorithms eliminate bias,” and “machine learning algorithms eliminate bias predictive.” The more than 3,450,000 results were scoped to fit
the topic. In our review of programs we look at (1) ways to identify and (2) eliminate bias in critical areas that affect minority engagement and the (3) predictive analytics on engineering success for individuals from historically minoritized populations. We also suggest ways for the RJ&E committee to play a role in building fair and ethically unbiased ML training algorithms and datasets. Similarly to previous topics, we found nuances among phrases like ‘data bias’ and ‘algorithm bias’ used indiscriminately throughout the literature on ML data and relationships. A brief glossary of standard key terms and their definition is presented before elaborating on the literature findings.

Key Terms

**Algorithmic bias**: bias in the training algorithms, for example in how the data and categories are coded and weighted

**Data bias**: biases in the data and how they are selected (e.g., by whom and what are their biases)

**Machine learning (ML)**: a form of artificial intelligence where a computer has the capacity to learn without explicitly being programmed

**Prediction bias**: the interpretation of and resulting implementation of changes or policies

Research on biases in machine learning falls into one of three categories: conceptual studies on how to identify biases, reviews and empirical studies on the root cause of biases and appropriate mitigation techniques, and comparative studies to evaluate the accuracy of different predictive algorithms used in education and hiring. We present research on ML designs and algorithmic attributes that either improved the predictability accuracy of a model or resulted in disparities or otherwise consequential outcomes for historically minoritized populations.

**Conceptual Research**

The following works represent conceptual research to help detect or identify source(s) of bias in ML model development processes and techniques to measure the amount of bias in ML models.

Pot et al. (2021) suggest, based on their assessment of different types of bias in radiology, that some biases are more problematic in practice in other areas. Using a healthcare equity framework, the researchers show how some biases in health care are desirable if they serve to mediate or
mitigate a known disparity and positively contribute to overcoming inequity. They specifically discuss the creation of deliberate bias in datasets, akin to oversampling, as a means of introducing a bias to compensate for an imbalance that is either already present in the data or likely to develop if a purely random sample were taken. The work further classifies bias based on perceptions of justice (e.g., distributive justice, relational justice).

Some researchers have taken a different approach to understanding bias and have pushed to change the language associated with it. Suresh & Guttag (2021) argue that the concept of “biased data” is too broad and therefore unhelpful in efforts to develop solutions for unwanted consequences of ML. They identify seven categories or sources of “bias” (discussed below) that taint ML and originate throughout various points in the data generating and algorithmic training process. Their article is similar to Tay et al. (2022), who identified six sources of bias by developing a conceptual framework to investigate and mitigate sources of unfairness in the ML process, and van Giffen et al. (2022), who describe eight types of ML bias. Compared to other sources (Fahse et al. 2021; Tay et al. 2022), Suresh & Guttag (2021) and van Giffen et al. (2022) extensively discuss the bias and include case study examples through real-world ML applications.

Of interest are the seven sources of bias and the relevant in-text example in Suresh & Guttag (2021, §§3.1–3.7; italics added):

3.1 “Historical bias arises even if data is perfectly measured and sampled, if the world as it is or was leads to a model that produces harmful outcomes…. Considerations of historical bias often involve evaluating the representational harm (such as reinforcing a stereotype) to a particular group” (e.g., an image search of women:men CEOs at Fortune 500 companies).

3.2 “Representation bias occurs when the development sample underrepresents some part of the population, and subsequently fails to generalize well for a subset of the use population.” It is a concern when sampling methods are limited to a portion of population, or the population of interest has changed or is distinct from the training dataset.

3.3 “Measurement bias occurs when choosing, collecting, or computing features and labels to use in a prediction problem…. Proxies become problematic when they are poor reflections of

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6 Defined as the fair distribution of goods (e.g., health outcomes and their equitable distribution within a population)
7 Defined as the quality of social relations among a population (e.g., how healthcare is provided and how people are treated regarding their health concerns)
the target construct and/or are generated differently across groups” (e.g., the quality of data varies across groups, the defined classification task is oversimplified [as in predictive policing]).

3.4 “Aggregation bias arises when a one-size-fits-all model is used for data in which there are underlying groups or types of examples that should be considered differently,” as when efforts to develop clinical-aid tools for groups with conditional distributions fail to account for the fact that pathology presents with different associated complications/symptoms across ethnicities.  

3.5 “Learning bias occurs when modeling choices amplify performance disparities across different examples in the data” (e.g., training models that limit the amount of identifying information).

3.6 “Evaluation bias occurs when the benchmark data does not represent the use population” (e.g., facial analysis tools based on White faces).

3.7 “Deployment bias arises when there is a mismatch between the problem a model is intended to solve and the way in which it is actually used” (e.g., risk assessment tools).

This article is helpful, especially for engineering, because it highlights sociocultural nuances, which present challenges for the field of biomedical engineering, for example, in terms of diagnostic and therapeutic devices and the diverse people they are meant to help.

In a systematic literature review on interdisciplinary views of ML biases and methods to avoid and mitigate biases, van Giffen et al. (2022) describe eight types of ML bias—social, measurement, representation, label, algorithmic, evaluation, deployment, and feedback bias—which they summarize across industry-standard processes for data mining to account for all phases of ML projects (see table 1 in the article). The researchers present 24 mitigation strategies through real-world case studies.

They also emphasize the role of human judgment in ML algorithms (see table 2 in van Giffen et al. 2022) and assign different methods to address bias in phases of projects, from business understanding to deployment. Among the human element considerations that stood out: in the business understanding phase, the authors recommend establishing diverse teams to introduce different perspectives on the ML task; and for the data understanding phase, they make a case for exchange with domain experts in the application context to identify features that should be included for model training (van Giffen et al. 2022).
Fahse et al. (2021) provides a framework for identifying and mitigating ML bias through the well-established CRISP-DM process/model. The research team identified eight types of bias—social, measurement, representation, label, algorithmic, evaluation, deployment, feedback—and 25 mitigation methods, which they then assigned to the 6 phases of the model. This paper is written to help practitioners who use ML make business decisions and to help project managers avoid biased and costly ML outcomes.

The Fahse et al. (2021) and van Giffen et al. (2022) papers are similar and report similar results. There is no comprehensive framework for defining how different types of bias occur in the ML process and how they might be mitigated or prevented. Last, it is interesting to note that CRISP-DM is the cross-industry standard for data mining, analytics, and large-scale projects (Wirth & Hipp 2000).

Tay et al. (2022) focus on ML measurement bias (MLMB) and cite two sources: data bias and algorithm training bias: According to Tay et al. (2022), “Data bias can occur in the form of nonequivalence between subgroups in the ground truth, platform-based construct, behavioral expression, and feature computing. Algorithm-training bias can occur when algorithms are developed with nonequivalence in the relation between extracted features and ground truth (i.e., algorithm features are differentially used, weighted, or transformed between subgroups).” The authors argue that “new statistical and algorithmic procedures need to be developed” to more accurately test and mitigate MLMB.

It is important to note that this article challenges the NAE topic idea that “using corrected data…would eliminate bias”: the sourcing of accurate “unbiased” data would reduce data bias but would still be susceptible to algorithmic training bias. The authors also highlight that dominant schools of thought perceive ML as advancing the prediction of human behavior/outcomes rather than using ML for explanatory inquiry. For some wicked problems, explanatory ML models may help identify a more efficient/effective root cause analysis to prioritize the effective mitigation of complex interconnected problems.

Tay et al. (2022) approach ML from a psychological/psychometric perspective to advance the accuracy and validity of predictive power in social science contexts of education and employment. There is a need to investigate sources of ML bias from a holistic methodological perspective rather
than a legal one. Many examples used to explain conundrums in ML algorithm development and use in human decision making are training the ML to replace human judgments (Tay et al. 2022).

McCradden et al. (2020) posit that standard solutions of algorithmic fairness rooted in model neutrality, typically through the omission of protected variables (e.g., race/gender), produces nondiscriminatory predictions by ensuring equal error rates across groups, but these can exacerbate harm to vulnerable groups and present an ethical threat to the use of ML in medicine. The article then deals with the concept of “engineering” ethics into algorithm designs, which the industry is pushing.

In addition to identifying bias, some articles have sought to assess it. Mukherjee et al. (2022) take issue with a recent paper that called out the bias of AI algorithms linked to underdiagnosis and exacerbated health disparities, but did not adequately account for confounding factors to the bias in their analysis. The piece discusses the importance of rigor and care in addressing bias in AI and warns against specious conclusions in analysis. The authors call for more discussion of fairness, its feasibility, and evaluation in medical AI models (Mukherjee et al. 2022).

Johnson (2021) claims that bias is difficult to identify, mitigate, or even evaluate using standard resources of epistemology and ethics. She claims that social technologies like social media are part of “seemingly innocuous” patterns of information processing. The author writes, “if ultimately our aim is to eliminate biases that are problematic—either epistemically or morally—then our first step should be to understand the origins and cooperation of bias more generally.” Johnson concludes that mitigating implicit biases will require unlearning patterns and associations between things in our environments and rewiring neural networks. In that spirit, perhaps some of the solutions to unbiased ML lie in teaching machines to “unlearn,” or empirically studying what “unlearning” looks like.

Hooker (2021) challenges the myth of the impartial model, which in fact reflects a dataset’s bias, and presents clear evidence from the literature that algorithms are not impartial. She uses ML problems to discuss how model design choices cause harm and identifies mitigation techniques for the algorithm instead of focusing on improving the data (e.g., cleaned, structured, complete, accurate). She emphasizes the importance of recognizing and investigating ML bias. She also discusses how diffusion of responsibility in computer science often presents itself as discussions
around what is and is not “out of scope.” She argues against the belief that algorithmic bias is a dataset problem, as it invites diffusion of responsibility, in that it absolves those who design and train algorithms from having to care about how the design choices can amplify or curb harm.

**Mitigating Bias Based on Root Cause**

As demonstrated in the section above, there are several sources of bias recognized among the research community. While there is not a consensus on terminology, most agree that classifying the source of bias as either primary (e.g., prior to model development, historical bias in data collection) or secondary (e.g., originating from training algorithms and interpretations) is critical for selecting appropriate mitigating techniques. In the following sections, we provide primary and secondary examples for mitigating ML bias across applications.

**Primary Causes of Bias**

The following studies consider methods for detecting the source(s) of bias and compare mitigation techniques and their outcomes in terms of model accuracy and predictability. Some articles present original research proposing new mitigation strategies or further conceptualizing what such mitigation strategies should aim to achieve.

Alelyani (2021) claims that the primary source of bias in machine learning is ground truth or “unbiased data,” while most of the research community is studying ways to mitigate algorithmic bias. The author proposes a technique to detect and evaluate ground truth bias to create more reliable and explainable ML models. The research draws on ML examples used to discriminate against people based on their race and/or gender, and shows that the ability to detect bias in an ML model can lead to identification of categories of attributes with a certain degree of confidence. If a model’s prediction changes dramatically by changing one attribute only (e.g., gender), this may be evidence of model bias. The author also introduces a new concept to evaluate and quantify ML bias: “alternation” is defined as a function that alternates between attributes’ values, so the values are swapped each time. Alternation changes the identity of an instance, allowing humans to check the dependency of the predictor on the attribute.

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8 Defined as the aim for the validity of a ML model compared to the results against the real world
Bias detection can take many forms, including changing the data or learners in multiple ways with the hopes of improving fairness. In a study by Chakraborty et al. (2021), the research team explores whether the root causes of bias are prior decisions about (i) what data were selected and (ii) what labels were assigned to the examples. The study focuses on an algorithm that removes biased labels and rebalances internal distributions so that, based on sensitive attributes (e.g., those defined by sex, race, age, and marital status), examples are equal in positive and negative classes. The testing of the authors’ “Fair-SMOTE” algorithm was just as effective at reducing bias as prior approaches. Further, models generated via Fair-SMOTE achieve higher performance than other state-of-the-art fairness improvement algorithms.

Hassani (2021) suggests that ML algorithms, when informed by corrupted data, will reflect social bias. The study explores how social biases are transmitted from bank account/loan application data to bank loan approvals by predicting either the gender or ethnicity of the customer. The research team assumed that if social biases were not included, then factors characterizing credit scores would be sufficiently different from those that can characterize either men, women, or any ethnic group.

Kallus & Zhou (2018) prove that, beyond detecting bias, in some applications (e.g., Stop, Question, Frisk) fairness-adjusted classifiers actually induce unfairness toward the target population because of systematic censoring of training data by biased policies. Data adjustments can mitigate bias and increase the fairness of ML outputs.

Chakraborty et al. (2021) identify five performance metrics (recall, false alarm, accuracy, precision, F1 score) and four fairness metrics (average odds difference, equal opportunity difference, statistical parity difference, and disparate impact) that are widely used in ML literature. Most algorithm approaches attempt to eliminate bias based on one protected attribute at a time. The Fair-SMOTE approach simultaneously reduces bias for more than one protected attribute (e.g., race and sex).

Pastaltzidis et al. (2022) propose data augmentation techniques to rebalance data-driven law enforcement projects for real-time crime detection. This article aims to codesign a data augmentation strategy for mitigating algorithmic bias risk in the context of legal and ethical conceptions of fairness and nondiscrimination, as defined by the European Union for a project that
develops ML-powered smart devices for real-time crime detection. The research team uses scholarship on fairness in ML algorithmic bias and discrimination due to biased data to build motivation for their methodological contributions. Additionally, they identify threats to the external validity of the RWF-2000 dataset, such as overrepresentation of minority subjects in violent situations that invalidate outputs for real-time crime detection systems. The techniques used in this article (e.g., data augmentation techniques to create pseudo instances to have more balanced training samples) improved the model accuracy by a margin of 1.2% and 1.4% across the balanced and unbalanced datasets.

Compared to other fields, the use of ML in health care might assist in explaining health disparities across subpopulations. Bernhardt et al. (2022) argue that current methods for experimental evaluation of ML bias in health care are insufficient to study algorithmic underdiagnosis. There is a growing concern that the use of ML medicine will amplify health disparities due to biases in training data. Specifically, Bernhardt et al. (2022) note that medical ML models frequently yield disparities in false positive rates across subgroups on the no-finding label—subgroups of people are misdiagnosed as not having a disease that they have. The models exhibit and potentially amplify systematic underdiagnosis and highlight multiple potential sources of bias in the referenced dataset that claimed to find algorithmic bias. This article also points to a lack of rigor in the collection, cleaning, and processing needed for the big data often used by ML models, where unknown biases inherent in the dataset propagate through the model’s predictability.

**Secondary Causes of Bias**

Secondary causes of bias emerge during algorithm training. Of the types of bias, racial bias appears to be the most documented across a range of ML-based analyses for this literature review.

Using a mixed methodology to study the counterfactual impact of racial bias features present in datasets, Sengupta & Srivastava (2022) study the influence of data bias on the human decision-making elements of ML model development. They demonstrate that models trained on biased data not only influence human decision making (e.g., for data scientists and engineers) but also magnify and propagate biases throughout the ML model development process. Their work is
grounded in Norman’s model of interaction and cognitive dissonance theory to support their argument of causation in decision making due to biases in the evaluation process of information presented to users.

The findings support how racially biased data influence and propagate through the human decision-making component of ML algorithms by yielding (i) racially dominant model outcomes (e.g., biases) that are then used as evidence to support the user in discriminatory decision making, or (ii) nonexplainable model outcomes that are uninformative for human decision making or interpretation of the model as there is inadequate information among the interaction of variables. There is a need for contextualized heuristics to help with the human decision-making component inherent to the ML model development process to understand how a solution may be biased and yield a more effective and contextually relevant interpretation of model outputs.

Allen et al. (2020) evaluate the accuracy of a predictive ML algorithm to determine mortality between White and non-White patients, looking at racial disparities in health care and specifically higher rates of poor patient outcomes for non-White patients. To address this disparity, the introduction and implementation of ML in healthcare settings must be carefully vetted to avoid increases in harm and racial disparities through biased predictions or differential accuracy across racial groups.

Kostick-Quenet et al. (2022) also looked at biases in health care and concluded that healthcare algorithms trained on data from majority populations pose myriad ethical, legal, and safety concerns regarding the accuracy and reliability of diagnosis for minorities and other disadvantaged groups. The authors argue that algorithmic bias is a fundamental challenge to making the descriptive and predictive precision of AI/ML equal across demographic groups. They cite specific examples and loopholes when applying existing guidelines for mitigating algorithmic bias in an ML tool for a real-world clinical environment. They point to the importance of data quality for mitigating bias as well as the developer’s ability to interpret ML outputs and analyze outcomes contextually, accurately, and precisely.

Currently, several legal guidelines and initiatives are aimed at reducing racial bias in ML, as not doing so results in racial injustice and civil rights violations (Kostick-Quenet et al. 2022). However, these legal guidelines do very little to inform the synthesis and analysis of results to leverage more
accurate and reliable interpretations that a trained researcher typically would provide (Kostick-Quenet et al. 2022).

Some researchers have explored unique approaches to underestimation bias and methods for regularization. Cunningham & Delany (2021) suggest that most schools of thought place a higher emphasis and responsibility on correcting data bias (e.g., historical bias) used to train algorithms. They claim that understanding the source of the bias is inextricably tied to the effectiveness of methods used to eliminate the bias. Benthall & Haynes (2019) propose simply that treating groups that have been segregated socially and in space similarly will reduce disparities: Rather than designing ML to integrate diversity, we should instead discover ways to organize groups in an unsupervised way (e.g., not using race as a category) before using fairness modifiers.

Almuzaini et al. (2022) put forth an anticipatory dynamic learning approach for correcting ML algorithms to mitigate bias before it occurs, as a means to maintain fairness. Given that input distributions change over time models will lose accuracy, which means that constraints to reduce bias against a protected class may fail. This can be remedied by dynamic learning. The research team uses relative distributions of applicants’ population subgroups (e.g., gender) to determine the critical parameters of importance for weighing fairness.

Kim & Cho (2022) propose three evaluation metrics to deal with algorithmic bias and develop seven methods to mitigate it: relabeling, generation, fair representation (for preprocessing), constraint optimization, regularization (for in-processing), calibration, and thresholding (for postprocessing). Their preprocessing approach is based on information theory to achieve fair ML by reducing the bias caused by protected features like age, race, and gender.

**Evaluating Model Interpretation and Predictability**

Most of the literature around unbiasing ML algorithms is dominated by methods for eliminating unfairness related to binary classification, which represents some of the most contested areas of scholarly disagreement (Bacelar 2021). While some scholars contend that quantifying fairness on a binary variable is more mathematically convenient, they also recognize that such oversimplification can lead to inaccurate model predictions.
With the growth of ML in applications to address disparities, new multilevel statistical methods are being developed to more readily capture social factors and their intersections. New calculations for representing intersectionality in a statistical model describe individual heterogeneity with discriminant accuracy. Luckily, the promise of ML applications to aid human decision making and streamline work is a catalyst for emerging techniques to facilitate fair ML models. Evans et al. (2018) suggest that, from a mathematical perspective, the complexity of binary variables can be countered with multilevel modeling; they propose a novel multilevel approach for exploring the intersectionality of all social strata in a dataset.

Trivedi (2022) makes the case that enhancing ML prediction capabilities for use in student retention mitigation will come from a critical review of existing ML practices. The author has done a comparative analysis of studies that predict student retention and provides a detailed overview of the methods used for such prediction along with a reference to the study of the compared model performance. The best-performing model averaged above 70% accuracy and was more accurate than that for predicting noncompleters. In science and engineering, neural networks (NN) models are used to predict incoming freshman retention and are more accurate than support vector machines in classifying students’ performance or retention.

He et al. (2018) developed a novel predictive analytic tool for STEM student success metrics that provides stakeholders with automated and timely information to assess performance and inform pedagogical strategies. Using a random forest ML algorithm, they can also tailor information for advisors to identify the risk levels of individual students in efforts to enhance persistence and graduation success in STEM.

Lwowski & Rios (2021) explore biases in different ML methods for the specific task of detecting health-related content on social media. The performance of the models was evaluated on two training datasets representing tweets about the flu in two types of American vernacular. The authors find that models that result in unfair predictions might vary from dataset to dataset. They note that, while the different ML models used to interpret social media influenza data are biased, as evidenced by comparing multiple models on the same datasets, the models may be biased differently in other datasets and tasks. Furthermore, although some NN methods achieve better
performance compared with traditional statistical methods, NN pose more difficulty for interpretation—a limitation for the application of some deep learning methods.

**Inconsistencies and Nuances**

The major nuance that we noted was the inherent bias in the interpretation of ML predictive models and the desire to quantify elements of an individual’s identity through data. Despite removing bias from an algorithm, it does not fully eradicate any level of bias from the respondents. Similarly, removing bias from survey data does not remove bias from an algorithm. Overall, there is nuance around where the bias comes from and how it is accounted for.

In addition, current approaches related to bias often overlook sociopolitical implications. When analyzing data, context matters, and this can pose an inconvenient variable for researchers. As with questions about how to teach ethics appropriately, accounting for bias poses similar challenges.

**Suggestions for the Committee**

Based on our comprehensive review of the literature on the development of data and relationships to support ML algorithms, we have several suggestions for points of impact on behalf of the RJ&E committee. We suggest a new ethically unbiased concept to describe ideal state parameters and interpretations for the use, development, and interpretation of ML algorithms. We use the term ethical because the motivation is to avoid activities (e.g., decisions) and organizations (e.g., data use and algorithm applications) that harm people or the environment. “Unbiased” means showing no prejudice to people concerning sensitive demographic identifiers.

Proactive systematic steps for the RJ&E committee are to assist in upgrading the FDA regulatory categories and guidelines for the classification of AI and ML use in medical equipment and settings, an area where biomedical engineering has overlaps. The use of heuristics or rubrics in ML model design keeps designers, analysts, and engineers aware and reflects the social conditions that are relevant to the context of their work. Similar to Pot et al. (2021), there needs to be a deeper awareness of how inequities factor into and multiply effects of social conditions in order to avoid technologies that are based on models that automate inequity and thereby propagate bias.
There are competing priorities and urgency to enact transformational culture change across sectors. One of the most considerable distinctions perceived while sourcing material for this topic is that academia is in its infancy in the study of the use of ML to replace human judgment and understanding of its ethical implications. In contrast, the industry is racing forward, and both public and private sectors are growing their use of ML algorithms to automate simple and more complex decision-making processes (Bacelar 2021).

Of particular relevance to engineering, Ribeiro (2022) writes about five tech companies that are “revolutionizing recruiting” using AI to recruit and hire qualified candidates in the STEM professions. AI is seen as a tremendous potential equalizer in terms of providing safety and transparency in the hiring process. Ribeiro presents AI as a help to humans, not as a replacement for human touch—it is meant to help recruiters and enable HR to operate more strategically.

As another application for ML, we briefly discuss work by Robson et al. (2022), which explains how AI is helpful in automating skills extraction and aligning training resources with required skills to advance or upskill human workers rapidly. The authors have created an AI service that can identify and compare knowledge, skills, and abilities in unstructured text using advances in natural language understanding (NLU) and machine learning. The purpose of the app is to bridge the gap caused by the rapid pace at which industry needs to evolve and the much slower pace at which academic programs operate and change. It is important to note that the authors explore this AI-training application through a lens of equity. As they state in their lessons learned in handling bias and developing a helpful AI service: “The need for in-depth knowledge of ML, NLU, and related data science and engineering processes should not be underestimated…. [A]pps like SkillSync operate in sociotechnical environments where technology and human behavior are intertwined. We made numerous pivots in the design of the app and its underlying AI services based on focus groups, trials, and real-world business requirements. We continue to fine-tune many aspects as we engage with more and more diverse users” (Robson et al. 2022, p. 2). The researchers specifically caution that “Underestimating the need for end-user input is a more fatal error than underestimating the complexity of the problems faced in transitioning to skills-based talent management and in using AI to support this transition” (Robson et al. 2022, p.2 ).
A review on fairness in machine learning Bacelar (2021) found that the underlying data (e.g., primary source) rather than the algorithm is the root cause of bias in ML models. This report relates to Tay et al. (2022) in that it addresses how the metrics for fairness are based on the definition of legal fairness, which often uses the 80% rule when determining whether a process has a differential effect on disadvantaged and privileged classes. While the efforts of academics toward unraveling ML conundrums are noble, engaging, and essential, engineering concerns require prioritization of ML hiring needs in industry, which is forging ahead in its own efforts. Engineering education in this area has been outsourced to private industry (in North America, Europe, Africa, and Asia) developing ML to aid in hiring practices (Corbett-Davies & Goel, 2018).

The literature on ML biases indicates that there is much work to be done, but we are hopeful that this review serves as a guide for future research priority areas to ensure that engineering as a field and profession is timely in supporting and contributing to the betterment of society with a focus on equity and justice for racial and ethnic minorities. Funding should support research collaborations within universities across departments of computing, public health, and biomedical engineering where these areas overlap to develop explanatory models for wicked problems.

References


The innovation sector has generated negative and positive popularity over the past decades. While innovation sectors focus on enriching various aspects of development (e.g., economic, industrial), some populations have experienced detrimental impacts. This section reviews literature on place-based innovation zones and criteria for evaluating zones that focus on increasing minority participation. We also discuss inconsistencies and nuances that emerged from the review, and end the section with suggestions for the committee. We found over 23,800,000 articles using the terms and phrases “innovation zones engineering technology,” “innovation zones engineering technology minority,” “tech industry community outreach minority engagement,” “silicon valley soft infrastructure,” and “place-based innovation zones.” Despite the initial results, there was a limited number of sources within the scope of this review.

**Key Terms**

**Innovation zone**: space where ideas can be discussed and hopefully commercialized (Koulopoulos 2009)

**Place-based innovation zone**: a conglomerate of universities/institutions, businesses, and industries to create hubs of innovation; emphasis on urban or regional transformation (Rissola & Haberleithner 2020); also known as innovation districts, Knowledge innovation zone, or keystone innovation zone (KIZ) (Ailstock et al. 2020; Amidon & Davis 2006)

**Place-based Innovation Zones**

According to Rissola & Haberleithner (2020), a place-based innovation zone comes from a bottom-up approach to promote transformation for a particular area. This approach ensures that
numerous parties are involved in tackling real-world problems, and more robust pathways are created to assist marginalized populations via workforce opportunities and educational partnerships (Ailstock et al. 2020). Below we highlight examples of innovation zones and criteria used for their evaluation.

Iyengar et al. (2017a) state that innovation zones are aimed at helping create better teaching, learning, and student outcomes, especially for underresourced school systems. Some states have used innovation zones to allow schools to gain more autonomy over their student outcomes by enabling them to control their staffing, curriculum, and finances. However, most philanthropists don’t invest in school district reform initiatives but prioritize charter schools. The size and complexity of urban districts often concerns, given the number of low-income students, students of color, students at decreased educational levels, and overworked instructors. Funders tend to provide small gifts toward a limited enrichment experience. According to the study, funders would be more willing to support school districts if they demonstrate constant improvement in student achievement and for the school to have full autonomy to create better teaching methods and learning strategies. The authors point out that a major shortcoming of innovation zones is a lack of support for teachers and advancing classroom learning.

With respect to structures, there are three types of innovation zones: district-led, third-party-led, and autonomous improvement. District-led innovation zones allow low-performing schools to be exempt from local and state regulations. They create a new system with a senior-level innovation zone leader who encourages principals to pick their staff to create a novel instructional program. Third-party-led innovation zones are when a third party (e.g., a nonprofit or charter organization) contracts with a low-performing school to create an innovation zone. Autonomous improvement zones can be for low- or regular-performing schools to come together to form a zone.

Innovation zones can also provide a unique approach to identifying policy barriers and improving the flexibility of learning modalities, especially in light of the decrease in the academic performance of students due to the pandemic (Jones & Chambers 2021). Innovation zones or districts of innovation encourage the creation of curricula, institutional approaches, and strategies that support students’ educational success.
Innovation zones can encourage the exploration of new approaches to real-world problems. The Best Babies Zone is a place-based innovation zone project focused on reducing inequitable infant mortality rates in Oakland, California (Vechakul et al. 2015). The project is a place-based initiative because it emphasizes the interactions of geography, culture, and the community’s social capital and local knowledge. A 12-week pilot program called Design Sprint was created for professionals to use a human-centered design process to simulate a local economy and increase community engagement. The authors posit that human-centered design can make the design process go faster and create more innovative solutions to complex problems. The human-centered design comprises three phases: understanding the motivation for the program, ideating different ideas, and implementation. The researchers obtained feedback from residents about their priority concerns: to support and expand employment opportunities, local businesses, and programs to address violence. Given the expertise of the local public health department, employment opportunities were chosen. In the end, a successful program was created to support local entrepreneurs, generate income, and increase access to goods. Human-centered design helped foster and strengthen collaboration in the community and encouraged the change from working for a community to working with a community.

Khan & Mikroglou (2009) focus on innovation zones as groups of academics (e.g., universities), businesses (e.g., incubators), research (e.g., research institutes), and government organizations that use knowledge to bring opportunities that might be overlooked. Different names for such agglomerate systems are hubs, clusters, knowledge zones, and innovation systems; all yield high levels of knowledge generation and innovation, often through research and development. According to the authors, innovation zones are fueled by government initiatives and are opportunities to create knowledge-based regional development. Regional development is more than being geographically close; it also requires face-to-face interactions to transfer knowledge. For an innovation zone to thrive, it must have technology infrastructure, which is the access of STEM knowledge to private industries. An innovation zone also receives benefits from the legislature, including more economic ease and partnership formation opportunities. The authors identify factors that yield the success or failure of an innovation zone: (i) one or more defined economic activities; (ii) knowledge infrastructure, media infrastructure, and technological services; (iii)
research activity focused on technological development and diffusion; (iv) entrepreneurship focused on innovation sectors of interest; (v) solid networks and relationships among the various stakeholders; (vi) investment capital and innovative funding methods; and (vii) commitment to a vision and plan.

Amidon & Davis (2006) describe knowledge innovation zones as “any geographic region, company, industry, or community of practice whose mission is to create and realize value from the flow of knowledge.” A knowledge innovation zone is where knowledge flows from one point to a place of the highest need or opportunity. Across knowledge innovation zones, the key ways to gauge innovation practices are through five types of capital: human, intellectual, infrastructure, social, and relationship and network. The authors mention several areas of opportunity, including leveraging other stakeholders instead of those involved in technology/research and design and academic-based domains. Knowledge innovation zones can contribute to urban revitalization, educational attainment, access to communication technology, export growth, job growth, and neighborhood gentrification. They are a platform for knowledge transfer and for spurring technological innovation across the private sector, government, and academia (Amidon 2005).

When it comes to innovation zones, Silicon Valley is one of the most popular and well-known. Several have tried to duplicate the concept in various locations. Hospers et al. (2009) reviewed the notion of cluster policy as a potential solution to mimic the successful geographical clustering of Silicon Valley. A cluster is a geographically close group of similar parties linked together. Clusters can range in the types of parties involved, from a university to a service provider; however, the geographical closeness of ideas to freely flow among parties remains. A cluster policy is a cluster’s government support mechanisms (e.g., development and sustainability). The authors state that governments should focus on sustaining clusters instead of subsidizing industries within a cluster because unintentional targeting can occur when certain ventures get more attention than others.

Similarly, focusing on a high-tech experience often has fewer employment opportunities. While duplicating Silicon Valley might appear to be a viable approach, potential competitive advantage can often decrease. The authors highlight three commonalities across strong-performing clusters. First, a cluster must have an economic structure that isn’t connected to its past. Second, global trends must be connected to local traditions to create growth opportunities. Last, the government
should play a role in a cluster only after it has been created. The authors encourage moving away from the Silicon Valley model and instead adopting what they call “regional realism.”

One study explored varying levels of access to tools among 160 8th graders in the Silicon Valley public school system. Barron et al. (2010) wanted to understand the relationship of experience with creative production activities (e.g., robotics, game design, and website creation) to the availability of computing tools and learning resources. They believe that demographic variables such as socioeconomic status and parent education levels impact computing technology usage. The study showed that students from more affluent school communities had more access to technological tools at home and therefore benefited from being more experienced in computing activities. However, students have varying breadths and depths of experience in computing despite the notion that all students today are technologically literate.

Internationally, Vesuvius Valley has become a new locus of innovation (de Falco 2018). The author describes the development of Naples, Italy, as an innovation hub that has gained attention over the years. Characteristics of innovative cities include those with diversity where numerous ideas are welcomed and accepted, there is an ability to decipher good from bad ideas, and there is the opportunity to network. To have a successful creative city, urban density is key. Since Apple placed its iOS academy in Naples, there has been an exponential shift from the city as an industrial hub to a thriving high-tech innovation city full of knowledge and creativity.

More recently, Silicon Valley has received more criticism. Noble & Roberts (2022) explored how its technocratic elites mask elements of race and gender through various mechanisms, from the capital to opposing public policy commitments to end discriminatory labor practices. The authors show that several elites operate in a postracialism ideology where race is no longer an area of concern, despite corporate acts that have uprooted and displaced African American and Latinx residents and disrupted cultural meccas. And despite numerous reports about racial and gender hiring bias, several technology CEOs and investors continue to use meritocracy to justify their actions. Some have adopted a mentality of colorblindness and gender blindness and used model minorities to hide the lack of domestic US minority groups in tech. Television shows like Silicon Valley display and normalize the White and male culture of Silicon Valley, while phrases like culture fit perpetuate heteronormativity. The reality is that domestic minority groups remain “structurally
marginalized without reparation and excluded from nearly every aspect of long term social, political, educational, and economic opportunity” (Noble & Roberts 2022).

**Criteria for Evaluation**

This section reviews evaluation metrics for increasing marginalized populations’ involvement. Few articles provided a specific way to measure innovation zones aside from stating that it needs to be improved, and even fewer articles explicitly aimed to enhance minority engineering participation.

White et al. (2017) extensively evaluated 11 early childhood innovation zone initiatives in Illinois. The innovation zones were created to support underserved children by increasing enrollment and quality, and improving ratings for teaching and learning, family and community engagement, leadership and management, and qualifications and professional development. Each zone had a team lead who helped in the design and testing of new models for their early childhood system. The zones were required to focus on vulnerable populations of children, such as those with disabilities or with linguistic challenges. Different results emerged through interviews and surveys with zone partners and state-level staff. For evaluation, the researchers looked at population enrollment across all zones and whether there was a shift in student enrollment types. The proportion of priority compared to nonpriority student enrollment was analyzed. Priority populations are those most vulnerable to risk factors that could impact future educational success such as children of teen parents, children in foster care, and children whose families are linguistically isolated. Nonpriority populations refer to students who aren’t vulnerable to risk factors. Also, the Illinois ExceleRate system was created to help innovation zones as they matriculated through the various improvement ratings.

A subset of questions from the survey given to the innovation center stakeholders was presented in the report. Most were Likert scale questions that asked participants to compare their experiences now and before the innovation project. Topics include describing levels of cooperation, collaboration, and engagement of early learning development professionals and other local partners in the community, the priority the community and other local partners place on early learning and development, and the number of high-quality learning and development programs (White et al. 2017).
Another area to consider is the level of engagement with local community members. For some communities, the placement of an innovation zone has led to the movement of marginalized populations out of a geographical area. There is balance to strike when scaling innovation to a formerly marginalized community to avoid gentrification, where new businesses and housing remain accessible to local inhabitants so that they are not simply replaced by outside wealthier or more skilled people. Jones & Chambers (2021) state that while innovation zones aim to create more student-centered spaces, there needs to be a focus on designing with intentionality for low-income, Black, and Brown students. Innovation zones should provide new flexible approaches to education that address systemic educational challenges. Also, local economic development practitioners need to account for marginalized groups. This includes skill training and targeted support (Lee & Rodríguez-Pose 2016).

Cyril et al. (2015) looked at the impacts of community engagement on health disparities of disadvantaged populations. For this study, the disadvantaged included people of low socioeconomic status, ethnic minorities, sexual minorities, culturally diverse populations, indigenous groups, and marginalized groups. Community engagement works with people with a commonality by geographic proximity, special interests, or similar situations. Using a sample of 24 studies, areas of community engagement that favorably impacted health outcomes included real power sharing, collaborative partnerships, bidirectional learning, using the voice and agency of communities, and bicultural health workers. The authors emphasize that it is critical to have community consultation and participation at all levels, from design to implementation, to improve health and health behaviors. Community-based participatory research was the most common model of community engagement for improvements in health behavior, public health planning, health service access, and health literacy for racial and ethnic minorities. In addition to community-based participatory research, other successful community engagement models for marginalized populations were Families in Our Community United for Success (FOCUS), Analysis Grid for Elements Linked to Obesity (ANGELO), Culturally appropriate Diffusion Communication (CDC), community empowerment, Community health worker (CHW), and participatory action. It is important to note that high-quality community engagement may be associated with low-quality research methodology; however, creating frameworks to account for these deficits is beneficial.
Hanson et al. (2016) analyzed the enrollment trends of preschool children of low-income families in two areas of Silicon Valley, Santa Clara and San Mateo. In Silicon Valley, most low-income children are from immigrant families, creating a unique paradigm considering that Silicon Valley has one of the highest preschool enrollments in the United States. An immigrant family in this context is defined as one with at least one parent born outside of the United States, and this study mainly included participants from Mexico and Central America. Some parents in the selected areas fear interacting with agencies, which they might ask for documentation, and feel uncomfortable communicating because of limited English proficiency. Compared to middle- to higher-income families, low-income immigrant families tend to have preschools that are in inconvenient locations, which yields transportation barriers and tends to be costly. While children tend to be raised in two-parent households, often only one works outside the home. The authors document that any outreach to this population should consider these factors.

A district-led local innovation zone in Tennessee found positive effects on student achievement compared to a state-led achievement school district in a subset of innovation zone schools where over 87% of students identify as Black and 89% were eligible for free or reduced meals (Pham et al. 2020). It is essential to recruit effective principals and teachers, but while an innovation zone must replace a principal, it is optional to replace teachers. This innovation zone used most of its funding for performance pay incentives to recruit and retain highly effective teachers. For innovation zone schools, the length of the average teacher experience decreased after they joined, and there were higher ratings from the Tennessee Value-Added Assessment System for principals and instructors. The first two years for this innovation zone showed the most positive and significant results compared to years five and six for math, reading, and science. The authors mention that innovation zones for high school students may be less impactful, and more attention should be paid to high student mobility rates.

Amidon & Davis (2006) also mention the need to improve evaluation metrics given the increased risks associated with innovation zones. They suggest using a triple knowledge lens that focuses on (i) the knowledge economy and business; (ii) knowledge society, community, culture; and (iii) knowledge-based infrastructure. A triple knowledge lens considers novel performance measures to assess the economy, organization, and infrastructure to ensure that an ecosystem
exists where stakeholders are viewed as more than financial entities. There is a focus on forging new networks. Across the knowledge innovation zones, the key ways to gauge innovation practices are through five types of capital: human, intellectual, infrastructure, social, and relationship and network.

One evaluation metric of innovation zones is their ability to create jobs, including those that are non-tech related. However, some researchers have shown that nontech jobs are at lower salaries and are hard to come by. Lee & Rodríguez-Pose (2016) explored the dynamic of poverty and high-tech industries, which are often considered a mechanism to create new jobs indirectly. But they are also associated with inequitable labor markets, as most high-tech jobs require higher levels of education. However, high-tech jobs are often multipliers, given the additional creation of nontradable jobs. Using a panel of 295 metropolitan statistical areas, the authors found that tech employment increased the wages of non-degree-educated workers. However, tech employment is not the sole determinant of decreasing poverty and often increases areas of urban inequity.

Another area to assist with evaluation metrics for an innovation zone, as suggested by Koulopoulos (2009), is an innovation portfolio. Koulopoulos (2009) describes an innovation zone as a space where ideas can be discussed and hopefully commercialized. However, a common shortcoming of innovation zones is an equal level of attention brought to a novel concept in conjunction with an organizational structure that doesn’t promote the nurture of an idea via time, budget, and resources. The author suggests sorting ideas using an “Innovation 2.0” portfolio to help showcase how innovation can occur among multiple dimensions. Table 2 shows the relevant dimensions to be considered to assess an organization’s innovation portfolio and brainstorm innovations. The table can be filled with an organization’s innovations over the past years and the organization can then assess where are the strengths and weaknesses lie. Also, the table can filled with innovation zones ideas, and the Innovation 2.0 portfolio can help the organization decide on evaluation metrics such as risks associated with the idea. Overall, the Innovation 2.0 portfolio can help keep numerous parties engaged and consistently promote the goals of the innovation zone.

Table 2: Adapted Dimensions of an Innovation 2.0 portfolio from Koulopoulos (2009).
For successful innovation zones, Iyengar et al. (2017b) offer the following guidance: set ambitious goals, guarantee autonomy, improve teaching and boost learning, follow the students, and be sustainable and scalable. After interviewing philanthropists involved in innovation zones, the researchers offer suggestions such as continuously asking about what works, waiting patiently for the best investment opportunity, and working with various stakeholders to design a high-impact investment. Also, start small before accelerating what works.

Inconsistencies and Nuances
The primary nuance found in our research for Topic 5 was the inconsistent terminology used to describe innovation zones. Some authors described an innovation zone as a knowledge zone (Amidon 2005; Amidon & Davis 2006), while others used a place-based innovation zone (Rissola et al. 2018, 2019; Vechakul et al. 2015), and others just used the term innovation zone (Armstrong & Yazdi 2004; Greenberg 2015; Iyengar et al. 2017b; Koulopoulos 2009; Rammert et al. 2018; White et al. 2017). While we argue that there needs to be a uniform definition for innovation zones, we also acknowledge the fluidity of a name. An innovation zone is composed of multiple parties within a geographical area, so it could be that the name of an innovation zone would change over time. However, a key feature of successful innovation zones is having a clear vision and purpose (Khan & Mikroglou 2009).

The sources revealed unique approaches to highlighting aspects of an innovation zone. Although a zone involves numerous stakeholders, from local community partners to philanthropic efforts, innovation zones appear to have different priorities. For example, de Falco (2018) discussed the start of an innovation zone based on Apple’s establishment of a training facility in a part of the Italy that was less industrial than in its vibrant past. Our review of the literature shows that some stakeholders focus on advancing technological aspects that might be lacking in their zone, while
others focus on the academic side. Several articles mentioned that community buy-in is key to a sustainable innovation zone (Amidon & Davis 2006; Jones & Chambers 2021; Vechakul et al. 2015; White et al. 2017). We found very little emphasis in the literature on community buy-in aside from authors’ closing recommendations.

Suggestions for the Committee

The primary recommendation is for innovation zones to promote their metrics of success. Creating an innovation zone allows local districts to recreate their image. In doing so, innovation zones need not only to articulate an action plan but also have repeated opportunities for check-ins. A comparative case study of a particular region, similar to the one conducted by Rissola & Haberleithner (2020), would be helpful in understanding best practices for innovation zones. As of June 2021, 25 states have an innovation zone (Jones & Chambers 2021); however, no such sizable comparative study exists to our knowledge.

Another recommendation would be for innovation zones to find alternative funding sources. Several sources described wanting fewer regulations from the government on their innovation zone. Since the goal of an innovation zone is to give autonomy back to the local populations and inspire creativity, having decreased involvement from the government would help do just that.

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