# Racial Equity and the Future of Work

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## Introduction:

Automation and artifical intelligence are changing the nature of work in ways that are having profound impacts on both the social and the built environment. One recent study estimates that 47% of U.S. jobs are at near-future risk of becoming computerized (Frey & Osborne, 2017). Scores of other reports and news articles profile the development of job killing robots and pontificate upon whether AI means the end of work (Kessler, 2018; Rifkin 1995). Yet most experts point out that such dire predictions typically fail to account for creation of new forms of work. Automation does not necessarily just replace humans, but rather enables humans to perform new activities (Woods, 1994). The automation of office tasks (e.g., answering phones or making copies) led to both decline in the need for secretaries while increases work for executives (Rifkin, 1995). Automated robots led to fewer workers on the factory floor but created jobs for the software engineers to program the robots (National Academies of Sciences Engineering and Medicine, 2017). Similarly, automation is computerizing aspects of driving, reducing the need for long haul truck drivers while increasing the need for a backup engineer to monitor the automation (Fagnant & Kockelman, 2015). Thus, the relevant discussion is not about the end of work, but rather who wins and who loses in the AI transformed workforce.

In the absence of conscientious effort to understand and proactively address questions of equity in the design, production, and dissemination of new technologies, it is likely that continued automation will likely exacerbate problems of racial and class inequality (NASEM 2017). One need only look to recent history for evidence. African American households bore much of the brunt from automation in agriculture and manufacturing in the 20$^{th}$ century, while reaping little of the associated gains (Srnicek & Williams, 2015). People of color are also overrepresented in jobs at high risk of automation, such as transportation, production, administrative support, and food preparation (Muro, Liu, Whiten, & Kulkarni, 2017). They are also underrepresented in the science, engineering and knowledge workforce who are not only more likely to benefit from continued technological change but are also largely responsible for designing the displacing technologies. These problems are compounded by spatial segregation and the emergent geography of the knowledge economy that favors skill-rich areas while leaving vulnerable populations further isolated.

Scholars and policy makers are only beginning to consider the equity implications of AI and the future of work. To help address this deficiency, we convened a series of NSF funded workshops during the spring of 2018, bringing together experts in the social sciences, computational sciences, and engineering in order to articulate a research agenda for understanding the challenges of shaping emergent technologies that result in "good" jobs for a wider range of workers. We then presented our findings before an audience of stakeholders representing community organizations, organized labor, workforce and economic development offices, state and local government, as well as the private sector to get feedback on the academic conversation in terms of feasibility, remaining questions and gaps, and the potential strategies for conducting future action research.[1] The workshops were organized around several thematic areas, with the goal of setting a research agenda for each and identifying opportunities for the cross-fertilization of knowledge across themes.

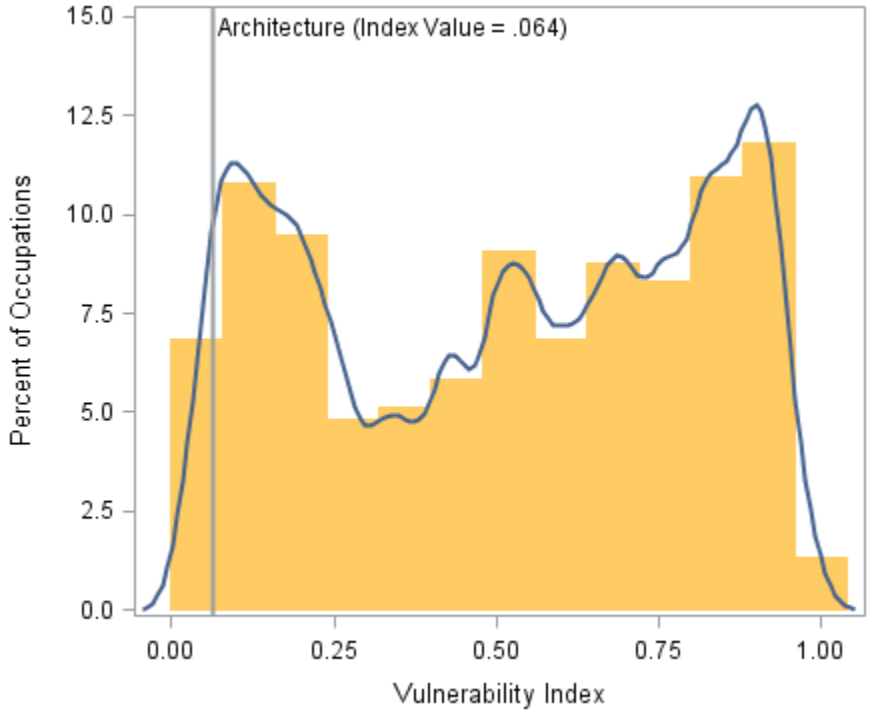
## AI and the Future of Equitable Work

Discussions on this theme focused on understanding the possibilities for emergent technologies to impact human work and how these technologies might be designed with equity in mind. Existing models measuring the impacts on automation on the labor force essentially focus on the skills and activities required by different occupations (Manyika, Lund et al. 2017, Frey and Osborne, 2017). Routine and repeatable activities are most easily automated, while human work is more secure in areas requiring adaptation, unpredictability, creativity, decision making and social intelligence (Parasuraman & Riley, 1997; Levy and Murnane. 2013). This includes occupations such as management and business; computers; engineering and science; education, legal, community service, arts, and media; and healthcare practitioners. It also includes architects, landscape architects, planners, and civil engineers, which are all in the bottom 10$^{th}$ percentile of AI vulnerable occupations —mainly because the importance of critical thinking, communications, active listening, complex problem solving and judgment skills (Figure 1).[2]

[1] Our project was supported by the National Science Foundation under grant number 1744356. All findings and views are the authors' and do not necessarily reflect those of the NSF. The workshop report, "Understanding Emerging Technologies, Racial Equity, and the Future of Work" can be found at this link: http://rbr.cs.umass.edu/htf/.

[2] Occupational tasks and skill ratings for occupations were reviewed O*NET Online, available at https://www.onetonline.org/, accessed on August 15, 2019.

**Figure 1:** Distribution of Occupations (n=695) according to predicted vulnerability to AI




*Source: Author's calculations of combined vulnerability probabilities from Frey and Osborne, 2017, and Manyika, Lund et al. 2017. Both measure occupational vulnerability to automation based upon skill requirements.*

But even resilient jobs are influenced by technological change. Over time, occupations evolve as new technologies continue to strip away routine tasks, while non-routine activities are consolidated and combined—making human work increasingly skill intensive and requiring more formal education. In this way, technological change is 'skill-biased' and has fostered inequality due to the growing mismatch between skills of those seeking work and skills needed in this new labor market, who are often racial minorities (Ryan & Bauman, 2013). Recent advances in artificial intelligence have also made great strides in developing adaptive algorithms to capture an ever-expanding collection of non-routine tasks.

With this rapid increase in automation also come opportunities to re-imagine the workforce with a focus on equity. We need to further develop the concepts of explainability, accountability, and fairness in AI (Miller, 2019; Miller, Howe, & Sonenberg, 2017; West, 2018) and develop analytic tools to help us understand existing biases in current systems. Such tools can build on past research that examined how AI can unknowingly inherent human stereotypes (Caliskan, Bryson, & Narayanan, 2017). For example, biased algorithms for job referrals have led to a disproportionately low number of racial minorities being hired (Guynn, 2017). Redesigning these AI algorithms with equity in mind could help address bias and counteract similar trends.

AI might also help us fill the data gaps that limit our understanding of potential impact of new technologies. Our workshop participants emphasized the need for better predictive models to help identify the gaps between employer needs and worker skills. The detailed data to fuel these models might

come from AIs that mine the text of online job boards or professional networking sites. With more information about skills gaps, schools can better tailor their curriculum. AI can also help us understand how technology is impacting workers, including the intended and unintended consequences of deploying automation in the workplace (Lee & Seppelt, 2012). The results from this analysis can be used to propose technology that enables participation in the job market from a broader range of populations and thereby increases equity and diversity, leveling the playing field.

## Intersectionality of Race, Gender and Skill

Intersectionality is a key lens for understanding equity in the workplace. It refers to the interlocking nature of systems of oppression affecting individuals and their life opportunities. Historical trends reveal the relative nature of occupational opportunity, and how ethnic minorities are typically the most vulnerable to replacement by automation. For example, white women do not have the same experiences as Black women in working on the built environment as designers or construction workers. Intersectionality provides us with the language and tools for analyzing the impact of interconnected identities on people's lives that complicates traditional understandings or discrimination and inequality.

Studies on the future of work need to consider how access is granted to some members of the workforce and withheld from others, and the role of the built environment in access to work. Policies and practices must be considered as intertwined with technological futures. For example, some buildings only have stairs for accessing the third and fourth floors. If you asked someone in 1990, when the ADA was passed, whether 30 years later a building could still exclude people with disabilities from the workplace, few would have predicted that future. Failing to incorporate intersectionally about the built environment and the future of work will yield solutions that exclude and alienate the most marginalized people in our society.

One of the major questions in thinking about technology and the future of work is how automation may interact with already pervasive and persistent racialized and gendered inequalities. Given economic shifts over the past half century that have increased inequality in the United States, how does automation accelerate these trends downward, and further segment the labor market along racial and gender lines? Intersectionality as a lens is needed for a fuller understanding of the effects of automation and AI-powered technologies on work and workers.

## Knowledge Production

Research on organizations and workers designing artificial intelligence knowledge systems is key to developing clearer understanding of equity, and who benefits from new technologies. The imagined goals and outcomes of automation technology are important to study, but notably difficult to measure. This kind of research requires close, qualitative study within design organizations.

We need to study by whom and how automation technology is produced. Our workshop participants noted that data on the AI workforce are often located in privately held companies, which means access to data that could provide even a basic idea of who is designing AI is missing. The experts noted that in AI, like in AEC, large market-dominating players are key to understanding how technology will be rolled out. They suggested research focusing on large organizational players is more pressing to conduct than equity dynamics within education systems (K-12 to higher education) because students will not shape technologies until many years down the road, while companies are shaping automation processes right now.

The various organizations in which knowledge production occurs may have very different processes and outcomes. Privately held firms are more opaque than public universities, for example. Information asymmetry occurs when private companies collect immense amounts of user data, while users are not privy to the information collected (including their own usage, or that their photos are in a facial recognition database). Research should examine organizational variation in knowledge and technology production.

However, there are increasing opportunities to develop research partnerships with private actors as they become more conscious and potentially liable for the societal impact of their technologies. For example, in the high-tech sector, firms have publicly expressed interest in equitable AI technology. Public value statements about diversity may lay groundwork for both conducting research with firms interested in equitable development of technology and communicating findings with firms that may lead to more equitable AI-powered technologies.

## AI and the Built Environment

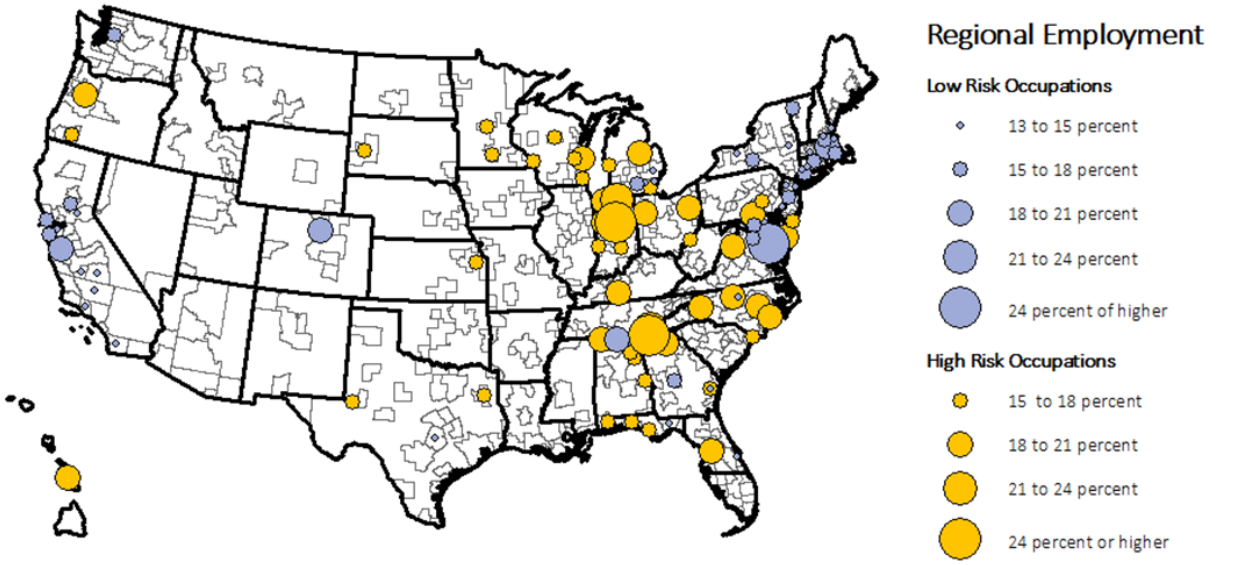
Among the least appreciated topics in discussions of the Future of Work, is how AI and related technologies will shape the built environment and whether this transformation will perpetuate, exacerbate, or mitigate historic patterns of race and class division and segregation.

The answer may depend on scale. At the inter-regional scale, the transfer of income and wealth associated with technological change has favored bigger cities as the preferred centers for knowledge production and transmission. With the notable exception of some University towns and tourist destinations, rural areas and smaller cities have struggled to find a niche in the "knowledge economy." The continued decline of manufacturing and agricultural occupations predicted by current models suggests a heightening of these trends. Thus, the cities that are most vulnerable to AI-induced job losses tend to be smaller, older, less racially diverse, and have lower levels of overall educational attainment (Figure2).

Figure 2

Metropolitan areas with large 2017 employment shares in occupations with high/low susceptibility to AI

**Figure 2:** Metropolitan areas with large 2017 employment shares in occupations with high/low susceptibility to AI




| Top High-Risk Metros | Top Low-Risk Metros |
|---|---|
| Dalton, GA | California-Lexington Park, MD |
| Kokomo, IN | Washington-Arlington-Alexandria, DC-VA-MD-WV |
| Cleveland, TN | Framingham, MA |
| Elkhart-Goshen, IN | San Jose-Sunnyvale-Santa Clara, CA |
| Gettysburg, PA | Boston-Cambridge-Newton, MA |
| Gainesville, GA | Boulder, CO |
| Florence-Muscle Shoals, AL | Silver Spring-Frederick-Rockville, MD |
| Sheboygan, WI | Lowell-Billerica-Chelmsford, MA-NH |
| Jacksonville, NC | Durham-Chapel Hill, NC |
| Burlington, NC | San Francisco-Redwood City-South San Francisco, CA |

*Source: Author's analysis of occupational susceptibility ratings (Frey and Osborne, 2017, and Manyika, Lund et al. 2017) merged with metropolitan employment data from the Bureau of Labor Statistics Occupational Employment Statistics (OES)*

Issues of gentrification, mobility, housing, and racial segregation are more salient at the intra-city scale. Of all racial groups, African Americans are the most physically isolated from jobs within a city (Squires & Kubrin, 2005). In the 1960s and 1970s planners coined the phrase "spatial mismatch" to describe the discordance between the physical location of jobs within a city and the populations that need them (Kain, 1968). At the time, job growth was mainly in the suburbs with needy populations increasingly concentrated in the urban core. In recent years, access to highly-educated talent has pulled many companies back downtown and contributed to rapidly increasing rents and intensified redevelopment pressures in many traditionally minority and ethnic neighborhoods (Florida, 2016).

Similar to the other themes, we need better data sources and analytical to fully understand these trends and their implications for the built environment. In particular, we need to better understand the interrelationship between job availability, housing location, and transportation options at highly gradual spatial scales in order to connect job openings with those who need them (Ong & Miller, 2005). Even less well understood are the unintended side-effects of AI on human behavior in the built environment. For example, the proliferation of more automated vehicles means that traffic routing and control decision will increasingly be in the hands of private, profit-motivated, entities that lack direct public accountability and are shielded by proprietary and increasingly opaque machine learning algorithms. It may be that these navigation systems routinely direct traffic to corridors that are commercially advantageous to the parent corporation or unintentionally choose routes that systematically limit a driver's exposure to a wider variety of ethnic/racial enclaves. The possible consequences are reminiscent of the urban renewal and highway building projects of the 1950s and 60s that helped shape patterns of segregation and inequality by directing investment to favored areas while isolated minority populations (Nall and O'Keif 2018; Karas 2015; Hirsch 1983).

## Conclusion

We are at a critical inflection point in our history where technology is drastically changing the nature of work. The increasing use of automation in the workplace will continue to eliminate, create, and transform jobs. With this emerging technology comes the potential for increasing inequality, especially for racial minorities. As such, there is a dire need to identify what is unknown as well as what can be done to ameliorate the negative effects of automation.

An interdisciplinary and convergent approach is needed to address the intertwined challenges of understanding emerging technologies and racial equity in workplaces. If current AI research efforts in academia and industry do not draw on the expertise of social scientists, there is a danger of reproducing existing inequalities in both the processes and products of that development. Likewise, if current social science efforts to understand inequality do not draw on the expertise of computer scientists and engineers who are designing new work systems, the understanding can at best be partial. Architects, planners, geographers and other scholars of the built environment can also play a critical role in this debate by focusing attention on the importance role of space, place and context in defining human experience and shaping one's exposure to different peoples, cultures and social issues.

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