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From Community Bias to Career Pathways: Rural–Urban Trends in Implicit Gender Bias and Engineering Participation

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Abstract

Women remain underrepresented in engineering, and implicit biases have been shown to significantly shape environments where career choices are made. While bias has been widely studied in general populations, less is known about how it differs across rural and urban communities and how these differences may influence the pipeline of women pursuing engineering. This study examines variation in adult implicit bias using Project Implicit data, with the goal of understanding the community contexts that may shape young women's career pathways.

Guided by social cognitive career theory, we hypothesized that adults in rural US communities would hold stronger implicit biases about which careers are appropriate for women than those in urban communities. We also examined broader demographic patterns to identify how implicit gender-career and gender-science biases vary across gender, education, and other characteristics. Using open-source Gender–Career and Gender–Science Implicit Association Test (IAT) data linked with demographic and geographic indicators, we applied quantitative comparative analyses to assess rural-urban and demographic differences across a decade of responses.

Findings show that implicit bias is widespread, and that while the hypothesis that rural respondents demonstrate stronger associations linking men with careers in science and engineering is supported, it is by no means the strongest trend observed in the data. The most striking finding is that women themselves demonstrate significantly stronger implicit bias regarding their own place in male-dominated fields compared to men, likely reflecting internalized societal associations rather than explicit endorsement. This suggests that community norms and self-perceptions reinforce barriers that may limit women's entry into engineering, particularly in rural contexts where role models and counterexamples are less visible, and highlights the need for targeted, context-specific strategies to counteract implicit bias and broaden women's participation in engineering.

Keywords: implicit bias, rural, engineering, gender, career, science

Introduction

It is well known that there is a significant underrepresentation of women in STEM fields. While this topic has been studied worldwide [1]-[3], the specific effect of different contributing factors on this underrepresentation remains unclear. This study specifically focuses on understanding the effects of regional background (rural versus urban) on implicit bias that may impact young women's career decisions and pathways. This focus is driven by prior findings on the unique educational opportunities for rural students, where they navigate the challenge of limited access to advanced coursework, extracurricular activities, and local career role models [4]-[6]. In addition, it builds on findings showing that rural students often rely on the support and guidance of their community, family, and/or religious institutions in deciding their future careers [7]. Guided by social cognitive career theory, this study utilizes a decade of Implicit Association Test (IAT) data to examine how demographic and geographic patterns in implicit gender-career and gender-science bias may be associated with factors that shape young women's career decisions and pathways.

Background

Project Implicit

This quantitative study uses implicit bias data from Project Implicit. Implicit bias refers to unconscious attitudes or beliefs that individuals may hold about social groups [8]. Project Implicit is a non-profit organization founded by three scientists: Dr. Tony Greenwald (University of Washington), Dr. Mahzarin Banaji (Harvard University), and Dr. Brian Nosek (University of Virginia), whose objective is to educate and provide a "virtual laboratory" for the public on implicit biases, attitudes, and differences [9]. A person's implicit biases are considered to be their own unique thoughts or beliefs, which are shaped by their immediate surroundings, environment, or culture [10]. The data collected from Project Implicit has been used in several well-received studies [11]-[13], with studies ranging from how implicit biases affect national gender gaps in math and science using data from gender equality index scores [13], implicit gender-career and gender-science bias analysis exploring the long-term effects of teacher's gender stereotypes on career outcomes [14], and using implicit bias training to create a more supportive environment for women in STEM [15]. This study uses implicit bias data collected from Project Implicit to investigate how surrounding environments (rural versus urban settings) may be associated with differences in implicit bias related to career pathways.

Although implicit biases have been shown to differ across both rural and urban communities (largely due to differences in environmental exposure and social context that shape unconscious associations), the extent to which the strength of these biases differs between rural and urban communities remains relatively unexplored [16]. Some studies suggest little to no difference in implicit biases on gender-career and gender-science topics among young women based on regional background (meaning little to no difference in associations between STEM topics like math being pleasant or unpleasant) [17]. However, other studies have shown that STEM career aspirations can change over time, depending on the environment in which youth are raised [18]. This is notably due to the lack of opportunities present for those living in rural areas in terms of advanced coursework in math and science, teaching capacity, and extracurricular programs or activities in STEM, compared to those living in urban communities [18].

This study examines implicit bias in different regional contexts through the framework of social cognitive career theory. Social cognitive career theory suggests that career development is shaped by the formation of interests, career choices, and performance outcomes [19]. Within this framework, there are three main concepts that are studied to provide further insight, which include self-efficacy, outcome expectations, and goals related to career choices [19]. Self-efficacy is shaped from four primary sources, which include personal performance accomplishments, indirect experiences, social persuasion, and physiological and emotional states. Outcome expectations are beliefs about the consequences or outcomes of an individual's actions or behaviors, which in turn influence the actions individuals choose to pursue. Finally, goals refer to an individual's intentions to engage in activities or achieve specific levels of performance, which are formed based on the first two concepts [20]. Social cognitive career theory has been used in several studies to explain the underrepresentation of women in STEM fields, particularly in relation to implicit gender bias and limited access to role models [21]-[23]. For this study specifically, social cognitive career theory provides a framework for interpreting how urban and rural contexts may shape implicit gender-career and gender-science biases, which in turn may be associated with young women's career aspirations and decisions.

The U.S. Census Bureau (2020) defines urban areas as contiguous, densely developed territories that contain at least 5,000 people or 2,000 housing units. Rural areas are defined as all areas (open countryside and settlements) located outside of this urban definition. This definition is built from census tracts, which are nationally consistent, relatively permanent geographic divisions of a county that serve as small statistical units for data analysis [24]. This study uses the geographic categorizations derived from Project Implicit data to delineate rural and urban areas, which assigns participants into Metropolitan Statistical Area (MSA) identifiers derived from the census-defined categorizations. According to the U.S. Census Bureau, an MSA is defined by one of two quantitative metrics. It must either have a city with a population of at least 50,000 or contain a census-defined urban area and have a total population of at least 100,000. MSAs usually include one or more central counties that contain both a core population area and adjacent communities that are linked economically and socially [25].

Within the IAT, participants self-report their location by inputting the name and ZIP code of the area in which they live. Project Implicit then categorizes this information using MSA identifiers, drawing on ZIP code-based classification systems such as those from the U.S. Department of Labor to identify metropolitan areas [26]. Under these criteria, an area is categorized as "urban" if the participant's ZIP code is found within an MSA, where the location is a high-density metropolitan area that includes both urban areas and integrated suburban subsections. On the other hand, an area is categorized as "rural" when the participant's location falls outside of the

MSA identifiers, where the location is a more isolated, low-density area. This ensures that there is a clear distinction between those living in a heavy metropolitan area and those in non-metropolitan areas. While this classification provides a practical method for distinguishing between metropolitan and non-metropolitan areas, it may not fully capture the complexity of rural–urban differences, particularly in regions that include suburban or peri-urban characteristics.

Several studies have compared rural and urban communities, with many focusing on differences in community characteristics, access to technology, and educational outcomes [27]-[29]. Related to this study, it has been shown that youth in rural communities face distinct challenges in career development, including limited educational resources, a shortage of high-paying local jobs, and the decision between remaining in their home community or relocating to an urban area for greater opportunities [30]. More specifically, in terms of gender and career development within rural communities, young women often experience the challenge of balancing personal career aspirations with traditional social expectations [30]. It has also been shown that young women in both rural and urban communities tend to make career choices based on factors such as financial goals, the desire to help others, and external influences, including input from significant individuals in their lives, digital media, educational environments, and their own self-efficacy beliefs [30], [31].

Building on this prior work, the present study examines how differences in regional context may be reflected in implicit gender-career and gender-science biases, providing insight into how these environments may shape the broader social and cognitive factors associated with young women's career development. By analyzing implicit gender-career and gender-science data through the framework of social cognitive career theory, this study seeks to understand how regional contexts may be associated with differences in implicit bias that shape young women's career aspirations and development. Because previous research identifies that rural settings often face unique challenges, it is important to investigate how these environments may contribute to differences in implicit biases related to career pathways. Accordingly, this study addresses the following research questions:

1. Is gender–career implicit bias stronger in rural settings than in urban settings?
2. What additional patterns emerge in gender–career and gender–science implicit bias across rural and urban populations?

Methodology

To examine the hypothesis that gender-career bias is greater in rural areas compared to urban areas, the data were quantitatively analyzed using a large open-source database, Project Implicit. This study focuses on data from the decade 2012-2022, to ensure that the findings reflect long-term yet current implicit gender-career and gender-science bias trends. Project Implicit collects and allows access to data surrounding implicit biases, gathered through their Implicit Association Tests (IAT) [32]. Specifically, this study focuses on both gender-career bias (measuring the implicit bias of males with careers and females with family-related roles) and gender-science bias (measuring the implicit bias of males associated with science and females associated with liberal arts). The Project Implicit database was selected for use due to the extensive set of existing data, allowing for large-scale population-level analysis rather than direct participant recruitment. The goal of the analysis was to compare the patterns of implicit bias related to gender-career and gender-science between rural and urban populations. The primary variable of interest in the study is the final IAT score, which reflects the strength of implicit bias.

In describing our methodology and use of Project Implicit data, it is important to note that some researchers have raised concerns regarding the interpretation and use of Project Implicit data [33] - [35]. Researchers argue that the test's reliability is based on context or in the test-taker environment, leading to concerns about the implicit bias measurements [33]. Additionally, researchers point out that while the IAT can reveal implicit bias, its ability to predict individual behavior remains debated [34]. Questions have also been raised about the Project Implicit dataset relying on voluntary participation and online testing, which may introduce biases into the data [35]. While these concerns are important, this study focuses specifically on gender-career and gender-science bias, where prior research suggests more consistent group-level patterns, reducing some concerns about instability [36]. Furthermore, the large (approximately 118,500) and diverse sample supports the identification of broad population-level trends, though it may not fully represent the U.S. population. Additionally, the IAT is used for its ability to capture implicit associations that individuals may not be able to consciously report. Accordingly, the results are interpreted at the group level rather than as indicators of individual attitudes or behaviors.

Implicit Association Testing

The Implicit Association Tests quantify the strength of associations between concepts and stereotypes. The IAT has been used in a variety of studies and is known for its reliability in measuring group-level patterns in unconscious associations [36] in areas ranging from race [37] to gender differences in math [38]. Specifically, the gender-career IAT measures implicit biases between traditional stereotypes (males with careers, females with family-centered roles) and non-traditional stereotypes (females with careers, males with family-centered roles). The gender-science IAT measures implicit biases between traditional stereotypes (males associated with science, females associated with liberal arts) and non-traditional stereotypes (females associated with science, males associated with liberal arts). This makes it a valuable tool to study implicit gender biases.

Individuals (above the age of 18) can voluntarily become participants in Project Implicit by going to the affiliated website, where they can take one of the fourteen tests available. The participants complete seven sections of rapid categorization, where they sort words into four groups, depending on the subject. For this study, the groups for gender-career bias would be male, female, career, and family, while the groups for gender-science bias would be male, female, science, and liberal arts. This test measures the participant's reaction time from pairing stereotypical and non-stereotypical pairings.

The test is conducted by having participants categorize words that appear on their screen as quickly as possible. There is a total of 4 categories, 2 of which are male and female, while the others are career and family. The screen will then flash a word or name and time how long it takes for the button corresponding to the correct category to be pressed. If the “wrong” category is selected, a red “X” will then appear on the screen until the mistake is fixed. There is a total of seven blocks of these tests, blocks 1, 2, and 5 test participants using only one concept (either gender or career) to test their reaction speed. Once the basis is identified, they use blocks 3, 4, 6, and 7 to test stereotypical and non-stereotypical pairings. For example, in blocks 3 and 4, participants were asked to classify a name or word as “male or career” versus “female or family”. While in blocks 6 and 7, participants were asked to classify a name or word as “male or family” versus “female or career”. Half of the participants completed the stereotypical pairing first, while the other half completed the non-stereotypical first.

Data Analysis

The open-source data for gender-career and gender-science implicit bias from 2012–2022 were obtained from Project Implicit and used for this study. The data were first filtered to remove any participants who had not completed sufficient demographic information (such as their gender, religiosity, education, primary caregiver, and postal code) to be fully analyzed in this study. Any participant outside the United States was also excluded from the dataset. Once finalized, participants were classified into geographical locations of either rural or urban areas based on self-reported locations. As described previously, the test directly utilized U.S. ZIP code information to distinguish between rural and urban communities.

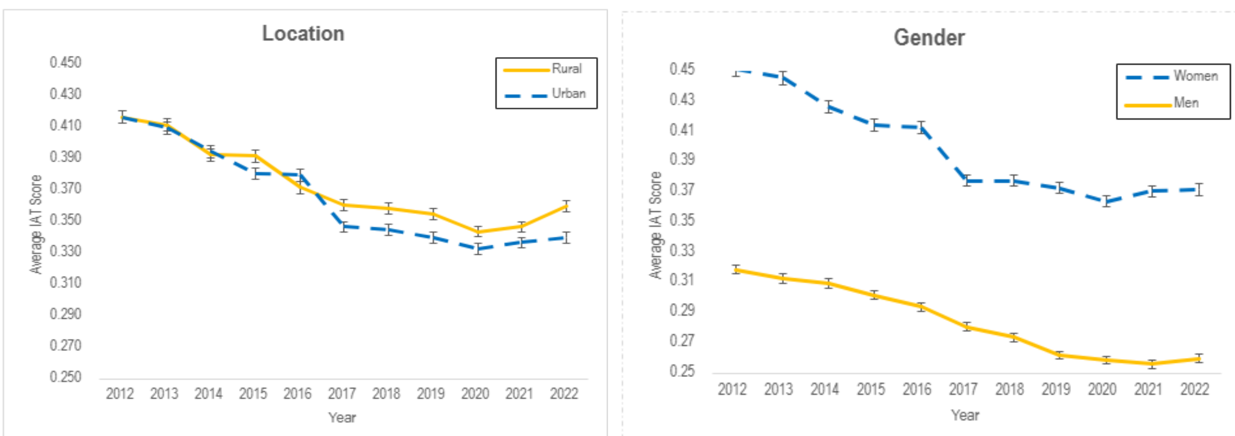
Because IAT scores exhibit substantial individual-level variability but greater stability when aggregated, this study focuses on group-level comparisons rather than individual-level prediction. Prior large-scale analyses have demonstrated that mean IAT D-scores provide a more stable indicator of cultural bias patterns than individual scores, making aggregation appropriate for examining systemic differences across populations [38]. Accordingly, mean IAT scores were used to represent implicit bias levels within groups (such as rural and urban). To assess differences between groups, independent samples t-tests were conducted to compare mean IAT scores across rural and urban populations for both gender-career and gender-science measures. This approach aligns with common analytical strategies used in large-scale IAT datasets, where the goal is to compare differences in magnitude across groups rather than model individual-level predictors. While multivariate approaches could further isolate the effects of demographic variables, this study prioritizes descriptive group-level comparisons to identify broad patterns in the data.

Although $p < 0.05$ is a commonly used threshold for statistical significance, large datasets can produce statistically significant results even for small effects. Therefore, a more conservative threshold of $p < 0.01$ was used to indicate meaningful differences. All comparisons met this threshold, indicating statistically significant differences between groups. However, given the large sample size, results are interpreted with attention to effect size and practical significance rather than statistical significance alone.

Findings

Gender-Career Bias

Figure 1 (left) shows the average IAT scores over the years 2012-2022 for geographic context-based gender-career bias, while Figure 2 (right) shows the average IAT scores over the years 2012-2022 for gender-based gender-career bias. As a reminder, a higher IAT score represents a stronger implicit bias. For Figure 1, participants in rural areas exhibit slightly higher average bias than those in urban areas over time. For Figure 2, however, women exhibit substantially higher average bias than men.



Figures 1 and 2: Geographic Context-Based Gender-Career Bias and Gender-Based Gender-Career Bias

Figure 3 shows the average IAT scores over the years 2012-2022 for the combined effects of gender (women vs. men) and location (rural vs. urban) on gender-career bias. This reconfirms that gender differences are more pronounced than geographic differences. Women in rural areas exhibit slightly higher bias than women in urban areas, while men show minimal differences across geographic contexts. This pattern highlights the stronger role of gender relative to location in gender-career implicit bias.

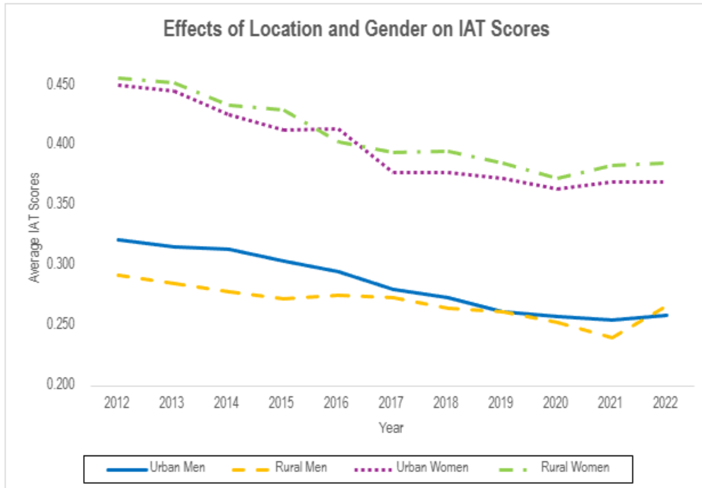
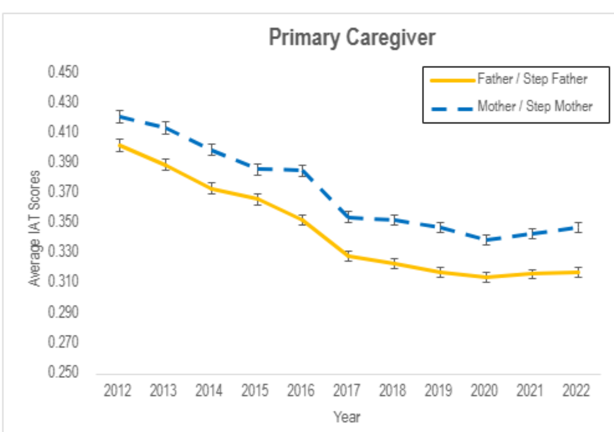


Figure 3: Effects of Location and Gender on IAT Scores

Figures 4, 5, and 6 show the average IAT scores over the years 2012-2022 for various external factors for gender-career bias. Figure 4 (left) shows the primary caregiver-based gender-career bias; Figure 5 (right) shows the education-based gender-career bias, and Figure 6 shows the religion-based gender-career bias. These characteristics were taken from the participant self-reports, where the data were categorized into two groups for comparison. The main distinctions for these include caregiving status (primary vs. non-caregiver), education level (college vs. non-college educated), and religious affiliation (religious versus non-religious). Figure 4 shows that participants whose mother or stepmother was their primary caregiver exhibit higher average gender-career bias compared to those whose primary caregiver was their father or stepfather. In Figure 5, no consistent trend is observed across education levels. In Figure 6, participants identifying as religious exhibit higher average bias than those identifying as non-religious. Taken together, these results suggest that gender-career implicit bias is more strongly associated with sociodemographic and experiential factors than with geographic context.



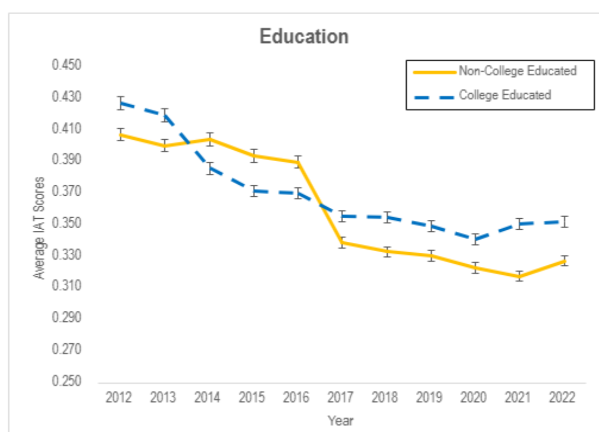


Figure 4 and 5: Primary Caregiver-Based Gender-Career Bias and Education-Based Gender-Career Bias

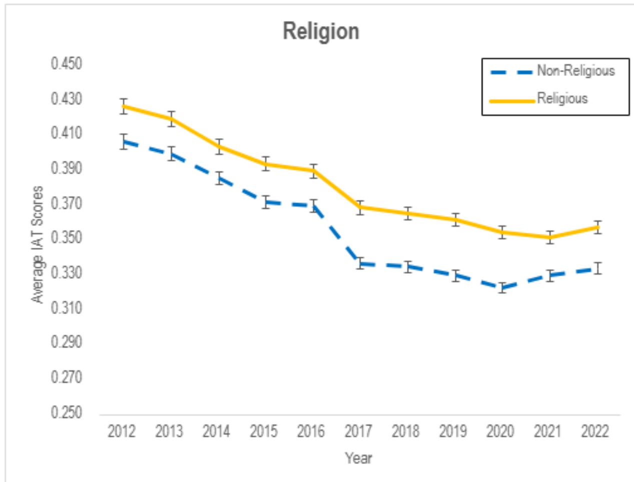
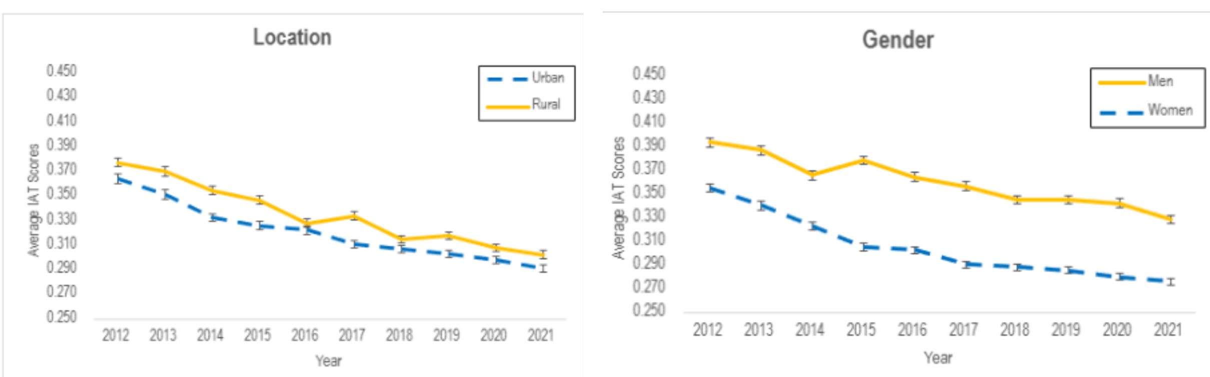


Figure 6: Religion-Based Gender-Career Bias

Gender-Science Bias

Figures 7 and 8 show the average IAT scores for geographic and gender-based differences in gender-science bias, respectively. In Figure 7 (left), participants in rural areas again exhibit slightly higher average IAT scores than those in urban areas. In Figure 8 (right), however, men exhibit higher average bias than women, which contrasts with the pattern observed in gender-career bias.



Figures 7 and 8: Geographic Context-Based Gender-Science Bias and Gender-Based Gender-Science Bias

Figure 9 shows the combined effects of gender and location on gender-science bias. Men exhibit consistently higher IAT scores than women across both rural and urban settings, with minimal geographic variation. In contrast, women in rural areas exhibit slightly higher bias than women in urban areas, though the difference remains modest.

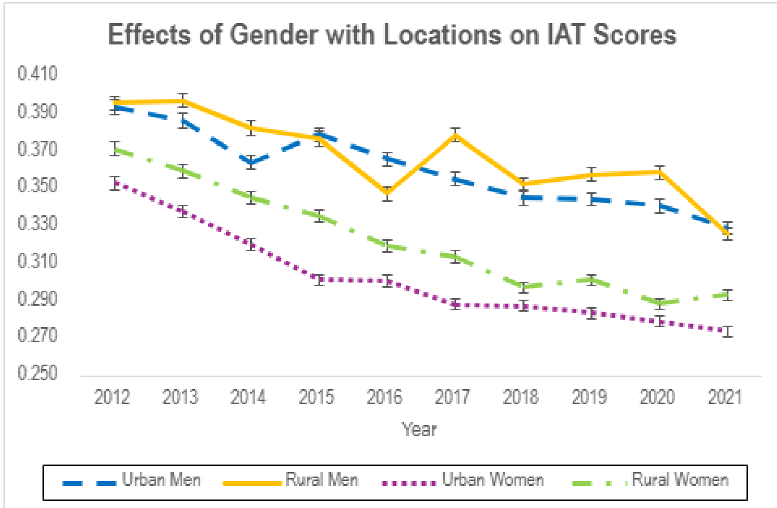
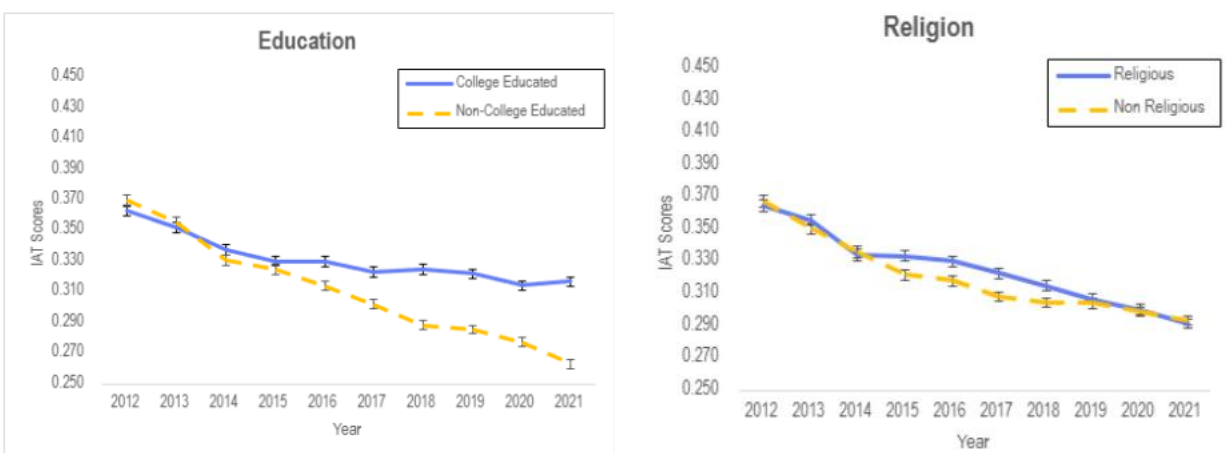


Figure 9: Effects of Location and Gender on IAT Scores

Figures 10 and 11 show the effects of additional demographic factors on gender-science bias. Figure 10 presents education-based differences, while Figure 11 presents religion-based differences. In Figure 10, no consistent overall trend is observed across the decade, despite some variation in recent years. In Figure 11, no clear relationship is observed between religiosity and gender-science bias. (Primary caregiver data were not available for the gender-science IAT and are therefore not included.)



Figures 10 and 11: Effects of Education on IAT Scores and Effects of Religion on IAT Scores

Discussion

The primary purpose of this study was to examine the effect of regional background on implicit bias to better understand young women's career decision-making, guided by social cognitive career theory. The results yielded two main findings. First, gender-career bias aligned more strongly with sociodemographic and experiential factors (most notably gender) than with regional background. This pattern is consistent with prior research identifying personal values such as the desire to help others, self-efficacy, and financial stability as dominant influences on women's career choices [30], [31]. It also aligns with social cognitive career theory, which emphasizes the central role of self-efficacy, outcome expectations, and personal goals in shaping career pathways [19].

The second key finding of this work is that, despite not being the largest driver, regional context is still a notable contributor to implicit bias. Women from rural backgrounds exhibited slightly higher levels of implicit bias in both gender-career and gender-science measures compared to their urban counterparts. Although modest, this difference suggests that regional background may contribute to differences in implicit bias through its influence on developmental contexts. Resource-limited STEM environments, common in rural settings [18], may shape exposure to role models, access to opportunities, and social reinforcement, which are factors closely tied to self-efficacy within social cognitive career theory. As a result, reduced access to STEM opportunities and role models may be associated with lower STEM-specific self-efficacy and stronger implicit gender–science associations, potentially discouraging pursuit of STEM careers. In contrast, young women in urban areas are more likely to encounter STEM-rich environments, including greater access to coursework, extracurricular opportunities, and visible role models [18]. These experiences may support the development of stronger STEM-related self-efficacy and more positive outcome expectations, which are associated with the formation of STEM-oriented career goals.

Taken together, these findings indicate that while individual sociodemographic and experiential factors are the primary drivers of implicit bias, developmental and educational contexts remain important in shaping how these biases form and persist. Efforts to broaden participation in STEM should therefore address both individual-level factors and structural disparities in access to resources and role models, particularly in rural communities. These results further suggest a need for targeted educational and community-based interventions that support rural young women in overcoming both structural STEM limitations and implicit gender–science bias.

One additional finding from this data is that men had stronger gender-science bias than women, whereas women had stronger gender-career bias than men. This pattern may reflect domain-specific internalization of societal stereotypes, where individuals tend to reproduce the associations most culturally linked to their socially salient roles. Men may more strongly exhibit traditional gender-science associations due to historical overrepresentation in STEM, whereas women may more strongly internalize or recognize societal expectations linking women with caregiving and men with careers, leading to higher bias in the gender-career domain.

Conclusion

This study examined demographic and geographic patterns in implicit gender-career and gender-science bias using a decade of Implicit Association Test data through the lens of social cognitive career theory. Gender-career bias was primarily associated with sociodemographic and experiential factors, highlighting the central role of personal values, self-efficacy, and outcome expectations in shaping career-related attitudes. While regional differences were smaller, women from rural backgrounds exhibited slightly higher implicit bias, suggesting that limited access to STEM resources and role models may influence STEM-specific self-efficacy and outcome expectations. These findings indicate that implicit biases are shaped by both individual characteristics and the developmental contexts in which they occur. Efforts to broaden STEM participation in rural areas should address structural barriers, expand educational opportunities, and provide visible role models to strengthen self-efficacy, align outcome expectations with STEM goals, and support the pursuit of STEM pathways.

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