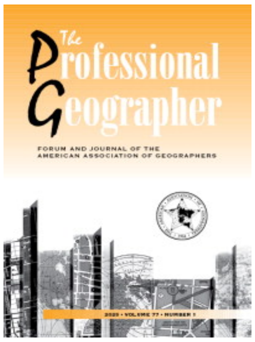

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Preparing for a Career at the Intersection of Geography and Computing: Availability and Access to Training Along Geocomputational Career Pathways

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The growth of the geospatial services industry is increasing the demand for a workforce with training at the intersection of geography and computing (i.e., geocomputation) in terms of skills, knowledge, and disciplinary background. To be more effective at increasing the supply of geocomputational professionals, we need to better understand the existing educational pathways that are available to acquire knowledge and skills in geography, computing, or both. In this article, we aimed to enhance our understanding of the current standing of geocomputational career pathways by (1) articulating the existing curriculum pathways from school to career and identifying broadening participation challenges associated with training opportunities; and (2) identifying specific gaps in knowledge, skills, and training needs and opportunities between geographers, computer scientists, and the geospatial technology industry. Our analysis of a survey of geocomputational professionals identified significant differences in knowledge, skills, and access to training between different educational pathways and between different demographic groups. **Key Words: computational thinking, diversity, inclusion, skills, spatial thinking.**

There is a growing demand for a workforce that can support solving geospatial problems rapidly. For example, when a disaster hits, time is of the essence and a swift informed response benefits from the use of large or interlinked geospatial data, which increasingly require computational resources. The growth of the geospatial services industry (AlphaBeta 2017) is increasing the demand for job candidates with geocomputational proficiencies. A 2020 survey of global enterprise leaders across all sectors found that 97 percent say it is either "difficult," "quite difficult," or "very difficult" to find and hire data scientists with expertise in spatial data analysis (Carto 2020). The same survey was conducted again in 2023, and 92 percent of respondents shared the same difficulty in hiring data scientists with this expertise (Carto 2023). Although there is a decreasing trend in hiring difficulty, we argue that the deficit of geospatially trained data scientists is not being addressed quickly enough.

Throughout this article, we refer to the intersection of geography and computing as *geocomputation*, whether it be in reference to skills, knowledge, or disciplinary backgrounds. The usage of this terminology is not ubiquitous, and workers that we qualify as geocomputational professionals might instead qualify themselves as geospatial analysts, environmental scientists, data scientists, cartographers, product engineers, urban planners, solutions engineers, and so forth. We are particularly interested in understanding where geocomputational professionals acquire their proficiencies. The Carto (2023) survey found that nearly 50 percent of respondents learned their spatial data science skills at work, and another 18 percent received training through online tutorials. This finding raises the question of whether formal educational pathways (K–12 and higher education) offer sufficient opportunities for career preparation in this growing industry.

To be more effective at increasing the supply of geocomputational professionals, we need to better understand the existing educational pathways that are available to acquire knowledge and skills in geography and computing, either separately or in combination. This article focuses on the context of the United States where a number of studies looked at ways to integrate geography and computing at different levels of education (Dony et al. 2019; Hammond, Oltman, and Manfra 2019; Shook et al. 2019; Bowlick et al. 2020; Bowlick et al. 2022; Shook et al. 2021). In the United States, formal educational pathways that integrate or intersect geography and computing (e.g., degree programs in GIScience, spatial data science, or spatial computing) are available but typically offered in either a geography or a computing department. Efforts to offer courses that engage faculty from both are still extremely limited because faculty often face administrative challenges that come with coordinating across different colleges. More important, however,

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any of these pathways have struggled to attract diverse student populations (Nelson, Goodchild, and Wright 2022).

Availability of Geocomputational Pathways

One of the main reasons for the difficulty of creating formal educational pathways at the intersection of two disciplines is that we still rely on a disciplinary way of training the workforce. Most students take courses that cover one subject and acquire a certificate or degree in one discipline (e.g., geography, geographic information systems [GIS], computer science, or computing) rather than a combination of fields.

Another challenge to the establishment of geocomputational educational pathways is that whereas the availability of K–12 learning pathways in computing is increasing, the number of learning pathways in geography is decreasing (D1ony 2023). Spatial thinking, a crucial element of geocomputation, has typically been taught in geography courses as part of the social studies curriculum, but only a few states still require geography for high school graduation (Zadrozny 2021). According to a 2015 report by the U.S. Government Accountability Office, "throughout the country … K–12 students may not be acquiring adequate skills in and exposure to geography, which are needed to meet workforce needs in geospatial and other geography-related industries" (U.S. Government Accountability Office 2015, 1). A more recent study of nationwide K–12 student-achievement trends in geography over the past 25 years (1994–2018) concluded that "schools … made no progress in bolstering overall achievement levels in geography" (Solem 2022, 150). Although this is a challenge specific to the United States, there is significant diversity in geography education globally (Solem and Tani 2017), and trends vary widely by country and their respective educational frameworks and backgrounds (e.g., Fortuijn et al. 2020).

Efforts to introduce geocomputation into single-discipline computing and geography college programs can be problematic. Computing programs are starting to offer courses that involve the use of location data. These courses, however, often lack the conceptual geographic knowledge (Sinton 2019) that supports understanding of spatial data quality standards that are required to avoid the risks of misused or mishandled spatial information, misinterpreted spatial analyses, and misinformed decision-making. On the other hand, geography departments are starting to offer courses that involve computational thinking (Bowlick, Goldberg, and Bednarz 2017), but course offerings are limited and the absence of related degree requirements can generate the misleading impression that combined training in geography and computing is not needed.

Interestingly, schools are starting to leverage geospatial technologies across several science, technology, engineering, and mathematics (STEM) subjects to support learning because they offer hands-on strategies to teach the concepts of data collection, data analysis, and science communication with geovisualizations (Hammond, Oltman, and Manfra 2019; Jant et al. 2020; Rubino-Hare et al. 2024). Plus, the use of geospatial technologies has shown added advantages to K–12 STEM learning overall. In a program funded by the National Science Foundation called the geospatial semester, fifty-three high school seniors were recruited for a course that emphasized the use of geospatial technologies for problem solving. Over the school year, students enrolled in the program saw more improvement in their ability to solve STEM-relevant problems than students enrolled in Advanced Placement Physics or Advanced Placement History (Jant et al. 2020). This example demonstrates how combined instruction can be advantageous to student learning.

Accessibility of Geocomputational Pathways

A few training programs are starting to bridge together geography and computing proficiencies (e.g., data science, spatial sciences, or spatial computing programs), but these efforts take time and money and have been too limited to meet nationwide workforce needs (Carto 2023). Additionally, these efforts do not focus on addressing challenges of student inclusion and belonging, which have been persistent issues in geography and computing programs.

The underrepresentation of women in computer science has been widely reported. A recent analysis of nearly 12 million papers revealed that "[b]ased on recent trends over the last 50 years, the proportion of female authors in Computer Science is forecast not to reach parity beyond the end of this century" (Wang et al. 2021, 84). This underrepresentation is also visible in geography. According to 2020–2021 data from the U.S. Department of Education's National Center for Education Statistics, only 39.9 percent of bachelor's degree recipients in geography were women, as compared to 58.4 percent of all degree recipients (National Center on Education Statistics 2021; Raphael 2023).

Studies have shown the far-reaching consequences of the underrepresentation of these groups in terms of innovation, bias, and workplace culture. In the first substantial piece of empirical research on women in the GIS profession, Betancourt-Mazur and Albrecht (2016) concluded that although women are not as grossly underrepresented in GIS as in the overall technology industry, they are likely underrepresented in certain sectors and positions. For example, the authors found that women are underrepresented in the private sector of the GIS industry, perform more analysis than computer programming tasks, and are underrepresented in positions that require managerial or highly technical skills (Betancourt-Mazur and Albrecht 2016). Because geography programs are the main pipeline to GIS jobs (Wikle and Fagin 2015), these findings suggest that diversity in undergraduate geography directly affects the diversity of the STEM workforce.

Study Objective

This study was conducted by a collaborative research practice partnership (RPP) that includes researchers and educators from different educational institutions (i.e., K–12, community colleges, and universities; Solem et al. 2021). Whereas a few of the partners in the RPP already consider themselves to be geocomputational researchers or educators, most consider themselves either geographers or computer scientists.

To facilitate a better understanding of the current standing of geocomputational career pathways in the United States and their capacity to address the aforementioned challenges, the RPP conducted a survey of professionals in the geospatial technology industry. In this article, we evaluate the accessibility of existing educational pathways and their effectiveness in recruiting professionals to the geocomputational workforce. Specifically, we focused on two research objectives: (1) articulating the existing curriculum pathways from school to career and identifying broadening participation challenges associated with each learning opportunity; and (2) identifying the specific gaps in knowledge, skills, and training needs and opportunities between geographers, computer scientists, and the geospatial technology industry.

Method

In 2021, we designed an online survey to ask professionals about their careers and usage of geography and computing to analyze and solve problems in their everyday work. To recruit survey participants, we adopted two outreach strategies that were deployed between January and November 2022. First, we contacted the chairs of university programs and institutes with degrees in geography, computing, or other disciplines that provide training in geocomputational proficiencies; we asked program chairs to distribute the survey to their program alumni. Second, we directly invited professionals to participate in the survey by posting messages on listservs and mailing lists of GIS-related organizations and affinity groups (e.g., San Diego Regional GIS Council), as well as by contacting them individually. Participation in the survey was voluntary and anonymous, and participants were able to opt out of any questions. We obtained ethical clearance for the survey from the San Diego State University Institutional Review Board for Human Subject Research (Protocol Number HS-2021-0258).

We designed the survey as part of a bigger research project to better understand how to create inclusive educational pathways toward geocomputational careers. For this article, we focused on forty-one questions that facilitate our understanding of respondents' educational pathways; their demographic information; their interest in or need for additional training in geography, computing, or both; and how they apply geography or computing to solve problems in their everyday work.

Inclusion Criteria

The survey targeted professionals who were at least eighteen years old and had experience and knowledge related to the geocomputational industry, education, or both. Although anyone with the valid link could access the survey, we stated the inclusion criteria on the survey consent form and participants provided consent to continue to the survey questions.

Survey Instrument

The forty-one questions included three demographic questions, ten educational and professional background questions, and twenty-eight questions relating to professional experience, knowledge, and employment situation. Some questions were only asked to respondents once they selected specific choices to prior questions (i.e., survey flow and branching), so the total number of questions asked to each respondent depended on their own answers.

The twenty-eight questions about professional experience, knowledge and employment situation included six multiple-choice, thirteen Likert scale, and nine open-ended questions. The first five questions (Q1–Q5) asked respondents about their familiarity with the terms "computational thinking," "geographic or spatial thinking," "GIS," "geocomputation," and "spatial data science." The next eighteen questions (Q6–Q23) consisted of three sets of six questions related to the use of each of three critical thinking skills (computational, geographic, and geocomputational) in practice, and the need for and access to training opportunities for those skills. The last five questions (Q24–Q28) focused on the level of agreement or disagreement between work-related statements and respondents' current or most recent employment situations. Appendix A provides a full list of questions, their respective question types, and any predetermined answer choices.

Educational and Demographic Category Grouping

To address the two research objectives, we categorized respondents into groups based on their educational pathway and demographic characteristics. Using the responses to the educational background questions, we grouped the respondents into four educational pathways: geography only (Geog), computing only (Comp), combined geography and computing (Geocomp), and other disciplinary pathways that are unrelated directly to geography or computing (Other). For example, respondents in the Geocomp group had at least one major, minor, or special emphasis in geography and at least one in computing as part of their undergraduate and/or graduate course work. Using the responses to the demographic questions, we grouped the respondents into three gender categories (Male, Female, NA_{gen} [prefer not to answer]), three ethnicity categories (Hispanic [i.e., Hispanic, Latino, or Spanish origin], non-Hispanic, NA_{eth} [prefer not to answer]), and two race categories (White, non-White).

Limitations of the Educational and Demographic Groupings. Our article shares differences between respondents across the described educational pathway and demographic groups. The intent of these particular groupings is to detect and better understand differences in the responses from groups that are typically underrepresented in the industry so that we can start to address identified challenges. These groupings, however, do not correspond tightly with definitions of "underrepresented" professionals in the industry. If we look at the gender categories used in this study, we might equate the categories "female," "other gender identities," and "prefer not to answer" with the groups that include professionals who are typically underrepresented in the industry, as compared to the category "male." Yet, many professionals who identify as male might still be underrepresented in the industry due to the intersectionality of their identities. Furthermore, we categorized respondents with an educational background in geography only as Geog; however, some within this group might have learned substantial geocomputational skills and knowledge (e.g., programming, database management, and tools/web-map development) within their geography curriculums.

Survey Respondents

In total, 147 survey participants accepted the consent form. Of the 147, we excluded twenty-nine respondents who did not answer any of the professional background, experience, knowledge, or employment situation questions; therefore, a total of 118 respondents were included in the analysis. Table 1 shows the number of respondents by educational pathways, academic degrees, and demographic characteristics. Because there were no respondents in the category of "other gender identities," we excluded it from the gender groups in the analysis.

Table 1 *The number of respondents by educational pathways, academic degrees, and demographic characteristics*

	Geog ($n = 77$)		Geocomp ($n = 11$)		Comp ($n = 4$)		Other ($n = 26$)	
	n	**%**	***n***	**%**	***n***	**%**	***n***	**%**
Degree								
Associate[a]	0	0.0	0	0.0	0	0.0	1	3.9
Bachelor	33	42.9	2	18.2	1	25.0	11	42.3
Master	30	39.0	6	54.5	3	75.0	11	42.3
Doctoral	14	18.2	3	27.3	0	0.0	3	11.5
Gender								
Male	45	58.4	6	54.5	4	100.0	16	61.5
Female	30	39.0	4	36.4	0	0.0	9	34.6
NA_{gen}[b]	2	2.6	1	9.1	0	0.0	1	3.8
Ethnicity								
Hispanic	9	11.7	2	18.2	0	0.0	6	23.1
Non-Hispanic	66	85.7	8	72.7	4	100.0	19	73.1
NA_{eth}[b]	2	2.6	1	9.1	0	0.0	1	3.8
Race								
White	62	80.5	7	63.6	4	100.0	19	73.1
Non-White[c]	15	19.5	4	36.4	0	0.0	7	26.9

[a]Associate degree or vocational certificate.
[b]Prefer not to answer.
[c]Biracial White respondents ($n = 4$) were classified as non-White.

Method of Analysis for Multiple-Choice Questions

We employed nonparametric statistical tests to evaluate the differences between educational pathway groups and between demographic groups. For the ordinal Likert-type questions (Q1–Q6, Q12, Q18, Q24–Q28), we used the pairwise Mann–Whitney U test to determine the significant differences between two groups, and Box-Whisker plots to visualize the data distribution. We selected the Mann–Whitney U test because it can be used when the data are not normally distributed, when the sample sizes are small, or when the variances are heterogeneous (Leon 1998). For the categorical questions (Q10, Q11, Q16, Q17, Q22, Q23), we applied the pairwise chi-square (χ^2) test and then analyzed the standardized residuals (e_r) to measure the significant differences and patterns between the groups. We also conducted the Fisher's exact test (FET), supplementing the chi-square tests, to deal with the small sample sizes.

Method of Analysis for Open-Ended Questions

Additionally, we analyzed the responses to two open-ended questions (Q20, Q21) asking respondents to describe the geocomputational tools and knowledge they used in the last two years for their work. For this analysis, we first identified common themes and key terms across all responses using text frequency analysis. Then we confirmed the validity of those themes through a quick scan of the responses and a closer reading of selected ones to understand the context of term usage. From the final themes, we developed a coding structure and code book. Our code book has seven major themes for the tools and knowledge used during professional work: (1) geospatial, (2) geocomputational, (3) computing/programming, (4) math/statistics, (5) data model/management, (6) subject matter, and (7) other. Here are a few examples that show how we categorized responses under three key themes.

- Tools
  1. Geospatial: ArcGIS, QGIS, GeoDa
  2. Geocomputational: ArcPy, GeoPandas, Rasterio, PostGIS
  3. Computing/programming: Python, C++, R
- Knowledge
  1. Geospatial: cartography, geovisualization, modifiable areal unit problem
  2. Geocomputational: "integrating Python code and GIS systems," "combining spatial relationships with coding logic to aggregate results at an appropriate scale," "automating spatiotemporal forecasting tasks on scale," "parallel computation for working with large geospatial data"
  3. Computing/programming: coding, high-performance computation

Appendix B provides a detailed description of the types of responses we coded under each category and more examples for each theme. Guided by the developed code book, coders manually assigned codes to specific responses. To ensure interrater reliability and quality control, multiple coders coded each response. As a result, two coders achieved an interrater reliability of Cohen's kappa score, $k = 0.78$, indicating a substantial level of agreement. In instances of a coding disagreement, coders discussed the discrepancies until reaching a resolution and, if necessary, they revised the code book. For the analysis, if a response included themes and terms that fit within two or more codes in the code book, the response would be assigned with multiple codes. In this case, we weighted each code by dividing one by the total number of theme categories assigned to the response so that the total value of each response equaled one.

Results

Findings for Groupings by Educational Pathways

Term Familiarity and Use of Critical Thinking Skills. Table 2 (Q1–Q5) provides p values of the pairwise Mann–Whitney U tests and Figure 1 describes the data distribution of responses in Box-Whisker plots to examine significant differences between the four educational pathway groups (Geog, Geocomp, Comp, and Other) on term familiarity related to geocomputation. The results show that Comp and Geocomp groups were more familiar with "computational thinking" than the Geog or Other groups (Table 2, Q1; Figure 1, top). The Geog respondents were more familiar with "geographic thinking" than respondents in the Other group (Table 2, Q2; Figure 1, second from the top). All four groups were familiar with GIS and there were no significant differences among them (Table 2, Q3; Figure 1, third from the top). The Comp group was more familiar with geocomputation than the Geog or Other groups (Table 2, Q4; Figure 1, fourth from the top). It is noteworthy that the mean response value for familiarity with the term geocomputation was higher among Comp respondents (4.75) than among Geocomp respondents (3.73); however, the difference was not statistically significant (Table 2, Q4, fourth column). We believe the primary reason for this result is the small sample size (Comp: $n = 4$, Geocomp: $n = 11$), which results in insufficient statistical power to detect a true difference between the groups. The Geocomp group was more familiar with "spatial data science" than the Other group (Table 2, Q5; Figure 1, bottom).

Regarding the use of geographic or spatial thinking and computational thinking for professional work, there were no significant differences between the educational pathway groups (Table 2, Q6 and Q12; Figure 2, first and second plots). Regarding the use of computational thinking, however, it is worth noting that there were marginally significant differences between the Geocomp and Geog groups ($p = 0.075$) and between the Geocomp and Other groups ($p = 0.051$), where Geocomp respondents needed to use "computational thinking" for their work more frequently than respondents in the *Geog* or *Other* groups (Table 2, Q12; Figure 2, second plot). In terms of their use of geocomputational thinking, those in the Geocomp group needed to integrate geographic and spatial thinking and computational thinking for their work more than those in the Geog group (Table 2, Q18; Figure 2, third plot).

Training Needs and Opportunities Related to Critical Thinking. Tables 3 and 4 present the results of the pairwise chi-square tests and pairwise FETs regarding critical thinking training needs and opportunities, by educational pathway group. The analyses identified that respondents in the Geocomp group were more likely to say they had "no access to training or professional development opportunities related to geographic/spatial thinking" than those in the Geog (e_r: Geog = –2.49, Geocomp = 2.49) and Other (e_r: Geocomp = 2.69, Other = –2.69) groups (Table 3, Q11). In addition, Geocomp respondents were less likely to say they had "some access to training or professional development opportunities related to geographic/spatial thinking," as compared

Table 2 Results of pairwise Mann–Whitney U tests (p values), indicating differences in geocomputational term familiarity between educational pathway groups

Questions

1. How familiar are you with the term "computational thinking"?
2. How familiar are you with the term "geographic or spatial thinking"?
3. How familiar are you with the term "geographic information systems or GIS"?
4. How familiar are you with the term "geocomputation"?
5. How familiar are you with the term "spatial data science"?
6. In the past 2 years, how frequently did you need to use geographic/spatial thinking for your professional work?
12. In the past 2 years, how frequently did you need to use computational thinking for your professional work?
18. In the past 2 years, how frequently did you need to integrate geographic/spatial thinking and computational thinking for your professional work?
24. [My current employment] is a good fit with my academic background.
25. I am/was interested in learning new skills.
26. This employer supports professional development and continuing education.
27. My coworkers reflect a healthy mix of racial and ethnic diversity.
28. My coworkers reflect a healthy mix of gender identities (male, female, nonbinary, other).

	Educational pathways					
Q No.	**[Geog, Geocomp]**	**[Geog, Comp]**	**[Geog, Other]**	**[Geocomp, Comp]**	**[Geocomp, Other]**	**[Comp, Other]**
1	0.002**	0.013*	0.106	0.694	0.001**	0.007**
2	0.695	0.545	0.001***	0.851	0.100	0.386
3	0.731	0.864	0.098	1.000	0.373	0.621
4	0.104	0.028*	0.328	0.533	0.083	0.026*
5	0.079	0.613	0.260	0.507	0.043*	0.406
6	0.502	0.181	0.260	0.552	0.930	0.529
12	0.075	0.260	0.454	0.869	0.051	0.228
18	0.019*	0.309	0.749	0.808	0.099	0.475
24	0.522	0.108	0.026*	0.429	0.416	0.838
25	0.780	0.718	0.036*	0.928	0.112	0.226
26	0.455	0.328	0.840	0.752	0.619	0.433
27	0.145	0.014*	0.442	0.344	0.071	0.008**
28	0.061	0.096	0.939	0.561	0.094	0.110

Note: Geog = geography; Geocomp = combined geography and computer science; Comp = computer science; Other = other disciplinary pathways.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

to respondents in the Other (e_r: Geocomp = –2.05, Other = 2.05) group. There were no other significant differences observed. The FETs supported all significant results of the chi-square tests (Table 4, Q11).

Level of Agreement or Disagreement with Statements Related to Current or Most Recent Employment Situations. Table 2 (Q24–Q28) shows that the different educational pathway groups exhibit significant differences related to employment situations, specifically in terms of career fit (Q24), interest in learning new skills (Q25), access to professional development opportunities (Q26), racial and ethnic diversity (Q27), and gender diversity (Q28). Geog respondents were more likely to agree with the statements, "my current (or most recent) career is a good fit with my academic background," and "I am/was interested in learning new skills," than those in the Other group (Table 2, Q24 and Q25; Figure 3, first and second plots). The Comp group was more likely to disagree with the statement, "my coworkers reflect a healthy mix of racial and ethnic diversity" than the Geog or Other groups (Table 2, Q27; Figure 3, third plot).

Use of Tools and Essential Knowledge to Support Geocomputational Tasks and Thinking in Professional Work. Figure 4 illustrates the percentage of responses coded under each theme in our code book by educational pathway group for the questions that asked respondents to describe the geocomputational tools and knowledge they used in the last two years for their work. Although the findings were limited by the number of responses, the results imply that tools and knowledge used in practice generally match the educational background of professionals. For example, respondents in the Comp group used more computational and programming tools and knowledge compared to respondents in the other three groups (Geog, Geocomp, Other), who used a range of tools and knowledge related to geocomputation.

Findings for Groupings by Demographic Characteristic

Term Familiarity and Use of Critical Thinking Skills. Table 5 (Q1–Q6, Q12, Q18) presents the p values of the pairwise Mann–Whitney U test results and Figure 5 describes the data

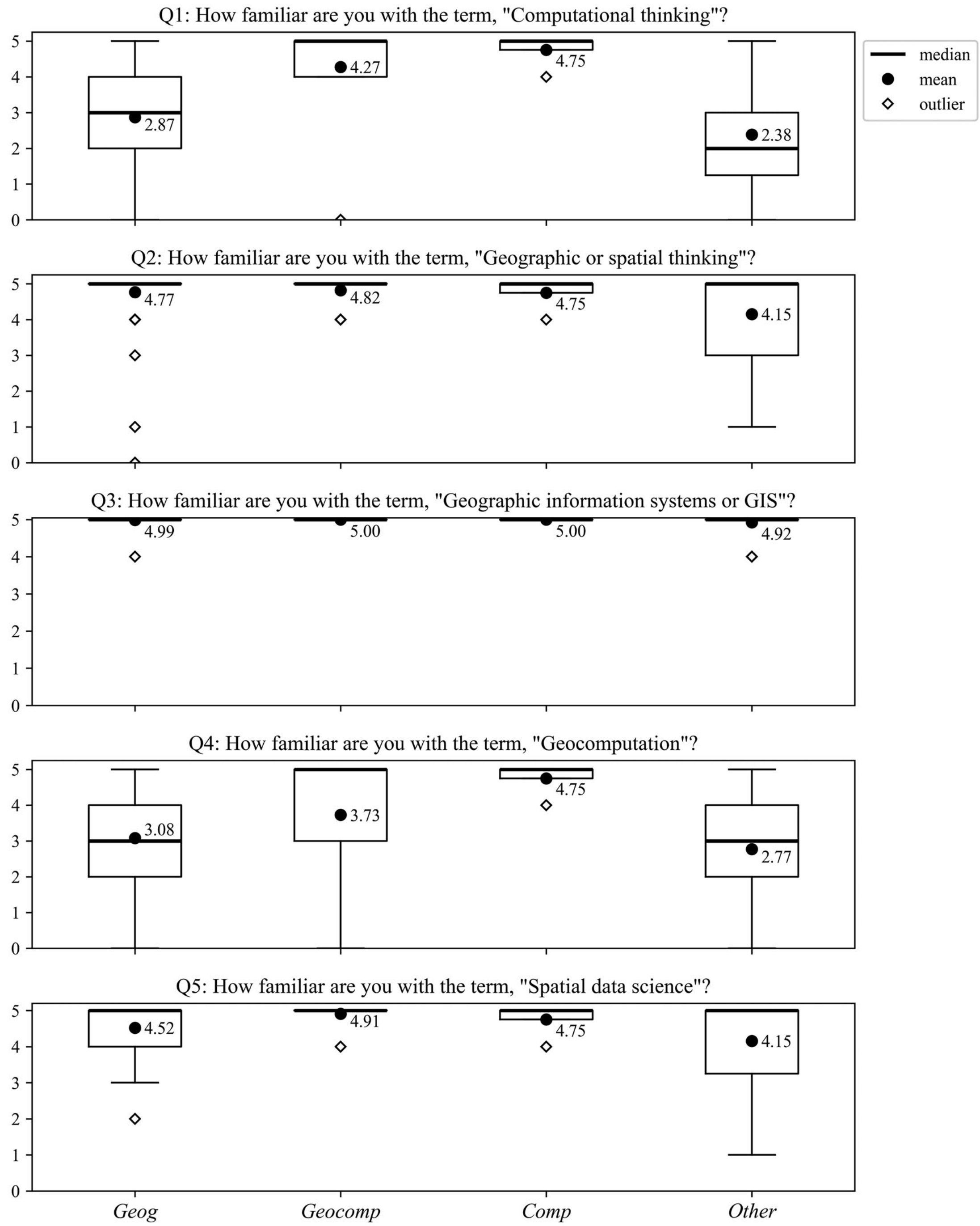

Figure 1 *Box-Whisker plots showing the data distribution for Q1–Q5, indicating geocomputational term familiarity, by educational pathway group.*

distribution of responses in Box-Whisker plots to examine significant differences between groups in three demographic categories (gender, ethnicity, and race) on geocomputational term familiarity and use of critical thinking skill related to geocomputation.

With respect to geocomputational term familiarity, respondents in the NA_{eth} group were less familiar with geocomputation than respondents in the Hispanic and non-Hispanic groups (Table 5, Q4; Figure 5, top). As for the use of critical thinking for professional work, White respondents indicated

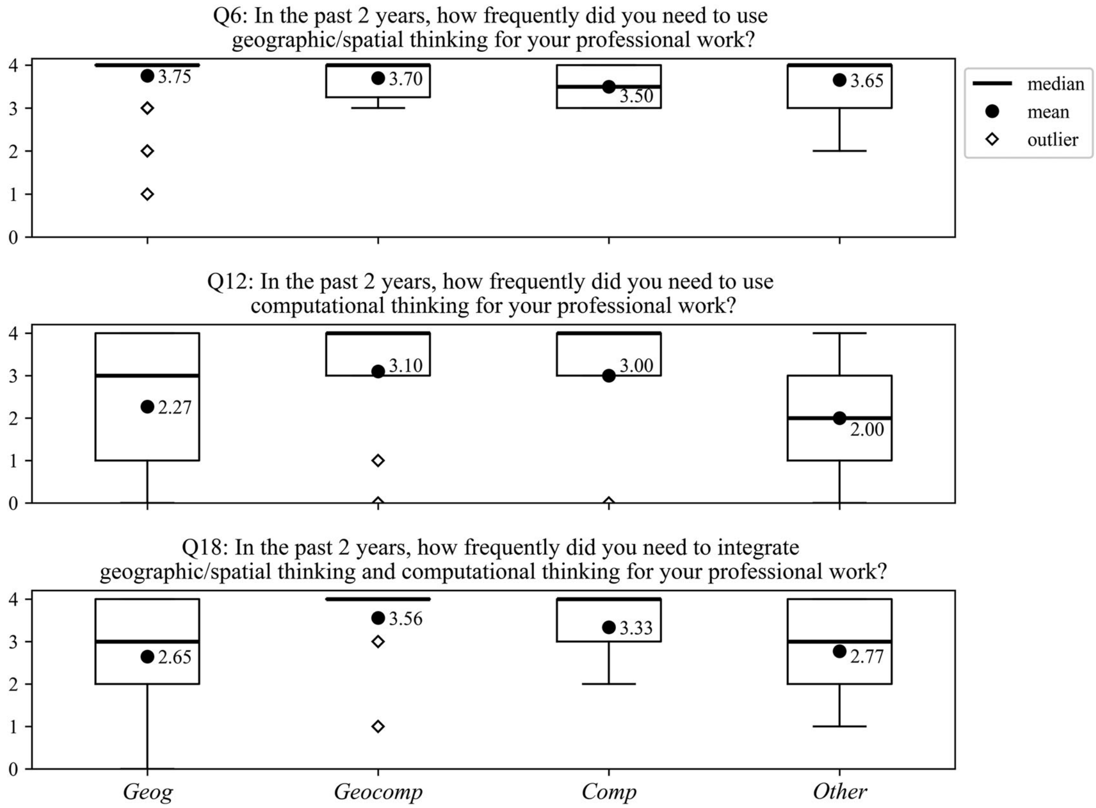

Figure 2 *Use of three critical thinking skills, by educational pathway group.*

Table 3 *Results of pairwise chi-square tests (p values) on critical thinking training needs and opportunities, by educational pathway group*

Questions
10. Do you need additional training in geographic/spatial thinking to fulfill your current professional responsibilities?
11. Do you have access to training or professional development opportunities related to geographic/spatial thinking?
16. Do you need additional training in computational thinking to fulfill your current professional responsibilities?
17. Do you have access to training or professional development opportunities related to computational thinking?
22. Do you need additional training in geocomputational thinking to fulfill your current professional responsibilities?
23. Do you have access to training or professional development opportunities related to geocomputational thinking?

	Educational pathways					
Q No.	**[Geog, Geocomp]**	**[Geog, Comp]**	**[Geog, Other]**	**[Geocomp, Comp]**	**[Geocomp, Other]**	**[Comp, Other]**
10	0.399	0.120	0.086	0.466	0.283	0.451
11	0.028*	0.537	0.384	0.133	0.011*	0.966
16	0.804	0.642	0.299	0.513	0.451	0.712
17	0.360	0.404	1.000	0.240	0.571	0.432
22	0.606	0.604	0.470	1.000	1.000	0.872
23	0.690	0.341	0.603	0.513	0.454	0.372

Note: Geog = geography; Geocomp = combined geography and computer science; Comp = computer science; Other = other disciplinary pathways.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

needing to use geographic or spatial thinking more frequently than non-White respondents. (Table 5, Q6; Figure 5, second from the top). Male respondents indicated needing to use computational thinking and geocomputational thinking for their work more frequently, compared to female respondents (Table 5, Q12 and Q18; Figure 5, bottom).

Training Needs and Opportunities Related to Critical Thinking. Tables 6 and 7 show the results of the pairwise chi-square tests and pairwise FETs

Table 4 *Results of pairwise Fisher's exact test (p values) on critical thinking training needs and opportunities, by educational pathway group*

	Educational pathways					
Q No.	**[Geog, Geocomp]**	**[Geog, Comp]**	**[Geog, Other]**	**[Geocomp, Comp]**	**[Geocomp, Other]**	**[Comp, Other]**
10	0.533	0.218	0.074	1.000	0.358	0.294
11	0.040*	0.695	0.538	0.256	0.012*	1.000
16	0.556	1.000	0.378	1.000	0.605	0.529
17	0.293	0.637	1.000	0.332	0.716	0.607
22	1.000	1.000	0.535	1.000	1.000	1.000
23	0.686	0.231	0.725	0.755	0.573	0.411

Note: Questions are listed in Table 3. Geog = geography; Geocomp = combined geography and computer science; Comp = computer science; Other = other disciplinary pathways.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

on critical thinking training needs and opportunities by different demographic groups, respectively. Respondents in the NA_{eth} group were more likely to say they had "no access to training or professional development opportunities related to geographic/spatial thinking," as compared to non-Hispanic respondents (e_r: NH = −2.192, NA = 2.192; Table 6, Q11). Similarly, non-White respondents were more likely to say they had "no access to training or professional development opportunities" related to geographic and spatial thinking and computational thinking than their White counterparts (e_{r_geog}: W = −3.144, NW = 3.144; e_{r_comp}: W = −2.639, NW = 2.639; Table 6, Q11 & Q17). The FETs supported all significant results of the chi-square tests (Table 7, Q11 & Q17).

Level of Agreement or Disagreement with Statements Related to the Current or Most Recent Employment Situations. Table 5 (Q24–Q28) depicts significant differences in the levels of agreement with statements related to employment situations reported by demographic groups. Female respondents were more likely to agree with the statement, "I am/was interested in learning new skills" than male respondents (Table 5, Q25; Figure 6, top). Hispanic respondents were more likely to agree with the statement, "my coworkers reflect a healthy mix of racial and ethnic diversity" than respondents in the non-Hispanic group (Table 5, Q27; Figure 6, bottom).

Use of Tools and Essential Knowledge to Support Geocomputational Tasks and Thinking in Professional Work. Figure 7 presents the percentage of coded responses by demographic group for the questions about the usage of geocomputational tools and knowledge for respondents' professional work. The different demographic groups had similar compositions of coded categories, with two notable differences. First, male respondents reported using more computational and programming tools, geocomputational tools, and geocomputational knowledge, compared to female respondents. Second, respondents in the Hispanic group mentioned more subject matter and other themes (not directly related to geocomputational tools and knowledge) than those in the non-Hispanic group.

Discussion

We surveyed professionals who consider themselves to be in positions that are at the intersection of geography and computing (i.e., geocomputation). Based on the educational background each respondent shared, the most common pathway these professionals took to a geocomputational career was a geography degree. The second most common path was a degree in a discipline unrelated to either geography or computing. The third most common pathway was a combination of geography and computing degrees. Finally, the smallest group of respondents, indicating the least frequently used pathway, were professionals with a computing degree. We were surprised that the second most common pathway to a geocomputation career was a degree in higher education unrelated to either geography or computing. Looking in more detail at this group, we found that they had educational backgrounds in engineering and earth sciences rather than in geography or computer science specifically. These fields are still closely related to what is required for a geocomputational career, however. Additionally, for 47 percent of this group, their higher education degree predates 2010, a time when GIScience and geocomputation were not as available as they are today.

When we presented the geocomputational professionals with five geocomputation-related terms, they were least familiar with the terms "computational thinking" and "geocomputation." Unsurprisingly, respondents having the least familiarity with those two terms were those with a degree in another discipline, unrelated to either geography or computing, and those with a geography degree but no computing education. On the other hand, respondents were most familiar with the term "GIS." In fact, all respondents rated their familiarity

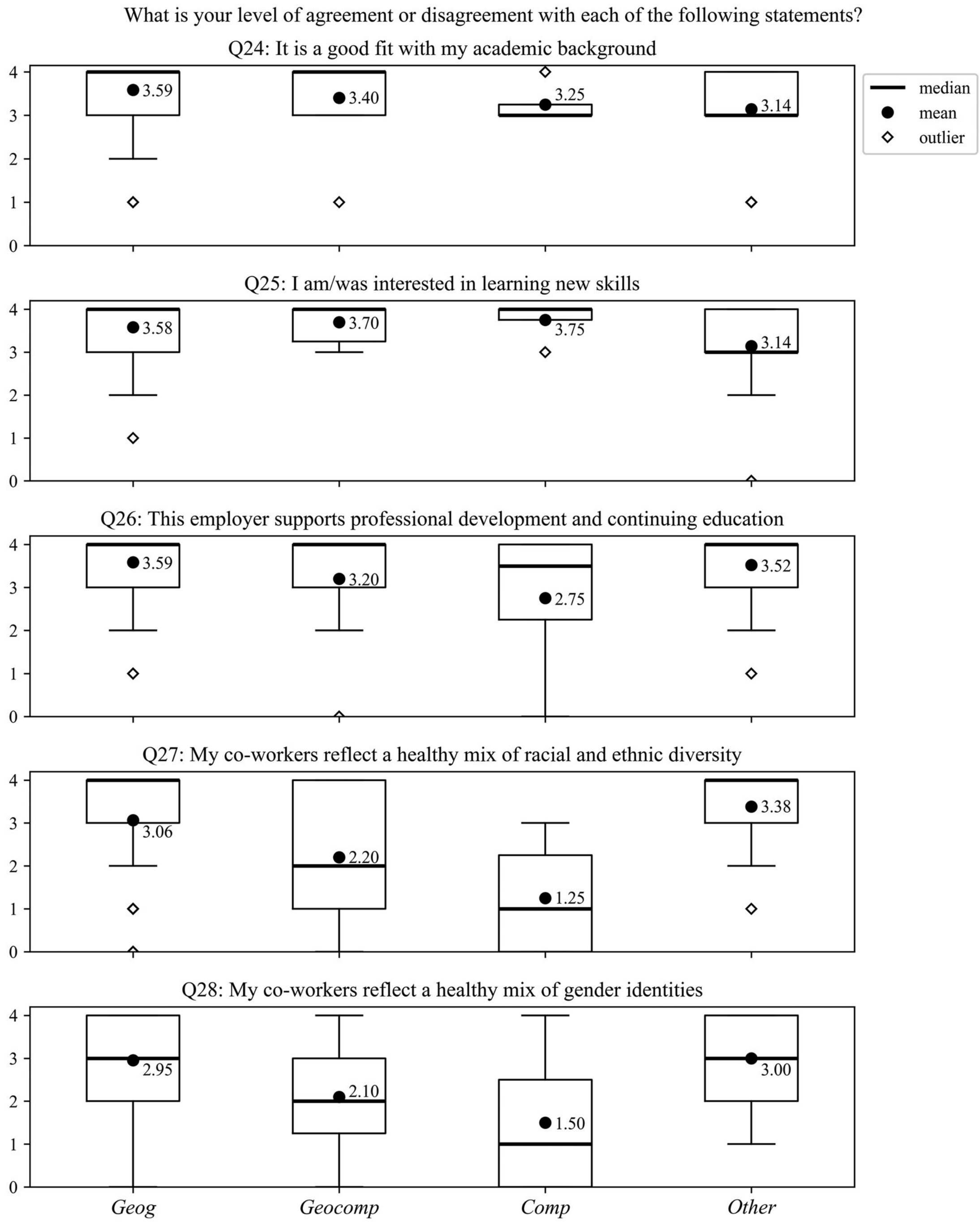

Figure 3 *Box-Whisker plots showing the data distribution of Q24–Q28, indicating the level of agreement with statements related to different employment situations, by educational pathway group.*

with "GIS" very highly, which confirms the prevalence of "GIS."

Respondents were also very familiar with the terms "geographic/spatial thinking" and "spatial data science," although White respondents indicated a higher familiarity with "geographic/spatial thinking" than their non-White counterparts. Terms containing "spatial" seemed to be more familiar across educational pathways than terms that contained variants of "computing." In spite of this finding, our survey indicates a lack of access to training or professional development opportunities related to geographic and spatial thinking. This result aligns with a reported decline in geography requirements for high school graduation

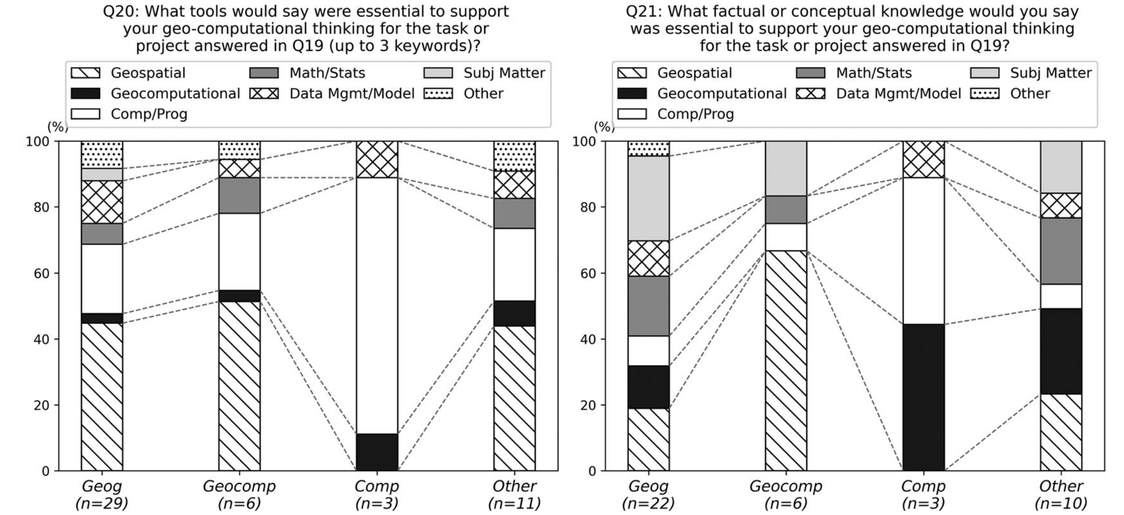

Figure 4 *The percentage of coded responses related to the geocomputational tools (left) and knowledge (right) used during everyday work, by educational pathway group.*

Table 5 *Results of pairwise Mann–Whitney U tests (p values) indicating differences in geocomputational term familiarity between demographic groups*

Questions

1. How familiar are you with the term "computational thinking"?
2. How familiar are you with the term "geographic or spatial thinking"?
3. How familiar are you with the term "geographic information systems or GIS"?
4. How familiar are you with the term "geocomputation"?
5. How familiar are you with the term "spatial data science"?
6. In the past 2 years, how frequently did you need to use geographic/spatial thinking for your professional work?
12. In the past 2 years, how frequently did you need to use computational thinking for your professional work?
18. In the past 2 years, how frequently did you need to integrate geographic/spatial thinking and computational thinking for your professional work?
24. [My current employment] is a good fit with my academic background.
25. I am/was interested in learning new skills.
26. This employer supports professional development and continuing education.
27. My coworkers reflect a healthy mix of racial and ethnic diversity.
28. My coworkers reflect a healthy mix of gender identities (male, female, nonbinary, other).

	Gender			Ethnicity			Race
Q No.	[M, F]	[M, NA_{gen}]	[F, NA_{gen}]	[H, NH]	[H, NA_{eth}]	[NH, NA_{eth}]	[W, NW]
1	0.784	0.100	0.130	0.160	0.408	0.192	0.403
2	0.686	0.193	0.315	0.389	0.132	0.261	0.395
3	0.883	0.767	0.819	0.473	1.000	0.745	0.359
4	0.197	0.100	0.259	0.337	0.027	0.040*	0.363
5	0.633	0.229	0.327	0.848	0.284*	0.260	0.352
6	0.243	0.312	0.214	0.094	0.143	0.302	0.011*
12	0.027*	0.387	0.096	0.696	0.491	0.518	0.368
18	0.026*	0.742	0.176	0.795	1.000	0.847	0.638
24	0.791	0.517	0.577	0.083	0.681	0.687	0.778
25	0.011*	0.347	0.950	0.986	0.223	0.197	0.346
26	0.561	0.737	0.561	0.121	0.584	0.819	0.890
27	0.691	0.807	0.901	0.021*	0.707	0.518	0.122
28	0.717	0.230	0.321	0.431	0.749	0.443	0.252

Note: M = male; F = female; NA_{gen} = prefer not to answer gender identity; H = Hispanic; NH = non-Hispanic; NA_{eth} = prefer not to answer ethnicity identity; W = White; NW = non-White.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

(Zadrozny 2021) and declines in geography degree enrollments, whereas there is an increase in computing pathways, both in K–12 and college. Respondents with an educational pathway that included geography and computing (Geocomp) were more likely to indicate having no access to this kind of training, although they used tools and knowledge related to geospatial topics in their professional work. This showcases that

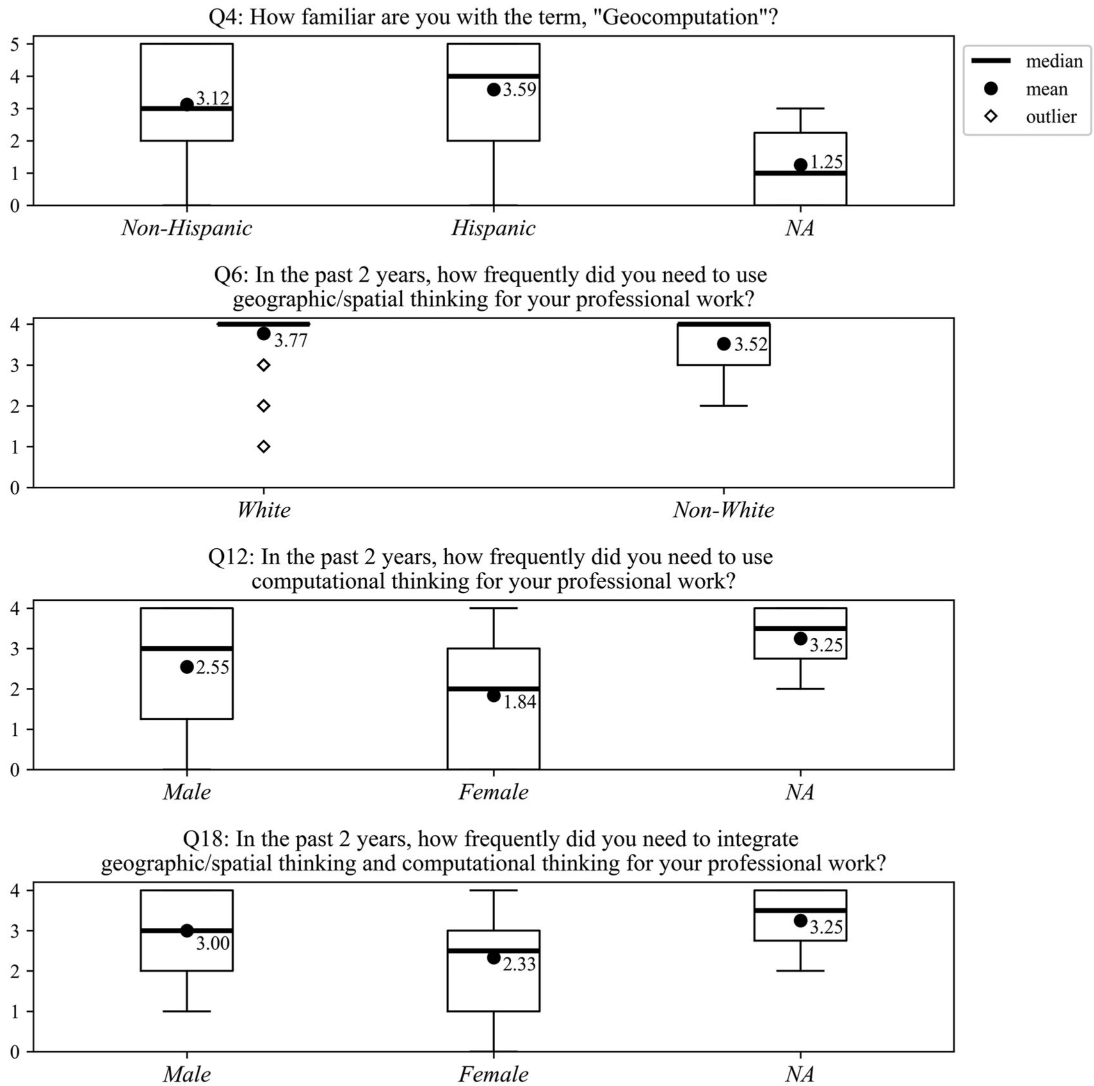

Figure 5 *Box-Whisker plots showing the data distribution for questions with significant Mann–Whitney U test results, indicating geocomputational term familiarity and use of critical thinking skills, by demographic group.*

professionals see the benefits of using geospatial tools and are willing to learn to use them, despite a lack of formal training. Yet, the use of geospatial data and tools without knowledge and training in spatial tools and thinking is a concern that should be addressed through the wider availability of geography training and educational pathways. Further, we find a racial bias in terms of access to training and professional development, where non-White respondents were more likely to report a lack of access to training for either geographic and spatial thinking or computational thinking.

Some findings align with the reported gender and racial bias in the technology industry. For example, respondents with an educational pathway that only included computing (Comp) were more likely to indicate that their coworkers do not reflect a healthy mix of racial and ethnic diversity. Further, male respondents indicated using computational and geocomputational thinking more frequently at work than female respondents. That gender gap, however, is smaller if we look at the use of geocomputational thinking, rather than the use of computational thinking, at work.

Although it would be a stretch to infer this directly, could it be that job positions requiring the combination of geography and computing create better opportunities for women than positions that only require computing? To support further exploration of this idea, female respondents were more likely to indicate interest in learning new skills than male respondents. Considering the reported lack of training and professional development for geocomputation, these positions might require people who

Table 6 *Results of pairwise chi-square tests (p values) on critical thinking training needs and opportunities by demographic groups*

Questions
10. Do you need additional training in geographic/spatial thinking to fulfill your current professional responsibilities?
11. Do you have access to training or professional development opportunities related to geographic/spatial thinking?
16. Do you need additional training in computational thinking to fulfill your current professional responsibilities?
17. Do you have access to training or professional development opportunities related to computational thinking?
22. Do you need additional training in geocomputational thinking to fulfill your current professional responsibilities?
23. Do you have access to training or professional development opportunities related to geocomputational thinking?

	Gender			Ethnicity			Race
Q No.	[M, F]	[M, NA_{gen}]	[F, NA_{gen}]	[H, NH]	[H, NA_{eth}]	[NH, NA_{eth}]	[W, NW]
10	0.455	0.692	0.581	0.231	0.479	0.781	0.075
11	0.251	0.104	0.636	0.959	0.090	0.002**	0.007**
16	0.658	0.450	0.617	0.136	0.052	0.537	0.185
17	0.219	0.391	0.730	0.972	0.420	0.219	0.018*
22	0.298	0.542	1.000	0.633	1.000	0.590	0.062
23	0.241	0.383	0.320	0.293	0.106	0.420	0.688

Note: M = male; F = female; NA_{gen} = prefer not to answer gender identity; H = Hispanic; NH = non-Hispanic; NA_{eth} = prefer not to answer ethnicity identity; W = White; NW = non-White.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

Table 7 *Results of pairwise Fisher's exact test (p values) on critical thinking training needs and opportunities by demographic groups*

	Gender			Ethnicity			Race
Q No.	[M, F]	[M, NA_{gen}]	[F, NA_{gen}]	[H, NH]	[H, NA_{eth}]	[NH, NA_{eth}]	[W, NW]
10	0.501	1.000	1.000	0.322	0.493	0.615	0.089
11	0.250	0.139	0.596	1.000	0.163	0.022*	0.016*
16	0.758	0.688	1.000	0.254	0.163	1.000	0.280
17	0.237	0.321	0.789	1.000	0.706	0.273	0.022*
22	0.450	1.000	1.000	1.000	1.000	1.000	0.068
23	0.214	0.463	0.365	0.409	0.299	0.271	0.696

Note: Questions are listed in Table 6. *Note:* M = male; F = female; NA_{gen} = prefer not to answer gender identity; H = Hispanic; NH = non-Hispanic; NA_{eth} = prefer not to answer ethnicity identity; W = White; NW = non-White.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

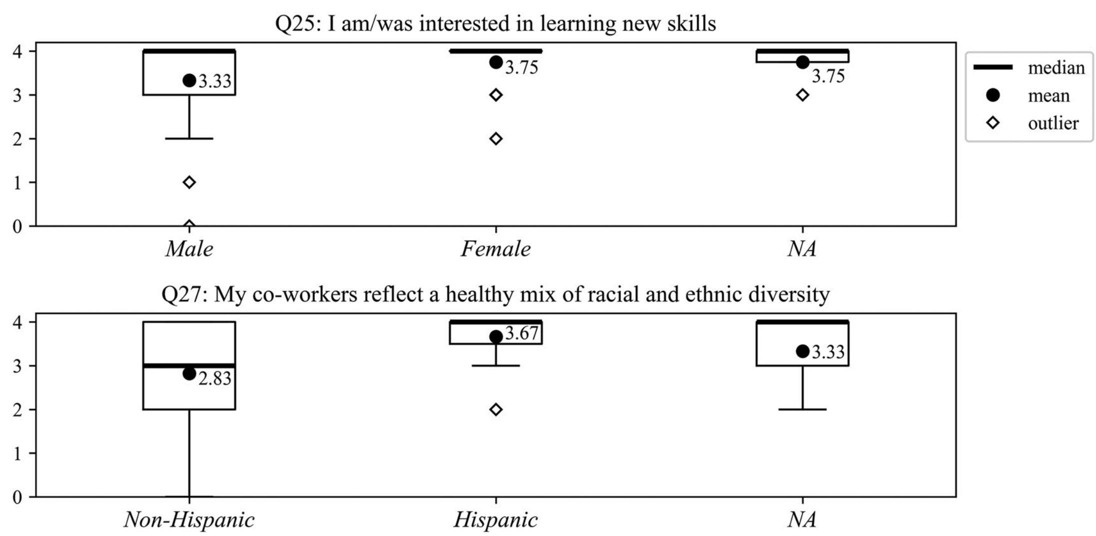

Figure 6 *Box-Whisker plots for questions related to agreement with statements about employment situations with significant Mann–Whitney U test results, by demographic group. Only significant results are shown (see Appendix C, Figures C.7–C.9, for the full results).*

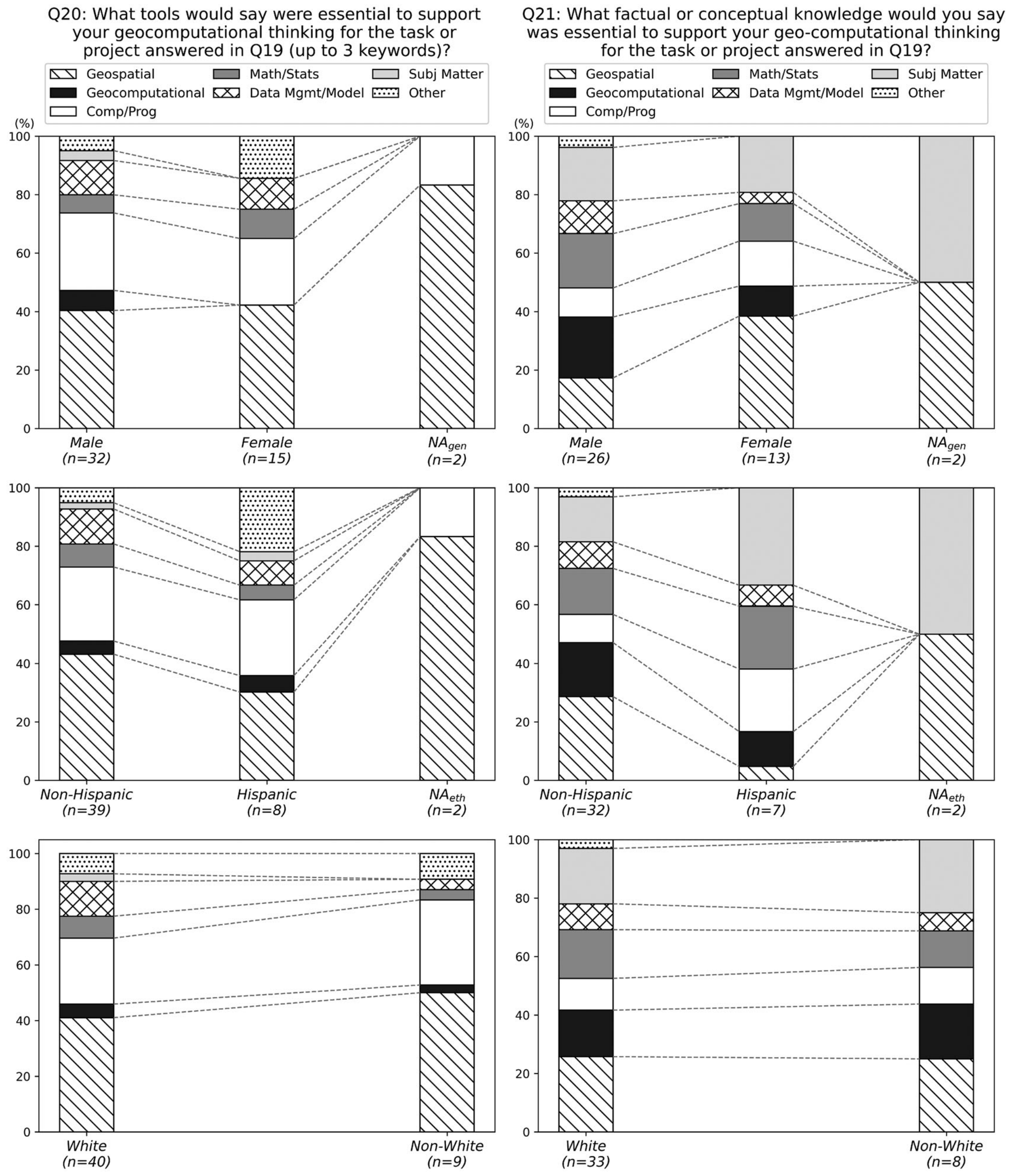

Figure 7 *The percentage of coded responses related to the geocomputational tools (left) and knowledge (right) used during everyday work, by demographic group.*

are more willing to "learn on the fly," something that women are reportedly more willing to do.

Some of the survey findings align with criticisms about the lack of diversity in the geography discipline. For example, geographic and spatial thinking was reported to be used more frequently by White respondents, and White respondents also indicated having a greater familiarity with the term "geographic/spatial thinking."

We also found expected results that can confirm soundness in the survey instrument and analysis. For example, we expected those with any computing education (Comp and Geocomp) to be more familiar with the term "computational thinking" than those without any computing education (Geog, Other). Similarly, it makes sense for those who have a geography education (Geog) to be more familiar with geographic thinking than those who do not (Other).

Also, respondents with a pathway that included both geography and computing (Geocomp) were more likely to say they use geocomputational thinking for their work, as compared to those with a pathway that only included geography (Geog).

Although this study has provided valuable insights articulating the current standing of geocomputational career pathways, we acknowledge several limitations that affect the interpretation and generalization of our findings. First, our results were based on small sample sizes, especially for respondents in the Comp, NA_{gen}, Hispanic, and NA_{eth} groups ($n < 10$). Therefore, our statistical analysis might have lower statistical power. To address the small sample sizes, we used nonparametric tests, the Mann–Whitney U test and the FET, which are considered more robust with small samples than parametric tests. Moreover, the chi-square test results were all supported by the FET. Regardless, the analysis results might not be generalizable because our small sample data might not be representative of the larger population.

Second, as previously mentioned, our groupings might not precisely align with industry underrepresentation definitions or educational background definitions, and certain categories might include underrepresented individuals or respondents with inaccurate educational backgrounds. Finally, we leveraged the RPP for participant recruitment. Although both geography and computer science researchers and practitioners are involved in the RPP, we have stronger connections to the geography discipline than computer science, which could have resulted in the low number of participants with a computer science educational background and biases in the study results.

Conclusion

There is a growing demand for a workforce with training at the intersection of geography and computing, in terms of skills, knowledge, and disciplinary background. In this article, we aimed to enhance our understanding of the accessibility and effectiveness of educational pathways at the intersection of these fields in supporting the current geocomputational workforce. Our survey findings illuminated professionals' perspectives on geocomputational knowledge and skills, employment situations, and access to or need for additional training in geography and computing, both separately and combined.

Moving forward, our results reinforce the call to establish inclusive and diverse geocomputational training and degree programs, to ensure that tomorrow's workforce receives the best that the geography and computing disciplines have to offer. In higher education, geography and computing departments should strive to integrate their degree programs to enable state-of-the-art and cutting-edge knowledge and skills to be taught more effectively by faculty in each respective discipline. It is essential for healthy workforce development that these efforts be rooted in a commitment to enable students from diverse identities and backgrounds to participate in these opportunities. This level of integration and commitment to engaging diverse perspectives pushes faculty to model interdisciplinary collaboration for their students, while making it more explicit and transparent to students that fully integrated and inclusive training in both disciplines is essential to avoid unethical or misinformed use of data, methods, software, infrastructure, and human resources. To enable that level of integration, however, there is a level of collaboration that needs to happen between colleges on U.S. campuses to enable students to access courses or degree programs that combine disciplines (e.g., taking a degree concentration from a different college, enrolling in a course cotaught by faculty from different colleges that counts toward their degree, etc.). Such exposure to different colleges is beneficial for students as it prepares them for interdisciplinary professions or convergence science.

Additionally, after graduation, there is a need for continuous professional development opportunities. This study identified a gap in postdegree opportunities to learn spatial thinking that are inclusive and engage participants across diverse demographic identities. To address this gap, higher education institutions could play a crucial role by staying connected to their alumni through inclusive continuing education programs and providing professional development for geocomputational professionals. ■

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Literature Cited

AlphaBeta. 2017. The economic impact of geospatial services: How consumers, businesses and society benefit from location-based information. https://www.alphabeta.com/wp-content/uploads/2017/09/GeoSpatial-Report_Sept-2017.pdf.

Betancourt-Mazur, L., and J. Albrecht. 2016. Women in the GIS profession. *Publications and Research*, October. https://academicworks.cuny.edu/hc_pubs/276.

Bowlick, F. J., D. W. Goldberg, and S. W. Bednarz. 2017. Computer science and programming courses in geography departments in the United States. *The Professional Geographer* 69 (1):138–50. doi: 10.1080/00330124.2016.1184984.

Bowlick, F. J., E. Shook, K. K. Kemp, and A. Padmanabhan. 2020. Building cyberliteracy through interactive lessons: Design, development, and deployment of Jupyter notebooks for geospatial computing education. ESS Open Archive. doi: 10.1002/essoar.10507513.1.

Bowlick, F. J., C. Thompson, C. Thompson, C. Cox, B. Clark, N. Drummy, J. Fox, A. Grady, L. Musshorn, and C. C. Dony. 2022. Understanding geocomputation education: A survey and syllabi informed review. Research in Geographic Education 23:20–51.

Carto. 2020. The state of spatial data science in enterprise. *Carto Reports*. https://go.carto.com/ebooks/state-spatial-data-science-2020.

Carto 2023. The state of spatial data science. *Carto Reports*. https://go.carto.com/state-spatial-data-science-2023.

Dony, C. C. 2023. Solving geospatial problems under extreme time constraints: A call for inclusive geocomputational education. In *Proceedings of the I-GUIDE Forum 2023: Harnessing the Geospatial Data Revolution for Sustainability Solutions*. October 4-6, 2023. Purdue e-Pubs. doi: 10.5703/1288284317669.

Dony, C. C., A. Nara, G. Amatulli, E. Delmelle, L. Tateosian, S. Rey, and D. Sinton. 2019. Computational thinking in U.S. college geography: An initial education research agenda. *Research in Geographic Education* 21 (2):39–54.

Fortuijn, J. D., Z. Kovàcs, A. L. Blanc, G. O'Reilly, L. Paul, and A. Pejdo. 2020. The challenges for geography in higher education in European universities. *J-READING Journal of Research and Didactics in Geography* 1 (9):49–60. http://www.j-reading.org/index.php/geography/article/view/253.

Hammond, T. C., J. Oltman, and M. M. Manfra. 2019. Geo-computational thinking in the third grade: Making computational thinking truly "for everyone, everywhere". In *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geo-Computational Thinking in Education*, ed. A. Magdy and C.C. Dony, 2, 1–5. New York: Association for Computing Machinery. doi: 10.1145/3356393.3365369.

Jant, E. A., D. H. Uttal, R. Kolvoord, K. James, and C. Msall. 2020. Defining and measuring the influences of GIS-based instruction on students' STEM-relevant reasoning. *Journal of Geography* 119 (1):22–31. doi: 10.1080/00221341.2019.1676819.

Leon, A. C. 1998. Descriptive and inferential statistics. In *Comprehensive clinical psychology*, ed. A. S. Bellack and M. Hersen, 243–85. Oxford, UK: Pergamon. doi: 10.1016/B0080-4270(73)00264-9.

National Center for Education Statistics. 2021. *Integrated Postsecondary Education Data System (IPEDS): 2021 completions survey*. Washington, DC: National Center for Education Statistics. https://nces.ed.gov/ipeds/.

Nelson, T. A., M. F. Goodchild, and D. J. Wright. 2022. Accelerating ethics, empathy, and equity in geographic information science. *Proceedings of the National Academy of Sciences of the United States of America* 119 (19):E2119967119. doi: 10.1073/pnas.2119967119.

Raphael, M. 2023. Reflections on the state of geography. AAG. https://www.aag.org/reflections-on-the-state-of-geography/.

Rubino-Hare, L., B. A. Whitworth, F. Boateng, and N. Bloom. 2024. The impact of geospatial inquiry lessons on student interest in science and technology careers. *Journal of Research in Science Teaching* 61 (2):419–56. doi: 10.1002/tea.21904.

Shook, E., F. J. Bowlick, K. K. Kemp, O. Ahlqvist, P. Carbajeles-Dale, D. DiBiase, E.-K. Kim, S. Lathrop, B. Ricker, P. Rickles, et al. 2019. Cyber literacy for GIScience: Toward formalizing geospatial computing education. *The Professional Geographer* 71 (2):221–38. doi: 10.1080/00330124.2018.1518720.

Shook, E., F. J. Bowlick, A. Padmanabhan, and K. K. Kemp. 2021. The hour of cyberinfrastructure (hour of CI): Early findings from pilot study to build cyber literacy for GIScience. In *2021 IEEE/ACM Ninth Workshop on Education for High Performance Computing (EduHPC)*, 9–15. Piscataway, NJ: IEEE. doi: 10.1109/EduHPC54835.2021.00007.

Sinton, D. S. 2019. Observations on the gaps and opportunities for geo computation. In *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Geo-Computational Thinking in Education*, ed. A. Magdy and C.C. Dony, 3, 1–4. New York, NY: Association for Computing Machinery. doi: 10.1145/3356393.3365370.

Solem, M. 2022. The National Assessment of Educational Progress (NAEP): A closer look at US gaps and trends in geography achievement. In *Assessment in geographical education: An international perspective*, ed. T. Bourke, R. Mills, and R. Lane, 137–52. Cham, Switzerlan: Springer International. doi: 10.1007/978-3-030-95139-9_7.

Solem, M., C. C. Dony, T. Herman, K. León, A. Magdy, A. Nara, W. Ray, S. Rey, and R. Russell. 2021. Building educational capacity for inclusive geocomputation: A research-practice partnership in Southern California. *Journal of Geography* 120 (4):152–59. doi: 10.1080/00221341.2021.1933140.

Solem, M., and S. Tani. 2017. Geography education, primary and secondary: International perspectives. In *International encyclopedia of geography*, ed. D. Richardson, N. Castree, M. F. Goodchild, A. Kobayashi, W. Liu, and R. A. Marston, 1–11. Hoboken, NJ: Wiley. doi: 10.1002/9781118786352.wbieg1014.

U.S. Government Accountability Office. 2015. K–12 education: Most eighth grade students are not proficient in geography. GAO-16-7, U.S. Government Accountability Office, Washington, DC. https://www.gao.gov/products/gao-16-7.

Wang, L. L., G. Stanovsky, L. Weihs, and O. Etzioni. 2021. Gender trends in computer science authorship. *Communications of the ACM* 64 (3):78–84. doi: 10.1145/3430803.

Wikle, T. A., and T. D. Fagin. 2015. Hard and soft skills in preparing GIS professionals: Comparing perceptions of employers and educators. *Transactions in GIS* 19 (5):641–52. doi: 10.1111/tgis.12126.

Zadrozny, J. 2021. *Social studies and geography survey for middle and high schools 2020–2021*. San Marcos, TX: Gilbert Grosvenor Center for Geographic Education. https://gato-docs.its.txst.edu/jcr:032c4e49-7dd9-4fd2-8b2f-58f2d5803b95/Social%20Studies%20Survey%202020%20-%2021.pdf.

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Appendix A. Survey Questionnaires

Q#	Measure	Response options	Question wording
1	Term familiarity	[0–5] (0 = I have never heard this term, 5 = I am very familiar with this term)	How familiar are you with the term "computational thinking"?
2			How familiar are you with the term "geographic or spatial thinking"?
3			How familiar are you with the term "geographic information systems or GIS"?
4			How familiar are you with the term "geocomputation"?
5			How familiar are you with the term "spatial data science"?
6	Usage, task description, tools, knowledge, need for training, and access to training related to geographic and spatial thinking	[Never; < 5 times a year; 5–10 times a year; almost every month; almost every week]	In the past 2 years, how frequently did you need to use geographic/spatial thinking for your professional work?
7		Open-ended text	In one sentence, describe a task or project you were involved with in the past 2 years that required you to use geographic/spatial thinking.
8			What tools would say were essential to support your geographic/spatial thinking for that task or project (up to 3 keywords)?
9			What factual or conceptual knowledge would you say was essential to support your geographic/spatial thinking for that task or project?
10		[I don't need; Yes, I need; I have sufficient training]	Do you need additional training in geographic/spatial thinking to fulfill your current professional responsibilities?
11		[I do not have access; I have some access; I have great access]	Do you have access to training or professional development opportunities related to geographic/ spatial thinking?
12	Usage, task description, tools, knowledge, need for training, and access to training related to computational thinking	[Never; < 5 times a year; 5–10 times a year; almost every month; almost every week]	In the past 2 years, how frequently did you need to use computational thinking for your professional work?
13		Open-ended text	In one sentence, describe a task or project you were involved with in the past 2 years that required you to use computational thinking.
14			What tools would say were essential to support your computational thinking for that task or project (up to 3 keywords)?
15			What factual or conceptual knowledge would you say was essential to support your computational thinking for that task or project?
16		[I don't need; Yes, I need; I have sufficient training]	Do you need additional training in computational thinking to fulfill your current professional responsibilities?
17		[I do not have access; I have some access; I have great access]	Do you have access to training or professional development opportunities related to computational thinking?
18	Usage, task description, tools, knowledge, need for training, and access to training related to geocomputational thinking	[Never; < 5 times a year; 5–10 times a year; almost every month; almost every week]	In the past 2 years, how frequently did you need to integrate geographic/spatial thinking and computational thinking for your professional work?
19		Open-ended text	In one sentence, describe a task or project you were involved with in the past 2 years that required you to use geocomputational thinking.
20			What tools would say were essential to support your geocomputational thinking for that task or project (up to 3 keywords)?
21			What factual or conceptual knowledge would you say was essential to support your geocomputational thinking for that task or project?
22		[I don't need; Yes, I need; I have sufficient training]	Do you need additional training in geocomputational thinking to fulfill your current professional responsibilities?
23		[I do not have access; I have some access; I have great access]	Do you have access to training or professional development opportunities related to geocomputational thinking?
24	Level of agreement or disagreement related to participant's current (or most recent) employment	[Disagree; Somewhat disagree; No opinion/Don't know; Somewhat agree; Agree]	It is a good fit with my academic background.
25			I am/was interested in learning new skills.
26			This employer supports professional development and continuing education.
27			My coworkers reflect a healthy mix of racial and ethnic diversity.
28			My coworkers reflect a healthy mix of gender identities (male, female, nonbinary, other).

Appendix B. Code Book for Q20 and Q21

	Major theme		Subcategory			
	Code	Description	Code	Description	Additional description	Examples
Q20: What tools would you say were essential to support your geocomputational thinking for that task or project (up to 3 keywords)?	100	Geospatial	101	Software	Geospatial software (e.g., GIS software)	ArcGIS, QGIS; Buffer tool, GeoDa; Orfeo ToolBox; Map, Web-map
			102	Analysis/modeling	Tools for geospatial analysis and modeling	
			103	Remote sensing	Tools for remote sensing applications	
			109	Miscellaneous	General or other terms related to geospatial tools (e.g., mapping, vector/raster data)	
	200	Geocomputational	201	Software/ programming	Tools include both geospatial and computing/ programming/data management components	ArcPy, GeoPandas, Rasterio, Dask-GeoPandas; PostGIS, GDAL
			202	Geospatial data management	Geospatial data management tools that involve computational components	
			209	Misc.	General or other terms related to geocomputational tools	
	300	Computation/ programming	301	Programming language	Programming language	Python, C++, R; Pycharm, Unity, Scikit-learn, Dask, Git, Cloud; high-performance computing
			302	Software	Computational software not specifically applied for geospatial applications	
			303	Platform	Computational platform not specifically applied for geospatial applications	
			309	Miscellaneous	General or other terms related to computational tools not specifically for geospatial applications	
	400	Math/stats	401	Math/stats software	Math/stats software not specifically applied for geospatial applications	R, RStudio, Statistics, Analyzation tool
			409	Miscellaneous	General or other terms related to math/stats tools not specifically for geospatial applications	
	500	Data model/ management	501	Software	Data modeling/management tools not specifically applied for geospatial applications	Microsoft Excel, Google spreadsheet; Apache Parquet
			502	Database management software	Database management software not specifically applied for geospatial applications	
			509	Misc.	General or other terms related to data model/ management tools not specifically for geospatial applications	
	600	Subject matter	601	Industry-specific subject	Industry-specific subjects not specifically indicating geospatial applications	FEMA Floodmaps, Storm water management model
			609	Miscellaneous	General or other terms related to subject matter not specifically indicating geospatial applications	
	700	Other	701	Other software	Other software not specifically applied for geospatial applications	Notepad, PowerPoint; Vehicle; Team
			702	Other hardware	Other hardware not specifically applied for geospatial applications	

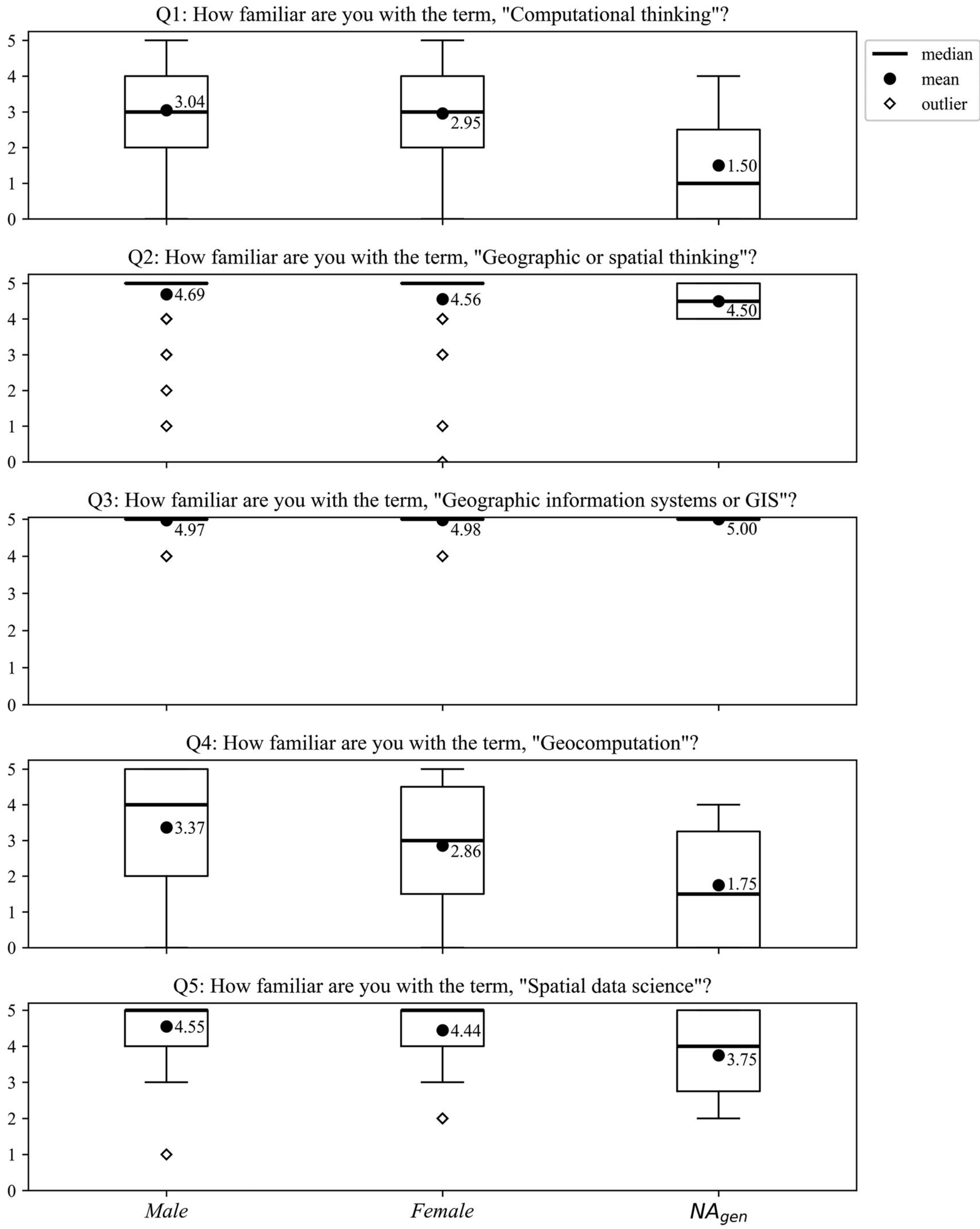
(*Continued*)

(Continued).

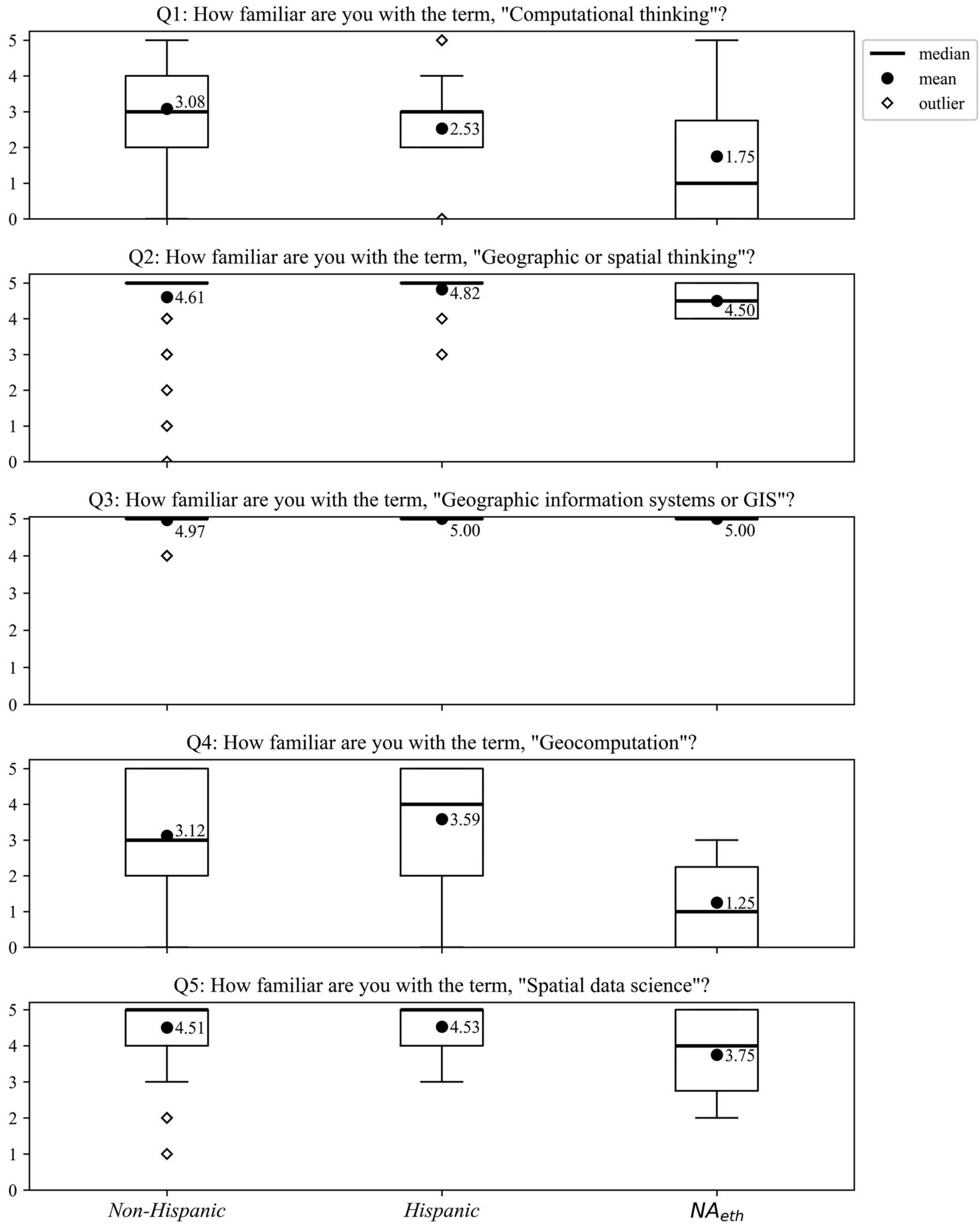
	Major theme		Subcategory			
	Code	Description	Code	Description	Additional description	Examples
			709	Miscellaneous	General or other terms not related to all the above categories	
Q21: What factual or conceptual knowledge would you say was essential to support your geocomputational thinking for that task or project?	100	Geospatial	101	Geospatial	Geospatial knowledge	Geometry, MAUP, Cartography, GeoViz; Spatial modeling/ analysis
			102	Geospatial analysis/ model	Knowledge specific to geospatial analysis/ modeling	
			103	Remote sensing	Knowledge related to remote sensing application	
			109	Miscellaneous	Other knowledge related to geospatial applications	
	200	Geocomputational	201	Geocomputational	Knowledge related to both geospatial and computing/programming/data management applications	Combining spatial relationship with coding, automate spatiotemporal model
			209	Miscellaneous	Other knowledge related to geocomputation	
	300	Computational/ programming	301	Computational/ programming	Computational/programming knowledge not specifically for geospatial applications	High-performance computation, coding, AI
			309	Miscellaneous	Other knowledge related to computing/ programming not specifically for geospatial applications	
	400	Math/stats	401	Math/stats	Math/stats knowledge not specifically for geospatial applications	Geometry, vector calculation, time-series analysis
			409	Misc.	Other knowledge related to math/stats not specifically for geospatial applications	
	500	Data model/ management	501	Data model/ management	Data model/management knowledge not specifically for geospatial applications	Data integration, relational database, data bias/ limitation
			509	Miscellaneous	Other knowledge related to data modeling/ management not specifically for geospatial applications	
	600	Subject matter	601	Subject matter	Subject matter knowledge not specifically for geospatial applications	Field work knowledge, domain-specific knowledge
			609	Miscellaneous	Other knowledge related to subject matter not specifically for geospatial applications	
	700	Other	701	Other	Other knowledge not related to all the above categories	Curriculum design

Appendix C: Box-Whisker Plots of Survey Questionnaires on Term Familiarity, Use of Critical Thinking Skills, and Employment Situations by Three Demographic Groups (Full Results)

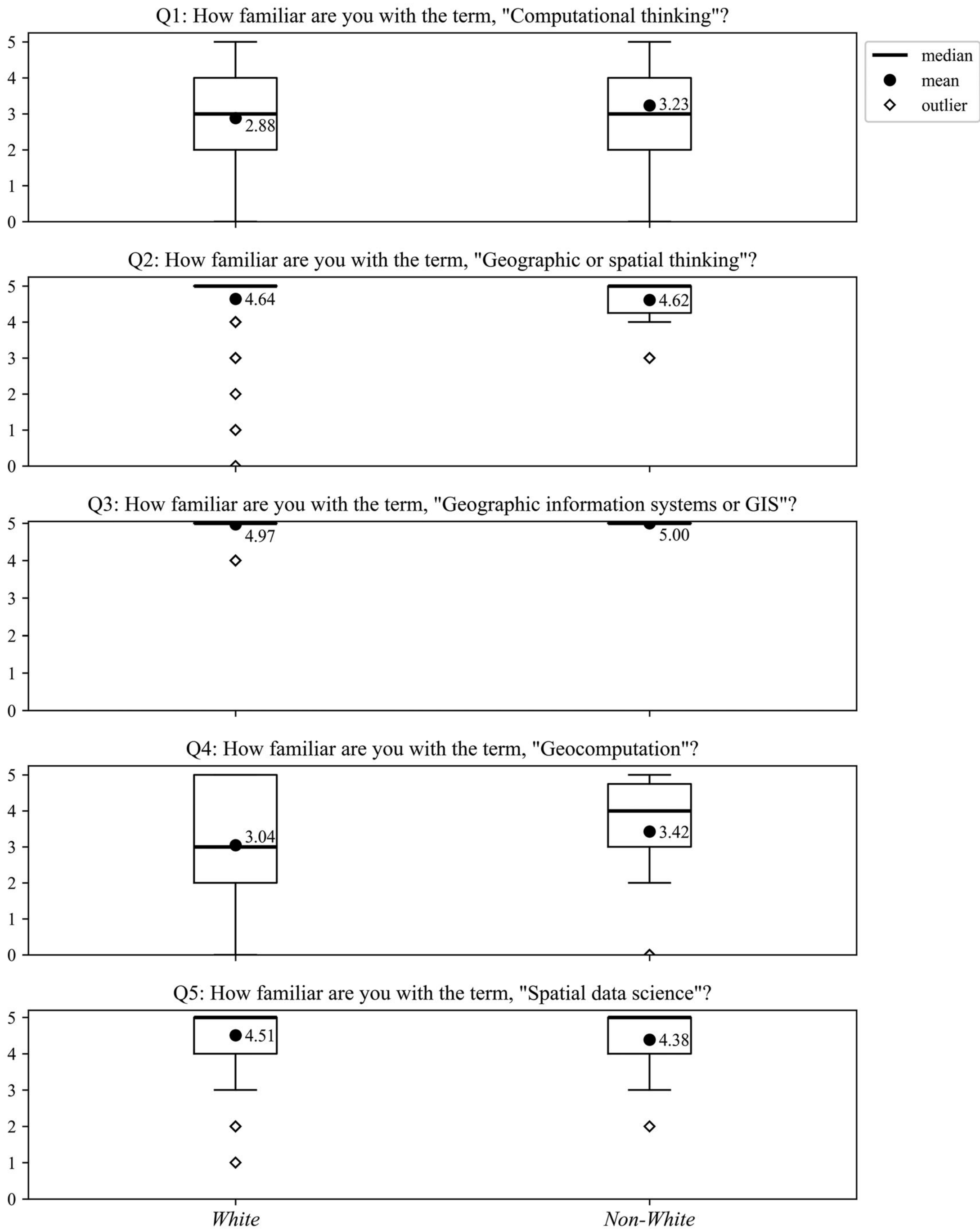
Appendix C.1 *Term familiarity by gender groups.*



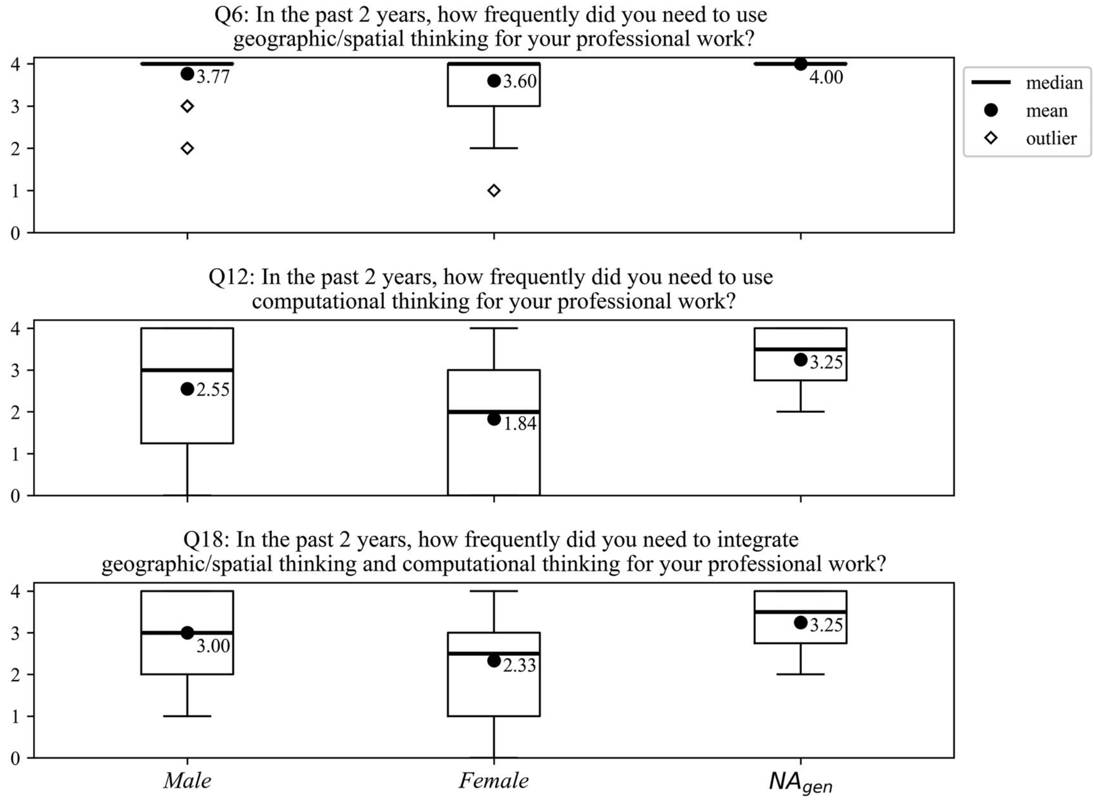
Appendix C.2. *Term familiarity by ethnicity groups.*



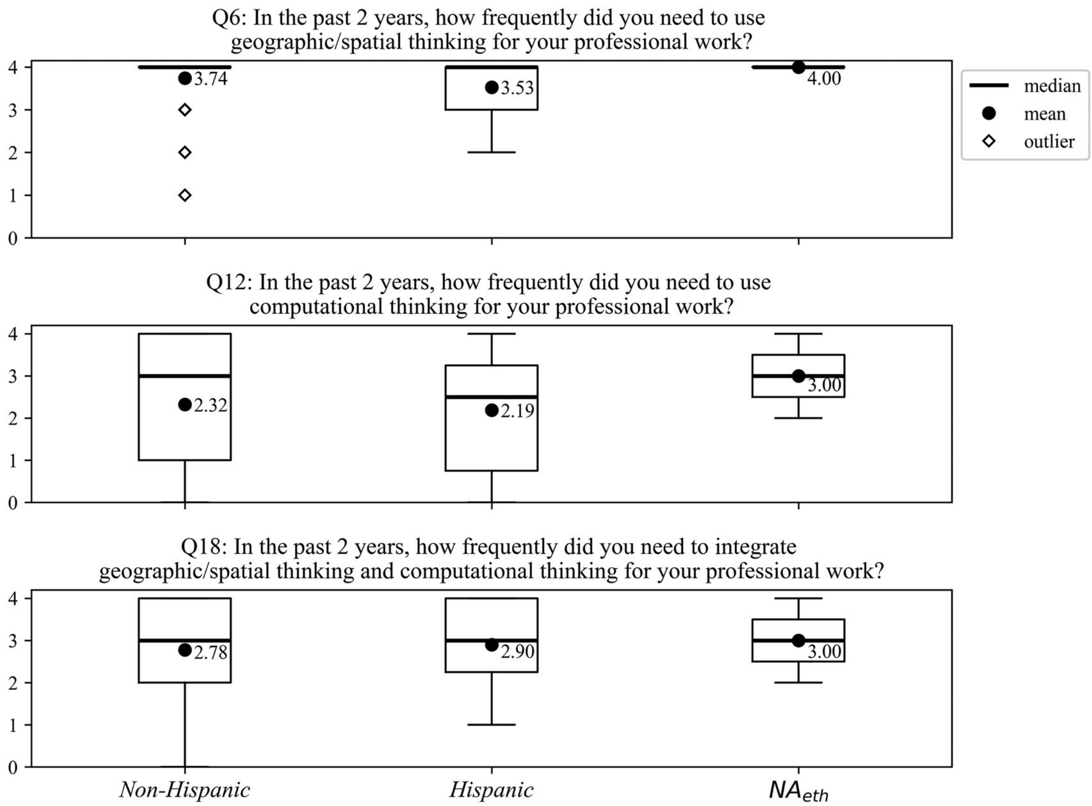
Appendix C.3. *Term familiarity by racial groups.*



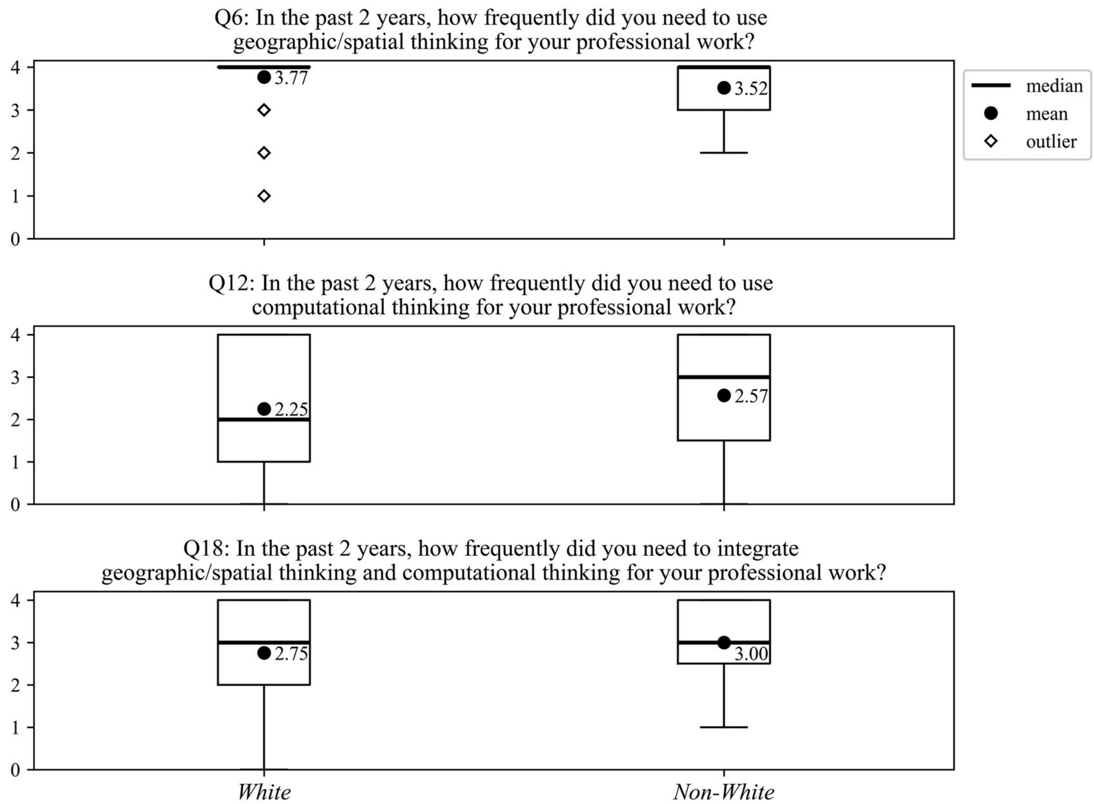
Appendix C.4. *Use of critical thinking skills by gender groups.*



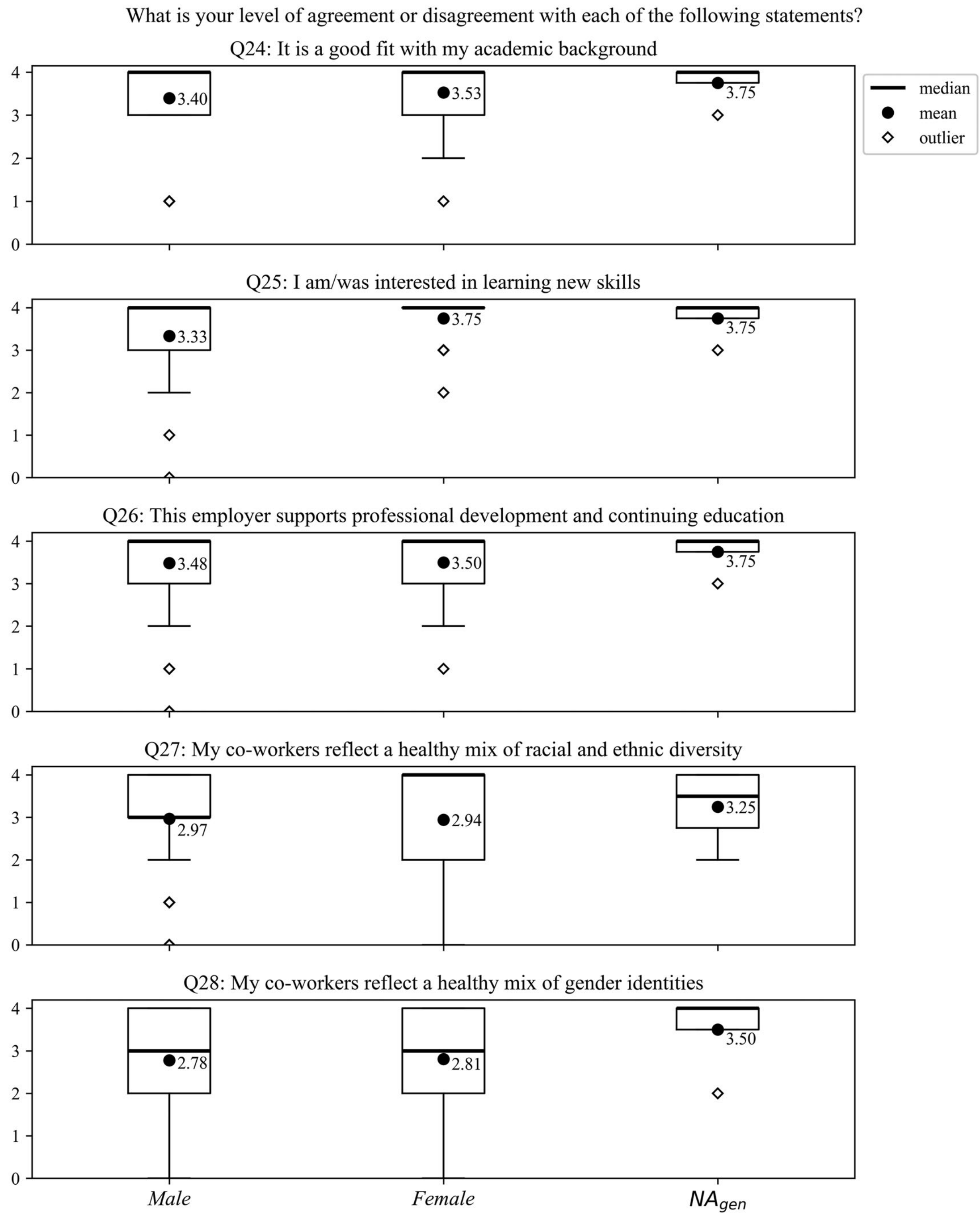
Appendix C.5. *Use of critical thinking skills by ethnicity groups.*



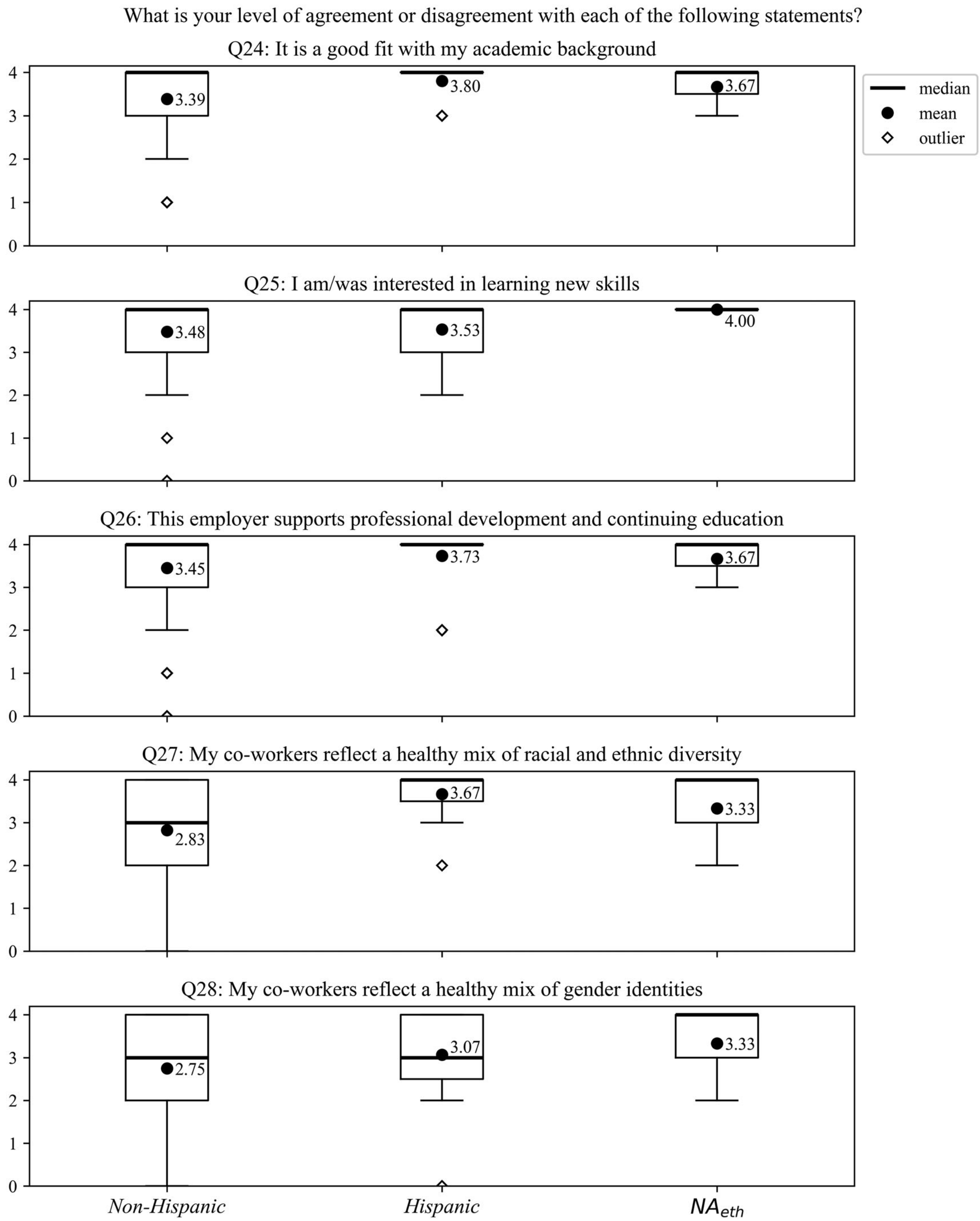
Appendix C.6. *Use of critical thinking skills by racial groups.*



Appendix C.7. *Level of agreement related to employment situations by gender groups.*



Appendix C.8. *Level of agreement related to employment situations by ethnicity groups.*



Appendix C.9. *Level of agreement related to employment situations by racial groups.*