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ARTICLE
The Mismatch Between Neuroscience Graduate Training and Professional Skill Sets

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Neuroscience career paths are rapidly changing as the field expands and increasingly overlaps with computational and data-heavy job sectors. With the steady growth in neuroscience trainees and the diversification of jobs for those trainees, it is important to identify the necessary skills in neuroscience career paths and how well graduate training is preparing our students for this ever-changing workforce. Here, we survey hundreds of neuroscience professionals and graduate students to assess their use and valuation of a range of skills, from bench skills to communication and management. We find that almost all neuroscience professionals report strongly needing management and communication skills, but that these were seen as are less important by graduate students. In addition, coding and data analysis skills are widely used in academic and industry research, predict higher salaries, and are more commonly used by male-identifying graduate students. These findings can help trainees assess their own skill sets as well as encourage educational leaders to offer training in skills beyond the bench, helping to catapult trainees into the next stages of their careers.

Key words: neuroscience graduates, graduate training, PhD paths, careers, skills

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> *"Despite a decade of attention, the mismatch between the purpose of doctoral education, aspirations of the students, and the realities of their careers —within and outside academia—continues."*
> *- Golde and Dore, 2001*

Since the founding of the first interdisciplinary neuroscience doctoral program at Harvard in 1966, the field of neuroscience has dramatically evolved and expanded. The past fifty years of neuroscience research have witnessed significant innovations in our ability to record, manipulate, and predict brain activity (Luo et al., 2018; Sejnowski et al., 2014). In addition to expanding the size of our datasets, these innovations are changing what kind of therapeutics are being developed, how artificial intelligence is implemented, and what kind of evidence is permissible in a courtroom. As a result, we need people in the workforce who understand the process and outputs of neuroscience research and who can communicate this to public shareholders.

In parallel with our changing field, more and more students are graduating with undergraduate and graduate degrees in neuroscience (Rochon et al., 2019; Akil et al., 2016). These degree holders can now be found in a variety of roles and job sectors, including applied and industry research, policy making, and consulting, reflecting the growing needs of our society (Society for Neuroscience, 2017; Akil et al., 2016). As more students earn degrees in neuroscience, it is important that we take into consideration the possible career paths and requisite skill sets for these graduates. Here, we survey individuals with neuroscience degrees in various sectors of society and ask them about the skills required for their work, both technical (e.g., coding, data analysis) and non-technical (e.g., mentorship, communication), recognizing the breadth of skills required in neuroscience and related fields.

Technical skills such as coding are becoming essential in our increasingly automated economy, beyond academic research (Cummins et al., 2019). Neuroscience has been deeply integrated with computer science for decades and is more recently intertwined with data science and machine learning (Akil et al., 2011; Paninski and Cunningham, 2018). This observation has inspired many leaders in neuroscience education to call for a focus on quantitative skill building, particularly coding (Akil et al., 2016; Grisham et al., 2016; Ramirez, 2020). But as datasets are getting bigger and basic programming skills are increasingly required for even wet lab research, the skills required to work with such data are not readily accessible for life sciences students, especially non-male students and those from historically excluded backgrounds (Cheryan et al., 2009; Baser, 2013; Owolabi et al., 2014; Rubio et al., 2015). Building on prior research, the present study investigates gender gaps in programming use in both neuroscience graduate students and professionals.

While doctoral training is adapting to prepare students for the changing technical demands of neuroscience research, it is unclear how well it has adapted to society's demand for more broadly trained individuals who can bridge the gap between neuroscience and the public. Skills such as communication, project management, teamwork, problem solving, critical thinking, and interpersonal skills have been repeatedly reported as lacking in STEM trainees (Tang et al., 2001; Smith et al., 2002; Radermacher and Walia, 2013; Spronken-Smith, 2018; Ganapati et al., 2021). As a result, many educational leaders have argued that STEM graduate education should include formal training in these and other areas, particularly teaching (Bridgstock, 2009; Feldon et al., 2011; Jackson and Bridgstock, 2018; Nyquist et al., 1999; Singh Dubey et al., 2021). Although research advisors often believe such training conflicts with research productivity

Job Category	Representative Position Titles	$N_{category}$
Applied/Industry Researcher	Scientist (Research, Principal); User Experience Researcher	13
Consultant	Scientific Consultant; Senior Analyst	7
Data Science & Software Engineering	Data Scientist; Analyst (Strategy, Senior); Software Engineer	13
Faculty Member (Non-profit, government, or independent research institute)	Professor (Assistant, Associate, Full); Assistant Investigator; Lecturer	61
Graduate Student	PhD student, Masters student	116
Industry Sales & Marketing	Sales Manager; Account Manager	3
Management	Project Director; Scientific Program Manager; Health Scientist Administrator; Director of Innovation Policy	17
Medical Professional	Psychologist (Clinical, Neuro); Assistant Professor (Clinical)	3
Science Communicator & Teacher	Writer (Science, Medical); Editor (Senior, Deputy, Executive Story); Freelance Science Communicator; High School Teacher	9

Table 1. Study participants by category of their current position (first column). The number of participants per sector is shown in the $N_{category}$ column. Representative job titles are also provided to illustrate the types of positions represented in our dataset.

(Thiry et al., 2007), training in communication or teaching can improve trainees' time in the lab. For example, there is evidence that time spent in the classroom as an instructor can significantly boost trainees' research skills (Feldon et. al., 2011).

To identify the skills used by graduate students and neuroscience professionals, we turned to skills assessments, a common tool to help educators identify gaps between skill sets held by recent graduates and professionals in the workforce. Skills assessments are especially useful in quickly evolving fields such as neuroscience (Cui and Harshman, 2020; Smith et al., 2002). For example, a previous study by Cui and Harshman (2020) performed a skills assessment on chemists in different job sectors to determine which skills are required to succeed in their respective professions. Interviewing chemists in academia, industry, and government, Cui and Harshman (2020) grouped knowledge and skills into twelve main themes and noted the importance of skills such as communication and management regardless of job sector. The authors concluded that while certain skills are rightfully emphasized in the training of chemists, it would also be beneficial to provide more catered skill training based on trainees' intended career paths.

In short, the demands on our graduates have changed dramatically in the past several decades. The diverse and ever-evolving nature of neuroscience career paths urges us to ask if neuroscience education and training are adequately preparing students with the skill sets they need to satisfy the demands of their future job sector.

To address this concern, we assessed the skills of professionals with neuroscience degrees to understand the mastery, frequency, and importance of various skills in their respective fields. In doing so, we find a mismatch between the skills emphasized in graduate school and the skills emphasized in a variety of workplaces. We also find evidence for the persistence of gender gaps in coding skills, even in current graduate students. This analysis highlights the importance of computational, analytical, managerial, and communication skills and can advise educational leaders and mentors on how to provide more efficient training for a diverse generation of future neuroscientists.

MATERIALS AND METHODS

Participant Recruitment and Eligibility

A 50-question survey was administered online via Qualtrics and distributed via social media (Twitter, professional groups on Facebook) and email (list serves such as the FUN Faculty List and personal communication). While the scope of this survey encompassed neuroscientists at various educational and career levels, we limit our analysis and discussion here to responses from current graduate students as well as neuroscience professionals (e.g., faculty members, industry professionals) to understand which skill sets are being utilized in these groups. Participants included in our analysis either held at least one degree (B.S., B.A., M.S., or Ph.D.) in neuroscience or related fields (e.g., Cognitive Science) and/or had at least one year of experience conducting neuroscience research, defined as "any research pertaining to the nervous system." The resulting participants (n=241) were currently working and studying at 213 different institutions, companies, and organizations in the U.S. and beyond.

Job Categorization

Participants were asked to self-identify their current position using provided job categories. Those who answered "Other" (5 participants) were sorted according to their position title (e.g., "Senior User Experience Researcher" was sorted into "Applied/Industry Researcher." Several related job titles were grouped, such as "Data Science" and "Software Engineer" due to low numbers of responses in individual categories. "Faculty member" includes anyone who self-identified as a faculty member, including one "Teaching professor" and three "Instructors," one of whom clarified that their role was equivalent to an associate professor in the U.S. We also conducted our analysis with these four individuals categorized as "Science Communicators & Teachers" but this did not change any of the conclusions in this manuscript. Our final grouping includes eight different job categories (Table 1).

As shown in Table 1, our final participant pool includes 116 current graduate students as well as 125 neuroscience professionals, including 61 faculty members and 64 participants in a wide range of other fields including consulting, government, industry research, and science communication. Within the graduate student participants, 65 were current PhD students, 5 were current Master's students, and 46 did not specify.

Survey

The full survey assessed a wide range of demographics, backgrounds, skills, and career path information. Here, we focused on a set of questions regarding the skills necessary for these professionals in their respective fields, akin to work in previous studies (Cui and Harshman, 2020; Jang, 2016). Note that this study assessed skills, rather than underlying abilities that may enable those skills. The list of skill items was developed *de novo* to capture the breadth of skills required in neuroscience research and career paths (see Table 2 for all items). In a Likert-style scale, participants were asked to describe their use of these 21 different skills. For each skill, participants were asked:

- What level of mastery in this skill do you need to do your current job? (0=None, 1=Basic, 2=Intermediate, 3=Expert)
- How often do you use this skill in your current job? (0=Never, 1=A few times a year, 2=Several times a month, 3=Weekly, 4=Daily)
- How important is this skill in your current job? (0=Not at all important, 1=A little important, 2=Somewhat important, 3=Very important, 4=Extremely important)

For numerical analysis, responses were converted to values 0 to 3 for mastery and 0 to 4 for frequency (how often) and importance.

Participants were also asked to, "Briefly describe one thing that either prepared you for your current position, or greatly helped your success." Responses to this question by neuroscience professionals (n=109 responses) were analyzed for key words and grouped into a set of codes. We then quantified the frequencies of the codes for each job category. Individual responses could have multiple codes. The top 10 most frequent codes can be seen in Table 4 and Figure3.

Skill Category	Individual Skills	Mastery α	Often α	Importance α
Bench	Molecular Biology Image processing and/or microscopy Managing lab resources Building or manipulating hardware Designing and planning experiments Performing surgeries on non-human animals Running physiology and/or behavioral experiments	0.853696 0.845626 0.857589 0.846364 0.851135 0.854401 0.854401	0.869509 0.849925 0.848231 0.840746 0.841128 0.844642 0.844642	0.869404 0.853429 0.856032 0.851486 0.852399 0.853572 0.853572
Coding	Coding to analyze data or run experiments Computational modeling Writing front-end code or developing software	0.897576 0.885371 0.885371	0.841235 0.807250 0.807250	0.841779 0.815021 0.815021
Data Analysis & Visualization	Running statistical analyses Generating figures	0.769681 0.769681	0.786061 0.786061	0.835464 0.835464
Management & Communication	Managing a team Writing (for a non-scientific audience) Communicating with other scientists and/or clients Verbally presenting information in front of an audience	0.678092 0.628697 0.621399 0.621399	0.392719 0.441684 0.425576 0.425576	0.572120 0.396392 0.433642 0.433642
Mentorship & Training	Mentoring students Teaching in a classroom setting	0.900136 0.900136	0.827227 0.827227	0.884174 0.884174
Scientific Writing & Synthesis	Writing (for a scientific audience, includes writing grants and papers) Synthesizing existing research	0.669985 0.669985	0.70185 0.70185	0.714812 0.714812

Table 2. Participants were asked to rate their mastery in as well as the importance and frequency of various individual skills. These skills were clustered into Skill Categories for analysis.

Salary Data Cleaning

Participants were also asked to report their annual salary as an optional question. Uninterpretable responses to this question were dropped: for example, if it was not clear that the response was a salary for a given year. If respondents gave responses that were by the month or for a 9-month salary, those responses were converted to yearly salary amounts. If respondents added any caveats about health insurance or tuition, those caveats were removed and unadjusted numbers were used. If participants gave a range, the middle of that range was used. Many responses to this question were not in US Dollars (USD). Responses were converted to USD according to exchange rates in October 2020. To identify meaningful correlations for the majority of salaries in our data, we sought to identify and remove outliers that did not represent the bulk of the data. To do so, all salaries were converted to Z-scores. Salaries with a Z-score greater than 2 were removed, resulting in the removal of 6 outliers. One of these outliers was $100/year, the other 5 were $215,000/year or greater. With these outliers included, there is still a positive correlation with Coding (p=0.03, r=0.21), however the correlation with Data Analysis becomes insignificant (p=0.08, r=0.17).

Survey Dimensionality Reduction

To reduce the dimensionality of our 21-skill profiles for further analysis, we computed a cross-correlation for all of the skills for all participants for each question to determine whether certain skills were correlated with each other (not shown). This analysis, along with the conceptual relationships between these skills, suggested that we could reduce our 21 skill items to fewer skill categories. Although participants were also asked about 'Working with patients in a clinical setting,' only Medical Professionals gave this category scores higher than 0 and these responses did not correlate with any other skill. It was therefore excluded in subsequent analyses, resulting in six final skill categories: bench, coding, data analysis, management and communication, mentorship and teaching, and scientific writing and synthesis (Table 2).

To confirm the statistical robustness of our skill category groupings, we computed a Cronbach's alpha for each category, for each of the three questions. Doing so resulted in a Cronbach's alpha higher than 0.60 for each category, with the exception of the frequency and importance of Management & Communication skills (Table 2). This likely reflects the diversity of skills that are included in this category.

Statistical Analysis

To determine differences between skill mastery, frequency, and importance between graduate students and three job sectors, we ran Dwass-Steel-Critchlow-Fligner pairwise comparisons. We also ran Dwass-Steel-Critchlow-Fligner pairwise comparisons to test for gender differences in skill use. Given that we tested for six different skills for each question, we used a Bonferroni correction to determine an appropriate alpha value (0.05/6 comparisons). We therefore considered pairwise comparisons significant with a p-value less than 0.008. To identify relationships between salary and skills in specific domains, a Pearson correlation value was calculated. Relationships were considered significant at p<.05.

	Mastery	**Frequency**	**Importance**
Graduate Students (n=116)	1. Designing and planning experiments (2.36±0.61) 2. Synthesizing existing research (2.31±0.65) 3. Verbally presenting information in front of an audience (2.28±0.72)	1. Communicating with other scientists and/or clients (2.97±1.11) 2. Synthesizing existing research (2.79±1.00) 3. Running statistical analyses (2.53±0.92)	1. Designing and planning experiments (3.45±0.85) 2. Running statistical analyses (3.33±0.79) 3. Writing (for a scientific audience, includes writing grants and papers) (3.25±0.84)
Professionals (n=125)	1. Communicating with other scientists and/or clients (2.62±0.28) 2. Verbally presenting information in front of an audience (2.35±0.32) 3. Synthesizing existing research (e.g., reading papers, producing literature reviews) (2.15±0.37)	1. Communicating with other scientists and/or clients (3.27±0.41) 2. Managing a team (2.70±0.46) 3. Synthesizing existing research (e.g., reading papers, producing literature reviews) (2.36±0.32)	1. Communicating with other scientists and/or clients (3.22±0.41) 2. Verbally presenting information in front of an audience (2.85±0.52) 3. Managing a team (2.66±0.51)

Table 3. Top skills for neuroscience graduate students (n=116) and professionals (n=125). Mean and standard deviation are shown in parentheses after each skill.

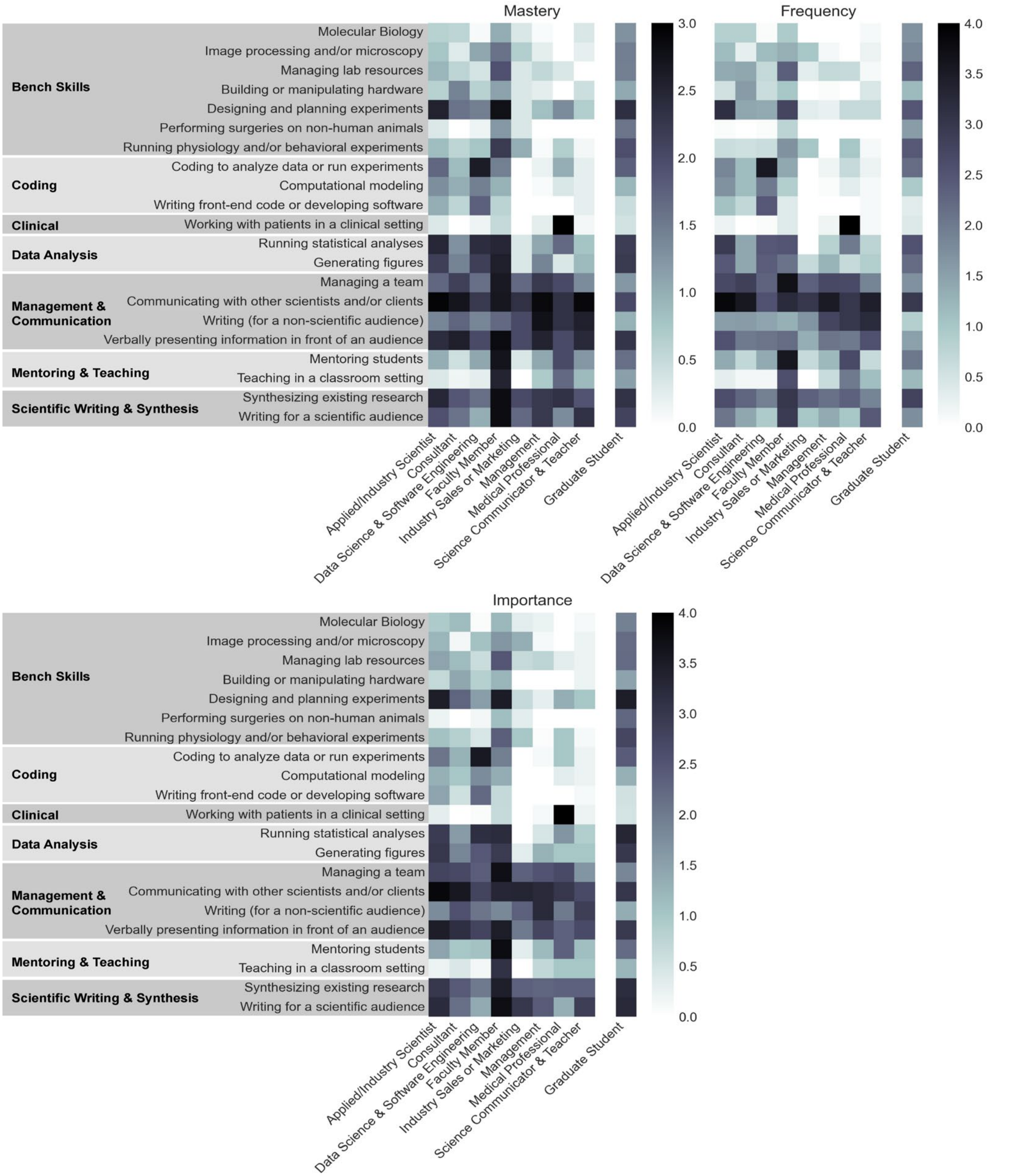

Figure 1. Mastery, frequency, and importance of 21 different skills across graduate students and different job sectors. Graduate students can be seen in the last, separated column. Skills are ordered based on their final groupings. Survey responses were converted to numbers for analysis Mastery: 0=None, 1=Basic, 2=Intermediate, 3=Expert. Frequency: 0=Never, 1=A few times a year, 2=Several times a month, 3=Weekly, 4=Daily. Importance: 0=Not at all important, 1=A little important, 2=Somewhat important, 3=Very important, 4=Extremely important.

RESULTS

Graduate Students Use and Value Different Skill Sets than Neuroscience Professionals

To better understand the skill sets of graduate students and neuroscience professionals, we conducted a survey in which participants were asked to rate their required mastery, frequency of use, and importance of 21 different skills. "Neuroscience professionals" were defined as postgraduates with a neuroscience degree and include both academic researchers, industry researchers, and individuals who are not conducting research (Table 1; Methods). The skills chosen represent the range of skills required in different career paths both in and out of academic research.

First, we looked at the top skills used by either graduate students (n=116) or professionals (n=125). As seen in Table 3, the top skills for graduate students and professionals are distinct, with only a couple of exceptions. Across all professionals, 'Communicating with other scientists and/or clients' was the highest ranked skill in mastery, frequency, and importance, but is only in the top three in frequency for graduate students. Similarly, 'Managing a team' is a top skill for professionals but does not appear in the top three for graduate students. There was notable variability across both graduate students and professionals, likely reflecting the variability in graduate school expectations and subfields, as well as the differences in skills used in different career paths.

To look for patterns in different career paths, we compared the skill profiles of graduate students with eight different job categories (Figure 1). Notably, the skills required in graduate students are visibly broad and different from those required by all neuroscience professionals.

Graduate students reported using and needing mastery in almost all of the bench skills we assessed, whereas within neuroscience professionals, only faculty members reported using and needing these skills. This high-level view of the data also illustrates the use and importance of coding in a variety of different job categories. "Coding to analyze data or run experiments," "Computational modeling," and "Developing software" were rated highly in several different career paths, including applied/industry science and consulting.

Faculty reported high mastery, frequency, and importance across a wide variety of skills, with higher reported averages in almost every category than professionals in other job sectors.

All Career Paths Master, Use, and Value Management & Communication Skills

Once we were confident that individuals and skills could be clustered into groups (see Methods), the averages of the mastery, frequency, and importance rankings of each skill category were plotted for graduate students as well as each of the job sectors (Figure 2). Several interesting observations emerged from this analysis, confirming the trends seen in the single item analysis.

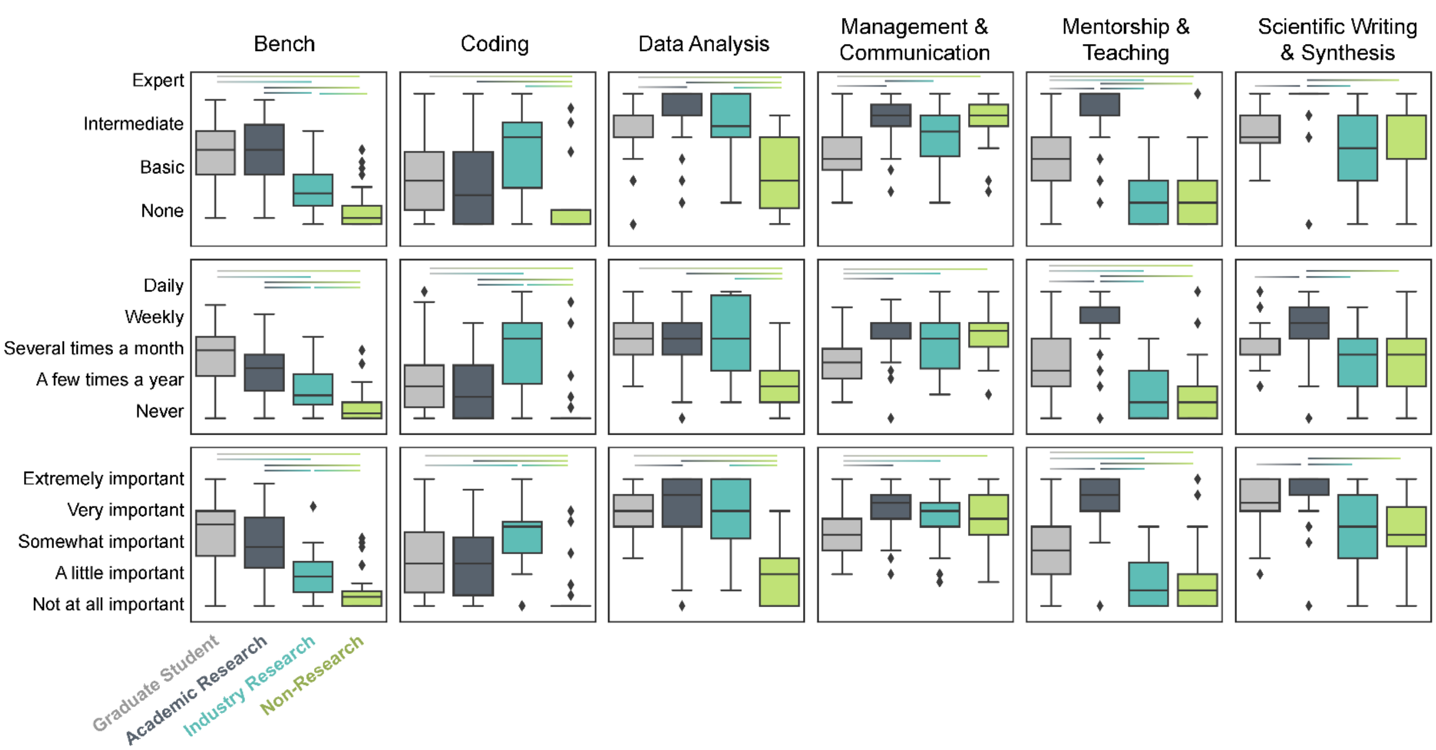

Figure 2. Graduate students and three different job sectors value and practice different skill sets. Median mastery (top row), frequency (middle row), and importance (bottom row) for six skill sets across graduate students (light gray) and three different job sectors (academic research: dark gray; industry research: teal; non-research: lime). Lines above box plots indicate p<0.008 as tested with a Dwass-Steel-Critchlow-Fligner test (see Methods for Details).

Theme	Definition	Representative Responses
Coding	Participant learned programming either informally or formally	“My previous work with computer programming helped to get me to my current position." “Extracurricular activities in data science and machine learning.”
Communication	Participant learned or practiced written or verbal communication	“The ability to communicate clearly.” “Making posters and PowerPoints.”
Mentors	Participant received positive mentorship and/or advocacy from others	“I was fortunate enough to do a PhD in a physiology lab with an amazing, open-minded advisor.”
Research Training	Prior research training, in any field, often graduate or postdoctoral training	“Research design and methodology, how to collect data through controlled experimental design.”
Interdisciplinarity	Combining training across fields or integrating insights from another field	“My experience and exposure to a broad range of scientific fields helped me with my current position, as well as learning how to ‘translate’ scientific language into lay language.” “I didn't NEED to study one thing, I've found interesting problems everywhere I've looked.”
Teaching	Prior teaching experience, either as a teaching assistant or instructor	“Teaching during postdoc.”
Data Analysis	Training or practice working with data	“One of the most important aspects of my undergraduate and graduate training was learning and applying computer science approaches to analyze data.” *(Also tagged with Coding)*
Persistence	Ability to persevere and put in effort even in challenging circumstances	“Luck, but also being stubborn"; “Working hard.”
Networking	Meeting others or working through connections	“Right place right time. Good social skills. Great letters of recommendation”; “Opportunities to network.”
Leadership	Experience leading a research group or student organization	“Getting involved in the leadership of science writing and science communication groups.” *(Also tagged with Communication)* “Leadership positions in student government and student organizations as a PhD student.”

Table 4. Dictionary for top themes identified in open-ended survey responses.

While Bench skills were frequently used, important, and required by graduate students and faculty, they were less prevalent in Industry research and Non-Research sectors. All sectors besides Non-Research jobs reported needing at least a basic understanding of Coding. This was highly variable even among researchers though, likely reflecting the fact that not all research requires coding experience. All sectors except Non-Research rated Data Analysis and Scientific Writing & Synthesis skills somewhat highly across questions.

Interestingly, neuroscience professionals regardless of job sector rated Management and Communication skills to be strongly required, very important, and frequently used. Graduate students reported significantly less use and importance of management and communication skills than all other job sectors.

Academic researchers rated Mentorship & Teaching the highest across mastery, frequency, and importance, reflecting the fact that faculty spend a significant amount of time mentoring students and teaching in a classroom setting. Faculty report that they need mastery in mentorship and teaching and that these skills are important — not simply that they regularly use them.

Open Ended Responses Reiterate Importance of Coding and Communication

We triangulated this quantitative skills assessment with an open-ended question which asked participants to describe one thing that prepared them for their current position. We thematically coded these responses for key words and then quantified the number of codes for each job category. Our analysis identified 10 themes that emerged from these

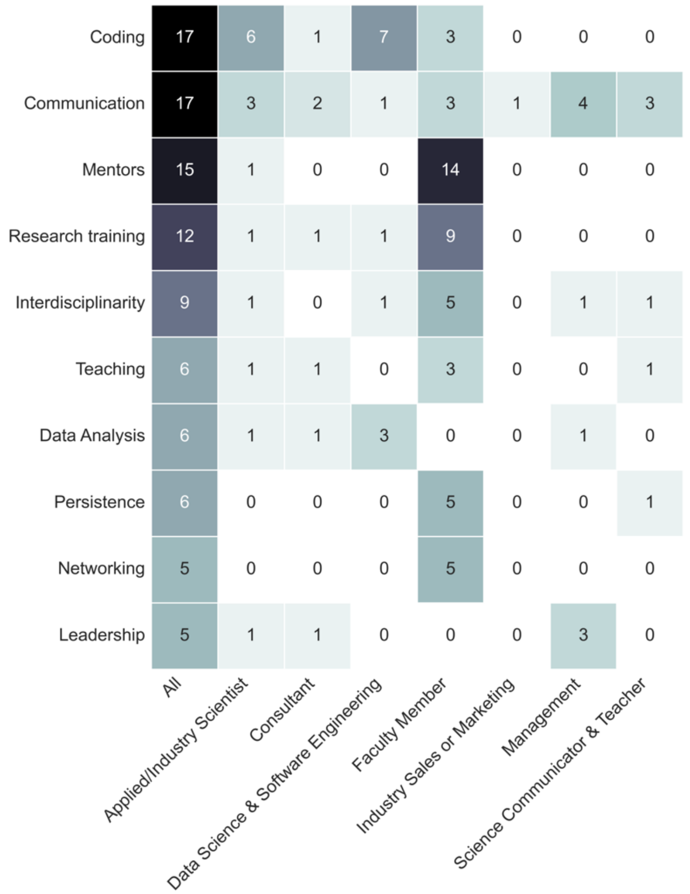

Figure 3. Frequency of open-ended response themes. First column is all responses (n=109), subsequent columns are frequency by job category. Heatmap is ordered by the first "All" column.

responses at least four times (Table 4). Many of these themes are similar to those asked about in the skills assessment, even though this open-ended question was asked first on the survey.

This exploratory analysis also identified additional skills that we did not include in the skills inventory, such as "interdisciplinarity," "persistence," and "networking." The quantification of all themes resulted in similar trends as the skills assessment, with coding, communication, and mentors emerging at the top (Figure 3). Notably, faculty strongly cite having good mentors as an element of their preparation. Applied/Industry Scientists and Consultants further iterate the importance of learning how to code, and communication was a common theme across professions.

Mastery of Coding & Data Analysis Skills Predicts Higher Salaries

Next, we asked whether the mastery of skills for a given career correlated with self-reported annual salaries (Figure 4). Neuroscience professionals reported a range of salaries, with Applied/Industry scientists reporting the highest salaries (median=$150,000/year) followed by Consultants (median=$100,000/year; Figure 4a). Although faculty reported having, valuing, and using skills more than any other neuroscience professional, this is not reflected in most faculty salaries (Comm and Mathaisel, 2003; Layzell, 1996). Faculty salaries were also highly variable, perhaps reflecting the vast differences in pay across universities (Johnson and Taylor, 2019). There was a positive correlation between Salary and the mastery of Coding (p = 0.048, r = 0.201) and Data Analysis (p = 0.042, r = 0.207) skills (Figure 4b). There was a negative but not statistically significant correlation between Salary and the importance of Mentorship & Teaching skills (p = 0.405, r = -0.086; Figure 4b).

Gender Gaps in Coding Skill Usage Persist in Graduate Students

Lastly, we asked whether there were significant differences in self-reported skill mastery between genders, within both graduate students and neuroscience professionals. Echoing many findings about the disparity between coding access and experience in male- and female-identifying individuals, neuroscience professionals who identified as female reported needing significantly less mastery in coding as well as data analysis (Figure 5; p =0.001).

Remarkably, this gender gap between male-identifying and female-identifying respondents in coding mastery persisted even in graduate students (Figure 5; p = 0.002). This difference held for graduate usage of coding as well (p = 0.001; data not shown) but not for importance (p = 0.049), perhaps reflecting that although female graduate students recognize the importance of coding, they are still not using these skills as often as male students. Our small sample of non-binary/self-identified students was more similar in coding skill mastery to female-identifying students.

DISCUSSION

Here, we describe the skill profiles of hundreds of neuroscience graduate students and professionals in an effort to understand neuroscience career paths and inform our graduate training. We find that graduate students occupy very different skill spaces than neuroscience professionals, who employ a wide variety of skills at work but tend to rely more on management and communication skills than graduate students.

Previous work has similarly identified a disconnect between the quality of management and presentation training in STEM graduate school and the importance of these skills in the workplace (Smith et al., 2002). While the differences between graduate students and professionals may reflect the fact that more so-called "soft skills" are primarily required in more advanced stages of all careers, they nonetheless underscore the importance of these skills across career paths and suggest that we should be training our graduates in these domains (Smith et al., 2002; Succi and Canovi, 2020). While others have noted the necessity of providing graduates with transferable skills such as being able to learn in groups and communication (Canelas et al., 2017; Ganapati et al., 2021; Scott et al., 2019; Smith et al., 2002; Watson and Burr, 2018), we provide evidence for the transferability of these skills specifically for careers of students with neuroscience degrees.

On the other hand, specialized skills such as bench work are frequently used by graduate students but do not directly transfer to non-academic careers. This lack of transfer

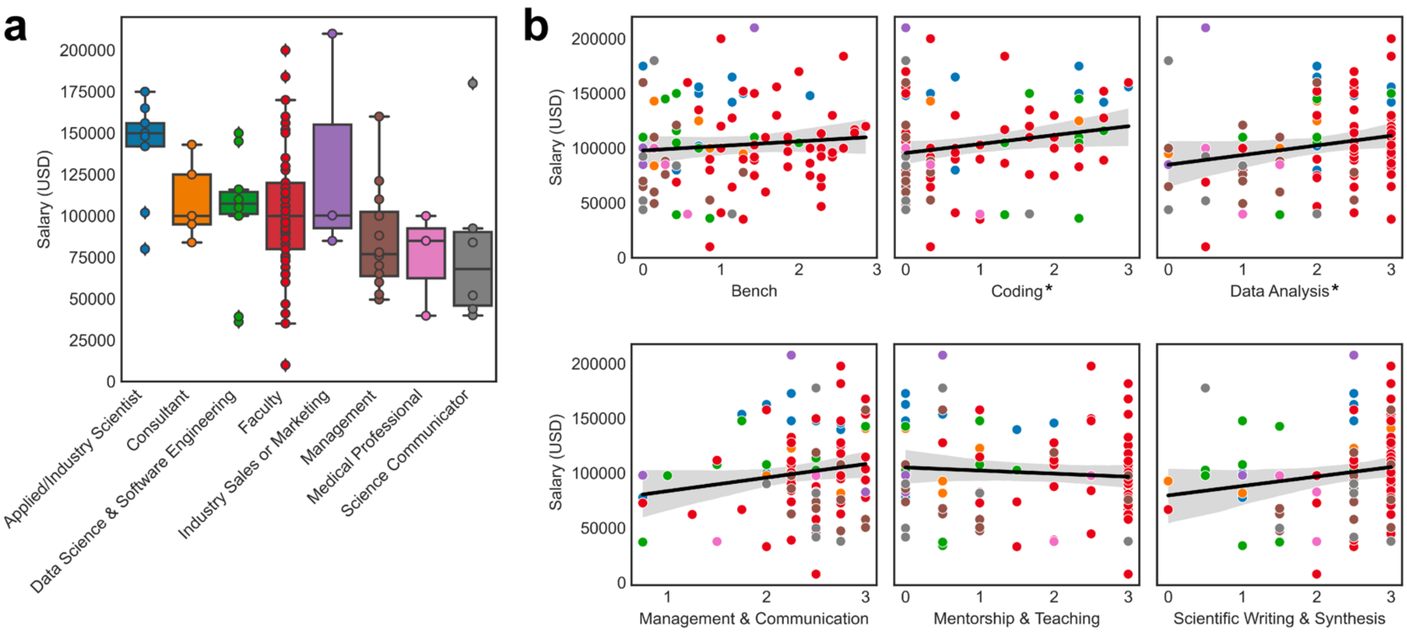

Figure 4. Relationship between yearly self-reported salaries (a) and mastery (0=None, 1=Basic, 2=Intermediate, 3=Expert) of six different skill categories (b). Individual data points are colored by job category. Black line is the linear regression model fit, the gray shaded area is the 95% confidence interval of the fit. Asterisks indicate correlations at p<0.05 as tested by a Pearson correlation.

between specialized skills obtained and used in graduate school to the workforce echoes studies of PhD holders in other fields, such as physical sciences (Smith et al., 2002). Still, technical, hands-on skill development is often necessary for more conceptual, non-technical skill development; a scientist needs to learn how to pipette before designing a new pipette protocol, or teaching others how to pipette. We did not directly study the longitudinal development of skills over time, though the shift from bench skills to other skills between graduate students and professionals in our sample suggests that this is a common transition.

In comparison to each of the neuroscience professional career paths, graduate students were most visibly similar to faculty members (Figures 1 and 2). This doesn't come as much of a surprise because graduate students are primarily trained by faculty, and graduate programs — particularly PhD programs — are almost exclusively designed to train future academic scientists (Golde and Dore, 2001). However, given that most PhD graduates will not end up in an academic job (Society for Neuroscience, 2017; Akil et al., 2016), the data we present here amplifies the call to provide more diverse training for our graduate students so that they can succeed beyond the academy (Golde and Dore, 2001; Hoyne et al., 2016). Faculty also use coding, management, and communication skills, so integrating additional training in these domains would assist graduate students regardless of their career goals.

Further, multiple job categories in addition to Data Scientists & Software Engineers reported needing coding, which also ranked at the top of responses to the open-ended question. This furthers an ongoing conversation about the need to teach coding to the next generation of scientists and knowledge workers (Akil et al., 2016; Grisham et al., 2016). We also show that there are salary benefits for jobs that require mastery of coding and data analysis (Figure 4). The salary benefits for these particular skills likely reflect the higher pay in data science, engineering, and computer science sectors more broadly, a trend which has been noted since the introduction of computers to the workplace (Krueger, 1993). The gender gaps that we observe, along with the benefits in salary, underscore that these skills should be offered not only as a matter of access, but also as a matter of long-term career equity. It is important that trainees are aware of the salary implications associated with different skill sets and that all trainees have access to a wide array of professional development opportunities to improve on these skills.

Considerations for Graduate Training

Our observations underscore the value of many different skills across both academia and industry, but do not call for a dramatic shift in the content or structure of graduate student education. Rather, we suggest that students be encouraged to seek professional development opportunities that are in line with their career goals (Spronken-Smith, 2018). These low stakes, development-oriented opportunities could be mentoring students in the lab, leading student organizations, presenting at conferences, or teaching in a classroom or informal outreach setting. Such professional development activities, while often seen as extracurricular, are core to a graduate students' training and ability to succeed in the workforce (Spronken-Smith, 2018). Indeed, graduate students are increasingly requesting professional development as a part of their training (Matyas et al., 2011).

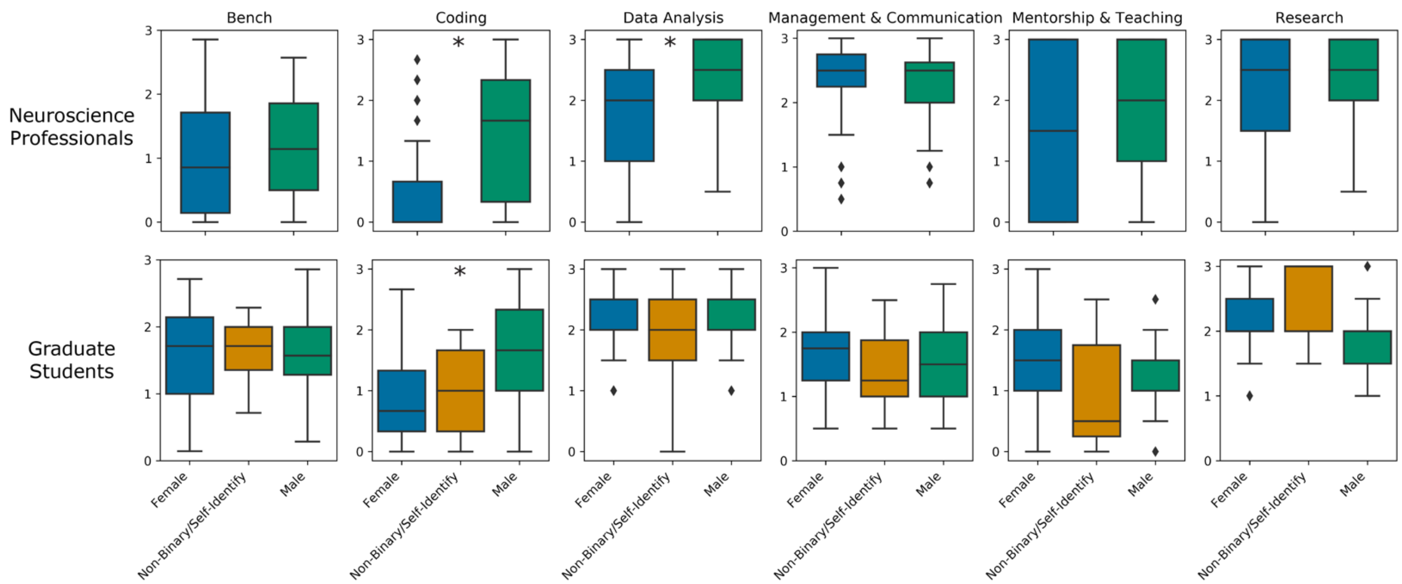

Figure 5. Gender breakdown of self-reported skill mastery (0=None, 1=Basic, 2=Intermediate, 3=Expert) in neuroscience professionals (top; 70 female, 55 male) and graduate students (bottom; 87 female, 21 male, 7 non-binary/self-identify).

Given the observations here, there are several specific ways in which graduate training could be improved. It is also important to consider the timing of these skill interventions—students need to see the value in these skill sets in order to dedicate time and resources to learning them.

First, students should be invited to develop “meta” work skills, intentionally working towards a skill set given their career goals (Bridgstock, 2009). The inclusion of practices such as skills inventories or Individual Development Plans—when implemented well—are a good step in this direction (Spronken-Smith, 2018; Tsai et al., 2018; Vanderford et al., 2018, http://aps.org/careers/guidebook/skills.cfm). Group work has also been shown to enhance professional behaviors and job preparedness, particularly building communication and team management skills (Senay, 2015; Cartwright et al., 2020). Such group work could take place in the lab setting, as students work on research projects, or in the classroom. Finally, graduate students can be encouraged to build metacognition about the ways in which they are already developing management and communication skills as a part of their research or life beyond lab.

Furthermore, providing graduate students with additional outlets to communicate their research, either verbally or in writing, is essential (Ganapati et al., 2021). Student-run writing groups such as NeuWrite (https://neuwrite.org/) or university-sponsored writing classes can give students necessary opportunities and critical feedback as they develop as writers. Additional opportunities for teaching — either as a teaching assistant in a course setting or by mentorship in a research setting — can be formative experiences during graduate careers (Feldon et al., 2011). While opportunities for graduate students to be a lead instructor are more common in the humanities and social sciences, they are often hard to come by or justify in STEM fields (Golde and Dore, 2001). However, given the clear importance of teaching in neuroscience, degree programs and departments should be open to the idea of providing PhD students with opportunities to serve as a lead instructor, after experience as a teaching assistant.

Finally, graduate students should be given access to and credit for coding classes, even informal ones, especially given that many degree programs do not include such courses (Society for Neuroscience, 2017; Juavinett, 2022). Interested graduate students can find free coding resources online from websites such as DataQuest.io or Software Carpentry (https://software-carpentry.org/lessons/), and free online textbooks paired with open access coding tools (e.g., https://github.com/jakevdp/WhirlwindTourOfPython/). With the clear gender gaps in coding use in the population of graduate students we surveyed, and the well-known differences in how male and female students perceive and approach coding, opportunities to learn coding should be specifically targeted to students who do not identify as male (Cheryan et al., 2009; Baser, 2013; Owolabi et al., 2014; Rubio et al., 2015). In doing so, we can provide the next generation of diverse graduate students with the training they need to succeed in neuroscience and beyond.

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