Understanding Computational Science and Engineering (CSE) and Domain Science Skills Development in National Laboratory Postgraduate Internships

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ABSTRACT

Background and Context: Harnessing advanced computing for scientific discovery and technological innovation demands scientists and engineers well-versed in both domain science and computational science and engineering (CSE). However, many universities lack the resources needed to provide integrated training. National laboratories offer internship opportunities capable of developing these skills.

Objective: We present an evaluation of federally-funded postgraduate internship outcomes in CSE at a national laboratory. We seek to answer three questions: 1) What computational, research, and professional skills do students improve through internships at the selected national laboratory? 2) Do students gain knowledge in domain science topics through their internships? 3) Do students' career interests change after these internships?

Method: We developed a survey and collected responses from past participants of five federally-funded internship programs and compare participant ratings of their prior experience to their internship experience.

Findings: Our results indicate that participants improve CSE skills and domain science knowledge, and become more interested in careers at national labs. Participants found skills developed during their internships to be relevant and useful in their post-internship positions.

Implications: The perceived impact of postgraduate internships often centers on *career opportunities and applications of course material*. We show national laboratory internships are an opportunity for students to build critical technical skills, in both CSE and domain science, that may not be available at all institutions. This suggests internships and other experiential learning in settings such as national laboratories have the potential to make substantial contributions to building technical competency in graduate students.

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KEYWORDS

Internship, Graduate Students, Computational Science and Engineering, National Lab

1 INTRODUCTION

1.1 The need for integrative training in computational science and engineering and domain science

Scientific discovery and technological advancement increasingly depend upon the use of advanced computing, including modeling and simulation (mod/sim), data science, and machine learning and artificial intelligence (ML/AI) [37, 38, 40]. The development and application of these tools has emerged as its own scientific discipline, *computational science and engineering, or CSE* [38], distinct from computer science, or CS. In many cases, the most effective use of advanced computing for scientific discovery and technology development occurs when students are cross-trained in both CSE and *domain science* areas such as engineering, physics, chemistry, or biology [28]. The value of these skills increases when scientists and engineers are able to make effective use of high performance computing (HPC) systems which are characterized by increasing complexity, including massive parallelization, heterogeneous architectures, and the use of complex programming models [13].

The need for CSE and HPC expertise is not confined to academic and research institutions. Industry's growing reliance on CSE and HPC is evident in the major investments in world-class supercomputers as listed in the TOP500 [43] and accelerating adoption of cloud-based HPC [31]. The ability to effectively use commercial computational software and scientific programming skills in languages such as C++, Python, and MATLAB has been identified as highly sought after skills for engineers at the bachelors, masters, and doctoral levels through analysis of job advertisements [16] and surveys of Ph.D. earners employed in industry [46]. Furthermore, both programming [16] and HPC [41] skills are associated with significant salary premium for engineers and scientists pursuing careers in industry.

1.2 Obstacles to integrated CSE/domain science training

Previous research on interdisciplinary CS and CSE training at the graduate level has focused heavily on students shifting into CS and CSE after completing undergraduate degrees in domain sciences (e.g., physics, chemistry, and biology). Depending on the major, courses, and experiential education options pursued by individual students, non-CS students can complete their degree with widely varying range of programming skills and experience.[1]. This variation can increase among students who gain professional experience prior to enrolling in graduate programs [25]. These challenges have led to the creation of ad hoc CS "boot-camps" within graduate programs to provide all students with the skills needed to succeed in future graduate courses [1, 26].

However, these models do not address the increasing demand for domain scientists trained in CSE skills [28, 42]. There are limits to the ability of academic institutions to provide both the expertise and hardware needed for effective training [22]. Training may be limited by lack of access to hardware, with many universities only able to support small-scale systems (e.g., [34, 45]). As a result, relatively few university students have access to modern supercomputers, which often have vastly different capabilities and architectures than those of smaller, more affordable clusters. Based on the November 2024 ranking of the top 500 most powerful supercomputers in the world [43], 173 supercomputers are located in the United States (US), the context in which this study is situated. Of those in the US, 67 are hosted in government research facilities, including 38 at Department of Energy (DOE) National Laboratories, 3 are hosted in research foundations, and 80 are hosted in industry and vendors. However, only 23 top-500 supercomputers are hosted by US universities. These computers are concentrated in 17 very high research activity universities [18] located in 9 states, further limiting access to hands-on training. These challenges increase at non-R1 universities, where access to smaller-scale clusters is often limited. [14].

Even in universities with access to larger-scale compute facilities, integrating domain sciences with CSE training faces institutional challenges. These include the constraints of existing curriculum requirements (e.g., [22]), lack of evaluation of learning outcomes (e.g., [47]), or inadvertently de-emphasizing computational skills when integrating domain science topics (e.g., [3, 11]). These challenges are often exacerbated by a shortage of faculty in key areas of CSE [48].

1.3 Models for integration of national laboratory resources with academic training and prior assessment

Making national laboratory computing resources and staff expertise available to university students is a possible solution to these challenges with multiple strategies. Because DOE computing resources are used by academic research groups across the United States, many research groups have developed their own internal documentation and training for the systems that they have access to, and the tools that are necessary of support their work.

A second related approach is to provide national laboratory computing time and staff support directly to university partnerships seeking to provide training at the institutional level [2, 36, 39]. These programs are often designed to increase skills needed for using national laboratory computing systems as part of dissertation research.

A third approach is to integrate students into national laboratory research that uses HPC through internships in a situated learning model [5]. In this approach, students gain direct access to communities of practice by working in a team of researchers using on-site HPC facilities.

Previous assessments of national laboratory internships not specifically focused on CSE shows multiple impacts, including:

- Increased retention in science, technology, engineering, and mathematics (STEM) careers [7, 17]
- Increased research skills [8, 17]
- Increased professional networks [8]

Internships in the broader field of computer science are linked multiple benefits, including:

- Development of technical skills [20, 21, 29, 40]
- Opportunities for career exploration [20, 21, 23]
- Expanded professional networks that contribute to future professional success [15, 23, 29]

However, the question of the development of specific technical skills in national laboratory internships, specifically in CSE and HPC, remains open. While there is substantial literature on training in HPC, these papers tend to focus on descriptions of internships at academic computing centers [19] or workshops designed for specific supercomputer sites (e.g., [4, 6, 12, 47]). The potential benefits of internships in the national laboratory environments, which combine expertise in CSE, domain science, and HPC operations has not been examined.

1.4 Research Questions

Our study aims to address this gap through an evaluation of federally funded, postgraduate (including postbaccalaureate-, master's-, and doctoral-level) internships hosted at the National Laboratory of the Rockies, or NLR. (At the time of the internships, the facility was known as the National Renewable Energy Laboratory, or NREL). To this end, we ask the following research questions:

Research question 1: What computational skills, research skills, and professional skills do postgraduate students improve through their internships at NLR?

Research question 2: What domain-science topics do postgraduate students gain more familiarity with through their internships at NLR?

Research question 3: Do postgraduate students' career interests change after their internships at NLR?

To answer these questions, we conducted a survey study with past participants of five federally funded internship programs hosted at NLR. These programs serve post-baccalaureate and graduate participants from a variety of disciplines and educational institutions. While this survey is specifically focused on the intersection of CSE and NLR's core research, results are likely to be broadly applicable to interdisciplinary training that combines CSE with other domain sciences.

We provide additional context of the internship programs and internship site in sections 2.1 and 2.2. Section 2.3 details the methods

used to design the survey as well as collect and analyze survey data. Section 5 includes discussion of our results, conclusions, and possibilities for future work.

2 METHODS

2.1 Host Institution

This study examines the impact of *federally-funded internships* in CSE at the National Laboratory of the Rockies (NLR), a Department of Energy (DOE) National Laboratory located in Golden, Colorado. The laboratory has additional campuses in Arvada, Colorado, Fairbanks, Alaska, and Washington, DC. As of 2024, the laboratory had 3,675 staff, including regular employees, postdoctoral researchers, visiting professionals, and subcontractors.

NLR's research focuses on energy systems and energy efficiency in support of the research objectives of multiple DOE offices, including the Office of Critical Minerals and Energy Innovation (CMEI), the Office of Electricity (OE), the Hydrocarbons and Goethermal Energy Office (HGEO), and the Office of Science (SC). NLR increasingly uses computational science tools, including mod/sim, data science, and ML/AI to perform this research. NLR's efforts in these areas are led by the Computational Science Center (CSC). CSC hosts Kestrel, NLR's third generation of High Performance Computing (HPC) that is available to all researchers funded by CMEI. The center also engages in research in computational science spanning fundamental work on algorithms, software development, scientific visualization, and application to a range of topics in energy systems [27]. As of November 2024, CSC staff includes 7 managers, 11 administrative staff, 65 scientific staff, 44 technical staff (responsible for operation of the HPC facilities), and 14 postdocs, or a total of 141 staff. Staff expertise covers a broad range of CSE topics, including modeling and simulation, data science and visualization, and machine learning and artificial intelligence. Staff expertise also includes software engineering, systems administration, and data center infrastructure management and facility integration.

NLR hosts interns in CSE through two mechanisms: federal educational fellowships, with financial support from the fellowship sponsor, and as temporary staff working on specific projects, with financial support from project funds. Federal educational fellowships specify that the student be achieving specific educational objectives while contributing to active research projects. Both types of internships are available to undergraduate, postbaccalaureate, and graduate students. Because CSE is often an advanced undergraduate or graduate-level topic, NLR's internships in this area are heavily weighted towards postbaccalaureate and graduate students. Based on this, the current study focuses on postgraduate students supported through federal educational fellowships.

2.2 Internship Programs Included

NLR currently brings postbaccalaureate and graduate student interns in CSE to the laboratory through five federally-funded educational internship programs. Four of these programs are funded by the DOE: the Computational Science Graduate Fellowship (**CSGF**), the Science Undergraduate Laboratory Internship (**SULI**) program, the CMEI High Performance Computing for Energy Innovation Internship program (**HPC4EI**), and the National Nuclear Security Administration's IMPACT Internship (**NNSA-IMPACT**). A fifth program is funded by the National Science Foundation (NSF): the Mathematical Science Graduate Internship (**NSF-MSGI**).

For all of these programs, each intern is assigned a mentor (i.e., a staff member at the national lab), and each mentor is expected to submit a plan to the sponsor that identifies learning objectives as well as scientific objectives for the internship. Once the internship begins, interns have the opportunity to learn from direct interaction with mentors and other members of the technical staff. In addition to this mentorship, NLR's HPC operations staff offers a broad range of structured trainings and tutorials on topics in HPC, as well as providing one-on-one advising when needed. Each of these programs has unique goals, eligibility criteria, and post-internship report requirements, which we describe next.

DOE CSGF is a highly competitive four-year fellowship for doctoral students in science and engineering who incorporate computational science into their work [24]. Applicants must be US citizens or permanent residents. As part of their fellowship, students must spend at least one semester at one of 21 DOE facilities pursuing a project outside of their dissertation work. The 20-30 students seeking placement each year work directly with practicum coordinators at different facilities to identify a facility, mentor, and project that meet their interests. Students must complete an initial practicum within the first two years of their fellowship and are free to participate in second or third practicums, either with the same DOE facility and mentor, or a different DOE facility and/or mentor. CSC manages placement within NLR, though assigned mentors and projects can within CSC or in another center with computationally intensive projects. While placements are generally made during the summer, they are also occasionally made in the fall or spring semesters.

DOE SULI is a one-semester internship program open to US citizens or permanent residents who are undergraduates, postbaccalaureate, or graduate students in their first two years since completing their bachelor's degree [10]. Students are not required to be majoring in a STEM field but must have at least 6 credit hours in STEM and a minimum 3.0 out of 4.0 grade point average. SULI students are eligible for placement at 17 different DOE facilities. Students may complete up to two placements, either with the same DOE facility and mentor, or a different DOE facility and/or mentor. Students may be placed for the summer, fall, or spring semesters.

The **CMIE HPC4EI** internship program is linked to the DOE's HPC4EI program [9]. The HPC4EI program matches DOE national laboratory computing capabilities with industrial partners to solve key challenges in industrial energy use and the manufacture of energy materials. As part of its industrial competitiveness mission, HPC4EI offers internships to US citizens in HPC-relevant fields as undergraduate, postbaccalaureate, and graduate students [35]. HPC4EI interns work directly on projects sponsored by the HPC4EI program.

NNSA-IMPACT targets building research capacity at Minority Serving Intuitions (MSIs) as defined by the US Department of Education [44]. NNSA-IMPACT is open to US citizens of all backgrounds, academic levels, and majors at these institutions [32]. Students can complete an in-person or virtual internship and have the option of extending into the academic year.

NSF-MSGI is open to doctoral students in mathematics, statistics, and applied mathematics. The goal of NSF-MSGI is to expose these

students to non-academic careers [33]. Unlike the other programs described, NSF-MSGI is open to international students. Students may complete multiple internships, but each internship must be with a different mentor.

All of these programs operated as fully virtual programs in 2020 and 2021 due to the COVID pandemic. DOE CSGF deferred all summer 2020 placements to summer 2021 placements, but did allow virtual placements in fall of 2020 and spring of 2021. Neither CMIE HPC4EI nor NSF-MSGI operated in summer of 2024 due to budget uncertainties.

2.3 Survey Design

The research team collaboratively designed the survey. Given the purpose of the survey to understand interns' 1) technical and professional skill development and 2) pathways to future careers across a variety of internship programs and projects, survey questions were organized and designed around the following themes: Computational Skills, Familiarity with NLR-relevant domain science topics such as energy generation and efficiency, Research Skills, Professional Skills, and Career Interests. Full questions for each theme are provided in Table 1.

For each theme, the research team identified relevant skills and topics based on their extensive experience with the internship programs described in Section 2.2. More specifically, four of the co-authors (Martin, Egan, Day, and Potter) have extensive involvement in NLR's internship programs. Michael Martin has served as NLR's coordinator for the DOE CSGF, CMIE HPC4EI, and NNSA-MSIIP programs as well as mentored students through the NSF-MSGI program. Hilary Egan has served as NLR's co-coordinator for the DOE CSGF program and has mentored students through the DOE SULI program. Marc Day has mentored students through the DOE CSGF and NSF-MSGI programs. Kristi Potter has mentored students through the DOE CSGF and SULI programs.

For the questions related to computational skills, inspiration was taken from a previous report on CSE education [38]. The research team iteratively adjusted the questions for clarity and understanding across each internship program's context.

Additionally, optional open-ended response options were provided for participants to describe other computational skills, research skills, professional skills, and topics that they improved or gained familiarity with during their internship to capture areas we did not explicitly ask about.

2.4 Participant Background Information

Participants were also asked to self-report the following academic background information:

- Prior experience at other Department of Energy National Labs (i.e., no experience, once, 2-3 times, or 4 or more times)
- Prior experience at other federal laboratories (i.e., no experience, once, 2-3 times, or 4 or more times)
- Year of first internship at NREL, as some participants may have extended their internship or returned to NREL at a later time
- Academic stage and major / field of study during internship at NREL or, for participants who were not enrolled in a degree program during their internship, major / field of study during degree prior to internship
- Location of internship (i.e., in person, hybrid, remote)
- Focus of internship on domain science topics (i.e., not at all, somewhat focused, very focused, or extremely focused)
- Current position at time of completing survey (i.e., in the same or different degree program, looking for employment, or currently employed)

Additional questions were asked based on participants' current positions to understand how their internship experiences may or may not have carried beyond their time at NLR. These questions are also provided in Table 1.

2.5 Participants

We recruited participants from five federally-funded internships at NLR as described in Section 2.2. Because these internship programs are open to a broader population than our intended focus, we applied the following inclusion criteria:

- Participants must have completed a bachelor's degree or equivalent prior to starting their internship at NLR
- Participants must have started their internship at NLR in 2018 or later
- Participants incorporated CSE into their internships, as evidenced by (1) the nature of the internship program (CSGF, HPC4EI, and NSF-MSGI), or, (2) for SULI and NNSA-MSIIP students, either (a) a mentor in CSC, or (b) use of NLR's supercomputer during their internship in another NLR center.

Many potential participants were identified given the research team's extensive involvement with the internship programs of interest. Public records of some internship programs were cross-referenced with internal NLR records to identify additional participants. Additionally, we contacted NSF-MSGI administrators for the list of past NSF-MSGI participants hosted at NLR. All study procedures follow our IRB-approved protocol (#DOE001036).

2.6 Data Collection

Participants were sent either a recruitment email or LinkedIn message in September 2024. The survey accepted responses for three weeks.

Because the authors have extensive experience working with these internship programs (see Section 2.3 for more details), Morgan Fong was recruited as a graduate student intern to the research team to manage distribution of the survey and removal of personally identifiable information from responses. Martin, Egan, Day, and Potter only had access to de-identified and aggregated data.

2.7 Data Analysis

All Likert-scale questions, except for questions related to Professional Skills, are coded on a scale of zero (i.e., "No experience," "No improvement," "No familiarity," "No increase in familiarity," "Not interested," "Not at all," "Not useful," "Not related,") to three (i.e., "Expert," "Substantial Improvement," "4 or more times," "Extremely familiar," "Substantial increase in familiarity," "Extremely interested,"

Table 1: Survey questions organized by theme. All questions were asked with respect to before the internship and during the internship. Questions on career interest were split by domain and sector. All questions use the program terminology in effect at the time of the survey.

Theme	Question Context, Response Options	Skills and Topics
Computational Skills	Prior to participating in [internship program], how much experience did you have with the following? *No experience, Some experience (e.g., 1-2 projects), Extensive experience (e.g., took advanced coursework), Expert (e.g., focus of degree, years of experience)*	1. Writing general-purpose programs 2. Writing programs for scientific problems 3. Writing distributed or parallel programs 4. Writing software collaboratively 5. Performing data visualization and analysis 6. Using AI/ML to develop models 7. Developing simulations of systems or phenomena (e.g., computational fluid dynamics, computational chemistry) 8. Using high performance computers or supercomputers 9. Using software libraries or open-source code
	During your internship at NREL, to what extent did you improve your skills in the following? *No improvement, Some improvement, Moderate improvement, Substantial improvement*	
Familiarity with Energy and Efficiency Energy Topics	Prior to participating in [internship program], how familiar were you with the following? *No familiarity, Somewhat familiar (e.g., news, social media), Very familiar (e.g., took advanced coursework) Extremely familiar (e.g., focus of degree)*	1. Renewable energy 2. Energy efficiency 3. Materials usage 4. Circular economies 5. Environmental justice 6. Energy equity 7. Sustainable Computing
	To what extent did your internship at NREL increase your familiarity with the following topics? *No increase in familiarity, Some increase in familiarity, Moderate increase in familiarity, Substantial increase in familiarity*	
Research Skills	Prior to participating in [internship program] how much experience did you have with the following? *No experience, Once, 2-3 times, 4 or more times*	1. Interview for a research position 2. Contribute to a research project 3. Work in a team with varying types of expertise 4. Author or co-author a research publication (e.g., journal article, conference paper, book chapter)
	During your internship at NREL, how much experience did you have with the following? *No experience, Once, 2-3 times, 4 or more times*	
Professional Skills	Prior to participating in [internship program], to what extent would you agree or disagree with the following statements? *Disagree, Somewhat disagree, Somewhat agree, 4: Agree*	1. I'm part of a research community where I can get feedback on my work 2. I can create an effective oral research presentation 3. I can design an informative research poster 4. I can discuss research findings with a technical audience 5. I can discuss research findings with a non-technical audience
	During your internship at NREL, to what extent do you agree or disagree with the following statements? *Disagree, Somewhat disagree, Somewhat agree, 4: Agree*	
Career Interests	Prior to participating in [internship program], how interested were you in a career in the following? *Not interested, Somewhat interested Very interested, Extremely interested*	1. Sustainability 2. Renewable energy 3. Another domain other than sustainability or renewable energy
	As a result of your internship at NREL, how interested were you in a career in the following? *Not interested, Somewhat interested Very interested, Extremely interested*	1. Industry 2. Academia 3. National Renewable Energy 4. Other Department of Energy National Laboratory 5. Other federal research facility 6. Non-Profit 7. Another sector other than the above
If currently in Different Degree Program, Looking for Employment, or Currently Employed	To what extent is your [field of study/positions applying for/ current position] related to sustainability or renewable energy? *Not related, Somewhat related, Very related, Extremely related* How useful are the skills you improved at NREL in applying for [degree programs/positions]? *Not useful, Somewhat useful, Very useful, Extremely useful*	1. Computational Skills 2. Familiarity with Sustainability and Renewable Energy Topics 3. Research and Professional Skills
If currently in the Same Degree Program, Different Degree Program, or Currently Employed	How often do you use the skills improved during your internship at NREL in your [current position]? *Never, Some of the time, Most of the time, All of the time*	1. Computational Skills 2. Familiarity with Sustainability and Renewable Energy Topics 3. Research and Professional Skills

"Extremely focused," "Extremely related," "Extremely useful"). Professional Skills were coded on a scale of 1 (i.e., "Disagree") to 4 (i.e., "Agree").

For professional skills and career interests, one-sided, paired samples t-tests were used to determine if participant ratings after internships are greater than their rating from before internships. For computational skills, research skills, familiarity with domain science topics, one-sided, one sample t-tests were used to determine if participants reported at least "Some improvement" for computational skills, one experience for research skills during the internship, "Some increase in familiarity" for familiarity with domain science topics. In other words, the t-tests for computational skills, research skills, and familiarity with domain science topics determined if participants' post-internship ratings were > 1.

Similarly, one-sided one sample t-tests were used to determine if participants current positions are at least "Somewhat related" to NLR domain science topics, if their skills are at least "Somewhat useful" in applications, and if their skills are used at least "Some of the time." $\alpha < 0.05$ served as the cutoff for statistical significance.

2.8 Limitations

The inclusion of a variety of internship programs provided a broader participant pool, and we are encouraged to see relatively high response rates across programs that indicate we may indeed have a representative sample of the intended population. However, the sample remains subject to self-selection bias based on the selectiveness of the internship programs and who chose to respond to the survey. Additionally, our statistical analysis remains limited due to small sample size. As a result, we rely on simple t-tests to perform simple comparisons and avoid non-normality tests with a small sample size. Similarly, we do not adjust the cutoff for statistical significance to avoid over correcting for a small sample size, though this may increase the rate of false positive findings. Throughout the results, we include figures that document the percentages of responses as well as the number of respondents to avoid overstating our claims.

For participants who completed their internships less recently, their responses may be less accurate. We attempted to combat this by ensuring our response options were specific as possible to help participants select the most accurate response.

3 RESULTS

The total number of interns by program as well as corresponding response rates are included in Table 2. Participants' background data are included in Table 3. For anonymity purposes, the following categories are grouped together: participants who reported being in the first or second year of their PhD during their internship, participants who reported being in the third year of their PhD or later during their internship. Additionally, participants' fields of study were grouped as follows: science (e.g., physical, life, and biological sciences), engineering (e.g., chemical and mechanical engineering), mathematics (e.g., math, applied math, statistics), computing (e.g., computer science, computer engineering), and interdisciplinary (e.g., fields of study that included more than one of the above).

Table 2: Total number of interns meeting inclusion criteria by program and year of internship and response rates. "NO" indicates the program was not operational for that year. "NP" indicates the program was operational, but NLR had no participation for that year.

Year	DOE CSGF	DOE SULI	NSF MSGI	CMEI HPC4EI	NNSA IMPACT	Total
2018	2	3	1	NO	NO	6
2019	3	1	3	NO	NO	7
2020	1	5	0	0	NP	6
2021	3	4	2	1	NP	10
2022	7	2	1	2	NP	12
2023	2	2	6	0	NP	10
2024	5	0	NO	NO	2	7
Total	23	17	13	3	2	58
Response Rate	52%	29%	38%	67%	0%	41%

Table 3: Participants' academic backgrounds and internship location.

Academic Stage During Internship	Post-Baccalaureate	3
	Master's	3
	Early Stage (1st or 2nd year) PhD	13
	Late Stage (3rd year or later) PhD	5
Major or Field of Study	Science	4
	Engineering	5
	Mathematics	5
	Computing	3
	Interdisciplinary	7
Internship Location	In-person	15
	Hybrid	4
	Remote/Online	5

Three participants reported at least one prior experience at a DOE National Laboratory, and no participants reported prior experience at non-DOE federal research facilities.

Participants generally reported their internships were focused on domain science topics (only 3 participants responded "Not at all"). At the time of their internships, participants were studying a variety of domain sciences and mathematics.

Averages and standard deviations for the main survey questions are included in Table 4. Next, we describe results by theme.

3.1 Computational Skills

On average, participants enter their internships with at least some experience across most computational skills. Additionally, participants report at least "some improvement" in general-purpose programming ($t(23) = 4.65, p = .000$), scientific programming ($t(23) = 4.66, p < .000$), data visualization & analysis ($t(23) = 5.17, p = .000$), use of HPC and supercomputers ($t(23) = 2.53, p = .009$), and using software libraries or open-source code ($t(23) = 5.35, p = .000$). The distribution of responses is provided in Figure 1.

Table 4: Descriptive statistics and t-test results. * indicates questions related to usefulness of skills in applying to positions, and + indicates questions related to use of skills in current position.

Question	Pre Internship Mean (SD)	Post Internship Mean (SD)	t-test
Computational 1	1.54(0.78)	1.67(0.70)	$4.65, p = 0.000$
Computational 2	1.67(0.92)	1.79(0.83)	$4.66, p = 0.000$
Computational 3	0.71(0.69)	0.79(0.98)	$-1.04, p = 0.846$
Computational 4	0.71(0.81)	1.08(1.06)	$0.39, p = 0.352$
Computational 5	1.50(0.72)	1.96(0.91)	$5.17, p = 0.000$
Computational 6	0.62(0.77)	1.00(1.22)	$0.00, p = 0.500$
Computational 7	1.29(1.00)	1.29(1.20)	$1.19, p = 0.122$
Computational 8	1.21(0.93)	1.62(1.21)	$2.53, p = 0.009$
Computational 9	1.62(0.97)	2.04(0.95)	$5.35, p = 0.000$
Familiarity 1	1.25(0.74)	1.83(0.76)	$5.36, p = 0.000$
Familiarity 2	1.21(0.66)	1.38(0.97)	$1.89, p = 0.035$
Familiarity 3	0.75(0.68)	0.88(0.99)	$-0.62, p = 0.728$
Familiarity 4	0.38(0.49)	0.50(0.83)	$-2.94, p = 0.996$
Familiarity 5	0.79(0.66)	0.62(0.82)	$-2.23, p = 0.982$
Familiarity 6	0.67(0.64)	0.54(0.83)	$-2.70, p = 0.994$
Familiarity 7	0.67(0.76)	0.88(0.90)	$-0.68, p = 0.749$
Research 1	0.79(0.78)	0.38(0.65)	$-4.73, p = 1.000$
Research 2	1.96(0.75)	1.50(0.83)	$2.94, p = 0.004$
Research 3	1.75(1.11)	1.46(0.93)	$2.41, p = 0.012$
Research 4	1.33(1.01)	0.88(0.85)	$-0.72, p = 0.761$
Professional 1	3.33(0.70)	3.67(0.56)	$-1.88, p = 0.036$
Professional 2	3.58(0.50)	3.46(0.98)	$0.68, p = 0.749$
Professional 3	3.42(0.58)	3.04(1.27)	$1.33, p = 0.902$
Professional 4	3.38(0.65)	3.54(0.83)	$-0.75, p = 0.231$
Professional 5	3.17(0.70)	3.00(0.98)	$0.64, p = 0.736$
Domain 1	1.54(1.02)	1.92(0.88)	$-2.39, p = 0.013$
Domain 2	1.62(1.01)	2.25(0.79)	$-3.98, p = 0.000$
Domain 3	1.38(0.77)	1.71(0.62)	$-3.39, p = 0.001$
Sector 1	1.29(0.55)	1.17(0.70)	$0.83, p = 0.792$
Sector 2	1.12(1.03)	1.08(0.97)	$0.24, p = 0.593$
Sector 3	1.54(0.78)	2.42(0.78)	$-4.14, p = 0.000$
Sector 4	1.54(0.83)	1.83(0.87)	$-2.60, p = 0.008$
Sector 5	1.25(0.79)	1.29(0.75)	$-0.27, p = 0.394$
Sector 6	0.67(0.70)	0.67(0.87)	$0.00, p = 0.500$
Sector 7	0.38(0.58)	0.46(0.59)	$-0.81, p = 0.213$
Computational*	2.40(0.74)		$7.36, p = 0.000$
Familiarity*	1.93(1.03)		$3.50, p = 0.002$
Research & Professional*	2.40(0.74)		$7.36, p = 0.000$
Computational+	2.26(0.75)		$8.04, p = 0.000$
Familiarity+	1.48(1.04)		$2.21, p = 0.019$
Research & Professional+	2.26(0.92)		$6.61, p = 0.000$
Related	1.80(1.32)		$2.35, p = 0.017$

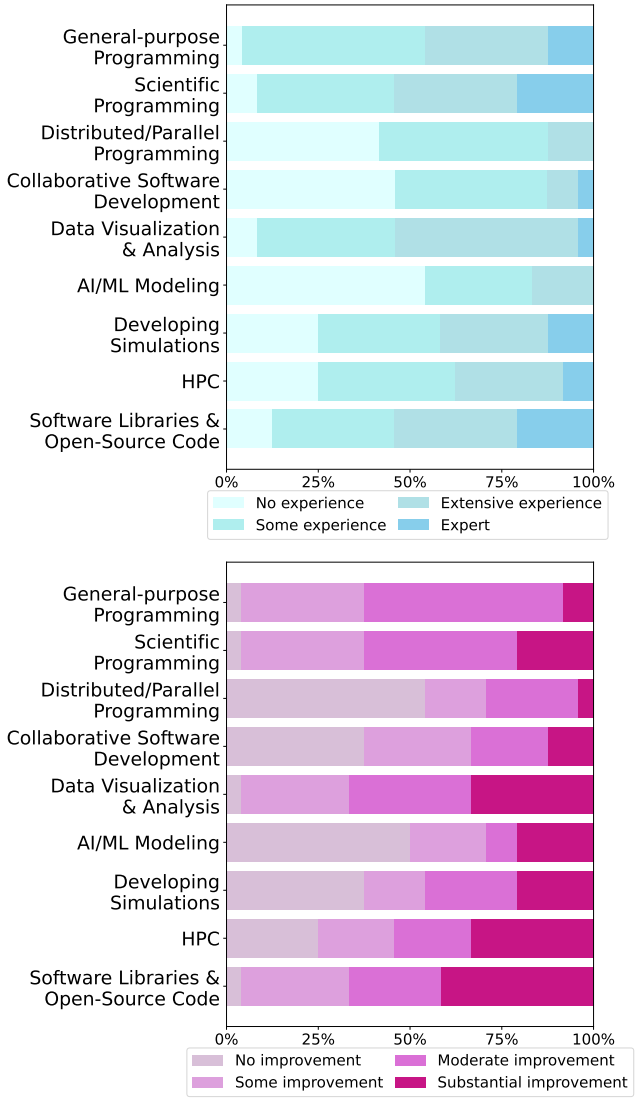


Figure 1: Participants' self-reported prior experience (left) and improvement of computational skills (right).

While the improvements were not statistically significant across all skills, we note that 21 participants reported "moderate improvement" or "substantial improvement" in multiple skills.

The open-ended responses mentioned additional specific skills such as MPI (Message Passing Interface) and manifold optimizations.

3.2 Familiarity with Domain Science topics

On average, participants enter their internships with some familiarity with the domain science topics of energy systems and energy efficiency, and little to no familiarity with other topics. Participants report at least "some increase" in familiarity in renewable energy ($t(23) = 5.36, p = .000$) and energy efficiency

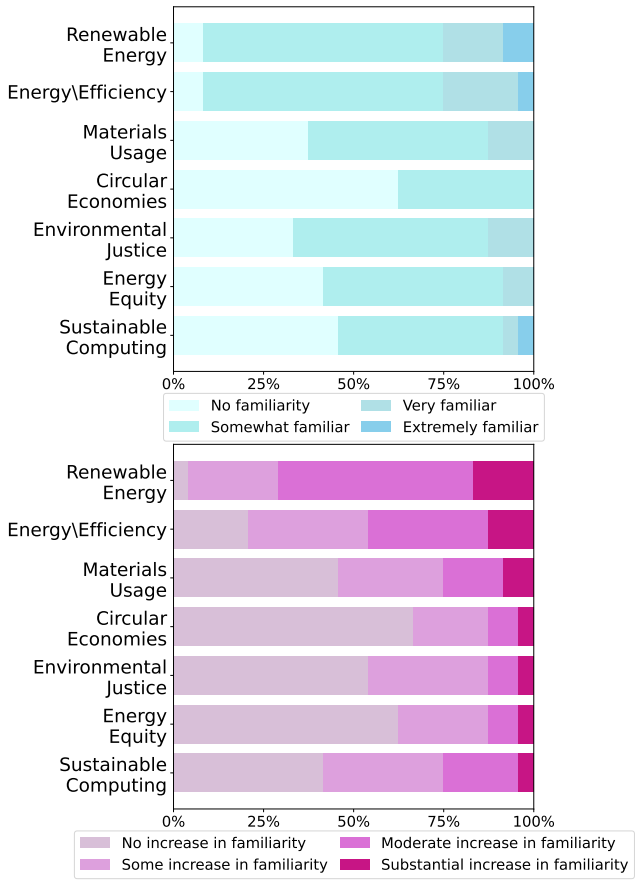


Figure 2: Participants' self-reported prior familiarity (left) and improvement of familiarity (right) with domain science topics.

($t(23) = 1.89, p = .035$). The distribution of responses is provided in Figure 2.

While the increases in familiarity were not statistically significant across all skills, we note that six participants reported "moderate increase" or "substantial increase" in one topic, and 13 participants reported "moderate increase" or "substantial increase" in multiple topics.

The open-ended responses echoed additional computational skills (e.g., computational methods for physics and chemistry applications) and other domain science topics (e.g., wind energy, power flows).

3.3 Research Skills

On average, participants enter their internships with at least one prior research experience with respect to working on research projects, in research teams, and toward authoring publications. Additionally, participants report working on at least one research project ($t(23) = 2.94, p = 0.004$) or at least one research team during their internship ($t(23) = 2.41, p = 0.012$). The distribution of responses is provided in Figure 3.

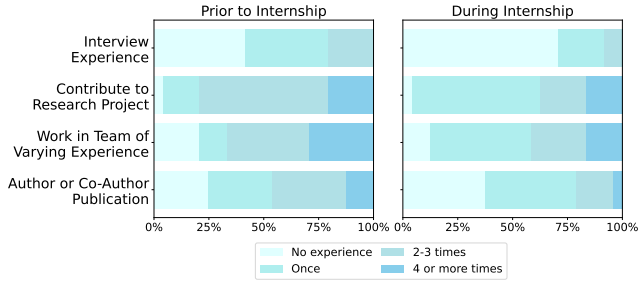


Figure 3: Participants' self-reported research experience before (left) and during (right) their internship.

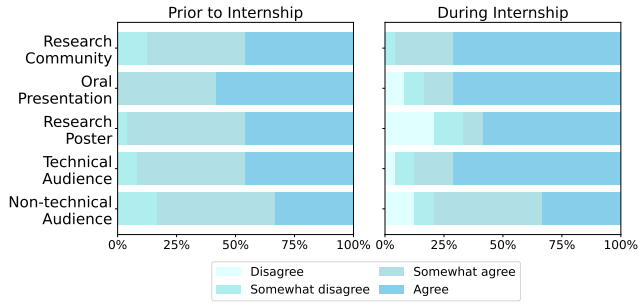


Figure 4: Participants' self-reported agreement with being part of a research community and with ability to communicate ideas before (left) and during (right) their internship.

The open-ended responses echoed similar experiences as our questions. For example, one participant noted "Remote collaboration" as a skill that improved, and another participant mentioned working in teams with varying levels of expertise as an important skill for their post-internship position.

3.4 Professional Skills

On average, participants enter their internships with the ability to communicate research across a variety of modes and are already part of research communities. Participants' agreement with the statement, "I'm part of a research community where I can get feedback on my work," is higher during their internship compared to before their internship ($t(23) = -1.88, p = .036$). While not statistically significant, we also note that more participants responded both "Agree" and "Disagree" with respect to these skills during their internship compared to before their internship. The distribution of responses is provided in Figure 4.

Five participants also mentioned networking or the networks they developed through their internships as professional skills in the open-ended responses.

On average, participants are interested across a variety of domains and sectors prior to their internships, except for non-profits or other unspecified sectors. Additionally, interest across all domains increased after participants' internships, and no participants responded "Not interested" to any of the domains. Across sectors, participants were more interested in careers at NLR ($t(23) =$

$-4.14, p = 0.000$) and other Department of Energy national laboratories ($t(23) = -2.60, p = 0.008$). The distribution of responses is provided in Figure 5 and Figure 6.

3.5 Career Interests

When asked about their current position at the time of completing the survey, 14 participants reported they were in the same or different degree program, and 10 participants reported they were looking for employment or currently employed. Of those in the same or different degree program, all participants reported enrollment in

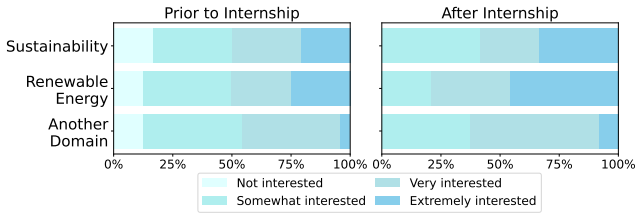


Figure 5: Participants' self-reported interest in career domain before (left) and after (right) their internship.

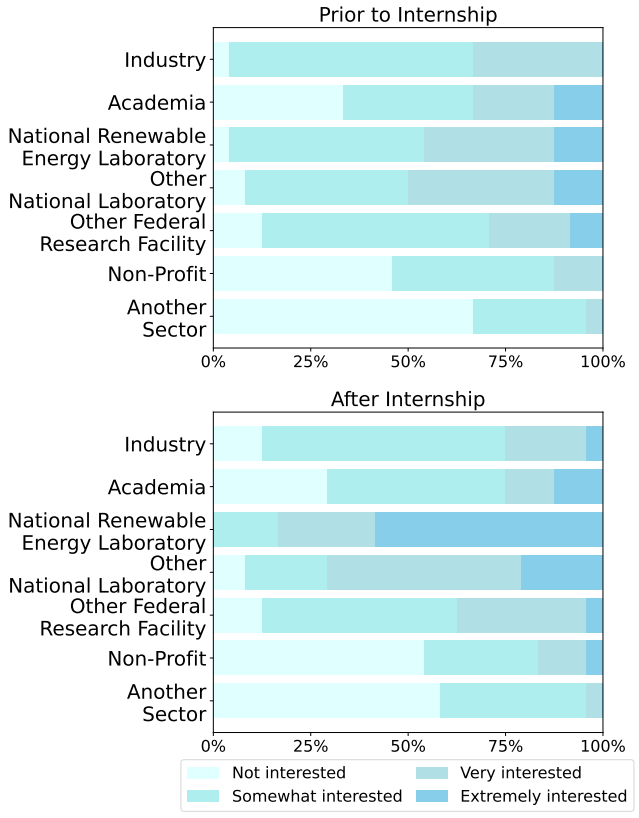


Figure 6: Participants' self-reported interest in career sector before (left) and after (right) their internship.

doctoral programs. Of those currently employed, participants reported working at DOE National Laboratories (including NLR), industry, academia, and government.

Out of the 15 participants who are not in the same degree program, only four participants reported they were looking for positions or currently in a field not related to NLR domain science topics. Additionally, participants on average reported skills improved during the internship were at least "Somewhat useful" in applying for positions.

Participants also reported skills improved during the internship were at least "Somewhat useful" in applying to their current position, and that they used these skills at least "Some of the time" in their current positions (see Table 4).

4 DISCUSSION

Students supported by federally funded graduate internships in CSE topics at NLR reported the largest improvement in computational science skills, followed by domain science skills. This improvement in computational skills may reflect both hands-on experience during their internship and the availability of tutorials at NLR. Students reported smaller improvements in their research skills. This may reflect that students often begin this internship with prior research experience through their undergraduate or graduate degree programs.

Students reported some shift in their career interests. They report increased interest in careers in the domain science topics researched at NLR. However, apart from a small increase in students interested specifically in NLR, students do not appear to have changed their interests in the career sector significantly. This may reflect that graduate students participating in internships outside of academia are more selective of the experiences they pursue to match their existing interests.

5 CONCLUSIONS

These results showed that the primary outcomes from CSE internships at NLR were increases in CSE and domain science capabilities. Improvements in research skills and career insights were present but less significant. This is the reverse of models that hold that the purpose of internships and other experiential learning is to develop non-technical skills. The increase in technical skills shown in this study suggests that internships at the postgraduate level may hold a role beyond introducing students to non-academic careers.

At a larger level, our results echo other calls to encourage graduate student participation in internships to provide supplemental training and additional learning opportunities outside of formal degree programs [30]. Our results emphasize the importance of federally-funded or other externally-funded programs in providing these internship opportunities that focus on educational objectives, rather than internships funded from research projects that may focus on hiring candidates whose skills best align with individual projects. This approach may be particularly valuable in CSE, where there is a large disparity in institutional resources and ability to offer cross-training between institutions.

To the best of our knowledge, this is the first study to evaluate graduate-level internship programs at the intersection of CSE and domain science. We encourage others to use our survey as part of

evaluation efforts of other internship programs to see if our results generalize to other host institutions and program contexts. We also suggest future work on the impacts of other models of using national laboratory capabilities to provide training in CSE and HPC, such as academic partnership programs.

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No discussion of computational science internships at NLR is complete without mentioning Mo Nelson, who passed away as this paper wound its way through the publication process. In her 18 years as an administrator in the Computational Science Center, Mo mastered the art of clearing up the paperwork disasters that well-meaning scientists excel at creating. She did so with humor, competence, and above all, compassion. More than one of these paperwork disasters was an obstacle that had to be overcome to make an internship possible. Her skill and dedication were also critical to linking the lab with several of the programs whose outcomes are described in this paper. Being able to quantify in a peer-reviewed journal the impact of these internships is a unique opportunity to celebrate our friend and colleague.

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REFERENCES

[1] Mireilla Bikanga Ada and Mary Ellen Foster. 2023. Enhancing postgraduate students' technical skills: perceptions of modified team-based learning in a six-week multi-subject Bootcamp-style CS course. *Computer Science Education* 33, 2 (2023), 186–210. https://doi.org/10.1080/08993408.2021.1959174

[2] ALCF. 2024. ALCF Lighthouse Initiative, https://www.alcf.anl.gov/lighthouse. https://www.alcf.anl.gov/lighthouse

[3] Maria Eftychia Angelaki, Fragkiskos Bersimis, Theodoros Karvounidis, and Christos Douligeris. 2024. Exploring the Awareness Outcomes of Educating ICT Students on the Environmental Implications of e-Waste Recycling and Energy Consumption in Data Centers. *IEEE Transactions on Education* 67, 1 (Feb. 2024), 143–152.

[4] Elizabeth Bautista and Nitin Sukhija. 2024. Data Analytics Program in Community Colleges in Preparation for STEM and HPC Careers. *The Journal of Computational Science Education* 15, 1 (March 2024), 59–63.

[5] Mordechai Ben-Ari. 2004. Situated Learning in Computer Science Education. *Computer Science Education* 14, 2 (2004), 85–100. https://doi.org/10.1080/08993400412331363823 arXiv:https://doi.org/10.1080/0899340041233136382

[6] Carolyn Connor, Amanda Bonnie, Gary Grider, and Andree Jacobson. 2016. Next Generation HPC Workforce Development: The Computer System, Cluster, and Networking Summer Institute. In *2016 Workshop on Education for High-Performance Computing (EduHPC)*. 32–39.

[7] Laleh E. Coté, Astrid N. Zamora, Julio Jaramillo Salcido, Seth Van Doren, Aparna Manocha, Gabriel Otero Munoz, Esther W. Law, and Anne M. Baranger. 2025. Where are they now? Academic and career trajectories of national laboratory STEM internship alumni from community colleges, compared to those from universities. *bioRxiv* bioRxiv 2025.03.24.645145 (2025). https://doi.org/10.1101/2025.03.24.645145

[8] Laleh E. Coté, Seth Van Doren, Astrid N. Zamora, Julio Jaramillo Salcido, Esther W. Law, Gabriel Otero Munoz, Aparna Manocha, Colette L. Flood, and Anne M. Baranger. 2025. "When I talk about it, my eyes light up!" Impacts of a national laboratory internship on community college student success. *PLOS ONE* doi.org/10.1371/journal.pone.0317403 (2025). https://doi.org/10.1371/journal.pone.0317403

[9] Department of Energy. 2024. High Performance Computing for Energy Innovation, hpc4energyinnovation.llnl.gov. https://hpc4energyinnovation.llnl.gov

[10] DOE Office of Science. 2024. Science Undergraduate Laboratory Internships (SULI): Where Students Come To Change The World, science.osti.gov/wdts/suli. https://science.osti.gov/wdts/suli

[11] Abel J. Duarte, Benedita Malheiro, Elisabet Arnó, Ignasi Perat, Manuel F. Silva, Pedro Fuentes-Durá, Pedro Guedes, and Paulo Ferreira. 2020. Engineering Education for Sustainable Development: The European Project Semester Approach. *IEEE Transactions on Education* 63, 2 (May 2020), 108–117.

[12] Anshu Dubey, Katherine M. Riley, and David E. Bernholdt. 2020. Teaching Software Sustainability for High Performance Computing at ATPESC. In *2020 IEEE/ACM Workshop on Education for High-Performance Computing (EduHPC)*. IEEE, GA, USA, 19–24.

[13] Thomas M Evans, Andrew Siegel, Erik W Draeger, Jack Deslippe, Marianne M Francois, Timothy C Germann, William E Hart, and Daniel F Martin. 2022. A survey of software implementations used by application codes in the Exascale Computing Project. *The International Journal of High Performance Computing Applications* 36, 1 (2022), 5–12. https://doi.org/10.1177/10943420211028940 arXiv:https://doi.org/10.1177/10943420211028940

[14] Scott Feister and Elizabeth Blackwood. 2022. HPC Workforce Development of Undergraduates Outside the R1. *Journal of Computational Science Educatione* 13, 2 (2022), 1–11. https://doi.org/10.22369/issn.2153-4136/13/2/2

[15] Camille Ferguson, Vanora Thomas, Juan Del Toro, Daniel Light, Kamau Bobb, Peta-Gay Clarke, Shameeka Emanuel, Ed Gronke, Mary Jo Madda, and Imani Jennings. 2024. The Important Role Social Capital Plays in Navigating the Computing Education Ecosystem for Black Girls. *ACM Transactions on Computing Education* 24, 2 (April 2024), 17:1–17:17.

[16] Gabriella Coloyan Fleming, Michelle Klopfer, Andrew Katz, and David Knight. 2024. What engineering employers want: An analysis of technical and professional skills in engineering job advertisements. *Journal of Engineering Education* 113, 2 (2024), 251–279. https://doi.org/10.1002/jee.20581 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/jee.20581

[17] Laura G Foltz, Sam C Gannon, and Stephanie L Kirschmann. 2011. *Making Comparisons & Examining Experiences: A Program Evaluation of the Department of Energy's Student Undergraduate Laboratory.* Doctoral Capstone Project. Vanderbilt University. https://ir.vanderbilt.edu/handle/1803/5198

[18] Indiana University Center for Postsecondary Research. 2021. The Carnegie Classification of Institutions of Higher Education, carnegieclassifications.acenet.edu/carnegie-classification/. https://carnegieclassifications.acenet.edu/carnegie-classification/

[19] Patricia Jacobs, Phillip List, Mobeen Ludin, Aaron Weeden, and Robert M. Panoff. 2014. The Blue Waters Student Internship Program: Promoting Competence and Confidence for Next Generation Researchers in High-Performance Computing. In *2014 Workshop on Education for High Performance Computing*. 49–55.

[20] Jin Kang and Audrey Girouard. 2022. Impact of UX Internships on Human-computer Interaction Graduate Students: A Qualitative Analysis of Internship Reports. *ACM Transactions on Computing Education* 22, 4 (Dec. 2022), 1–25.

[21] Amanpreet Kapoor and Christina Gardner-McCune. 2019. Understanding CS Undergraduate Students' Professional Development through the Lens of Internship Experiences. In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*. ACM, Minneapolis MN USA, 852–858.

[22] Mayank Kejriwal and Victoria Petryshyn. 2024. Advancing computational sustainability in higher education. *Nature Computational Science* 4, 6 (June 2024), 382–383.

[23] Kristina Kramarczuk, Kate Atchison, Monica Hilliard, Jandelyn Plane, Sally Bond, Caitlin Rudy, and David Weintrop. 2024. Micro-internships and Career Focused Programs as Mechanisms for Diversifying Computing. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*. ACM, Portland OR USA, 694–700.

[24] Krell Institute. 2024. Computational Science Graduate Fellowship, www.krellinst.org/csgf/. https://www.krellinst.org/csgf/

[25] Quintin Kreth, Mary Eve Spirou, Sarabeth Budenstein, and Julia Melkers. 2019. How prior experience and self-efficacy shape graduate student perceptions of an online learning environment in computing. *Computer Science Education* 29, 4 (2019), 357–381. https://doi.org/10.1080/08993408.2019.1601459

[26] Louise Ann Lyon and Emily Green. 2020. Women in coding boot camps: an alternative pathway to computing jobs. *Computer Science Education* 30, 1 (2020), 102–123. https://doi.org/10.1080/08993408.2019.1682379

[27] M. J. Martin, A. Anderson, D. Sickinger, C. Tripp, and K. Munch. 2025. Integrating Energy-Efficient Computing with Computational Research to Accelerate Energy Technology. *Computing in Science and Engineering* 27 (2025), 18–27. https://doi.org/10.1109/MCSE.2025.3549359

[28] Lois Curfman McInnes, Paige Kinsley, Mary Ann Leung, Daniel Martin, Suzanne Parete-Koon, and Sreeranjani Jini Ramprakash. 2023. Building a Diverse and Inclusive HPC Community for Mission-Driven Team Science. *Computing in Science & Engineering* 25, 5 (Sept. 2023), 31–38.

[29] Mia Minnes, Sheena Ghanbari Serslev, and Omar Padilla. 2021. What Do CS Students Value in Industry Internships? *ACM Transactions on Computing Education* 21, 1 (March 2021), 1–15.

[30] Zachary F. Murguía Burton and Xiangkun Elvis Cao. 2022. Let graduate students do internships. *Matter* 5, 12 (Dec. 2022), 4100–4104.

[31] Marco A. S. Netto, Rodrigo N. Calheiros, Eduardo R. Rodrigues, Renato L. F. Cunha, and Rajkumar Buyya. 2018. HPC Cloud for Scientific and Business Applications: Taxonomy, Vision, and Research Challenges. *Comput. Surveys* 51, 1, Article 8 (Jan. 2018), 29 pages. https://doi.org/10.1145/3150224

[32] NNSA and ORAU. 2024. National Nuclear Security Administration Minority Serving Institutions Internship Program, orise.orau.gov/nnsa-msiip/. https://orise.orau.gov/nnsa-msiip/

[33] NSF. 2024. National Science Foundation Mathematical Sciences Graduate Internship Program (NSF-MSGI), orise.orau.gov/nsf-msgi//index.html. https://orise.orau.gov/nsf-msgi//index.html

[34] David S. Ochs and Ruth Douglas Miller. 2015. Teaching Sustainable Energy and Power Electronics to Engineering Students in a Laboratory Environment Using Industry-Standard Tools. *IEEE Transactions on Education* 58, 3 (Aug. 2015), 173–178.

[35] ORAU. 2023. 2023 High Performance Computing Summer Internships, www.zintellect.com/Opportunity/Details/DOE-EERE-HPC-2023. https://www.zintellect.com/Opportunity/Details/DOE-EERE-HPC-2023

[36] ORNL. 2024. OLCF Pathways to Supercomputing, www.olcf.ornl.gov/community/pathways-to-supercomputing. https://www.olcf.ornl.gov/community/pathways-to-supercomputing/

[37] Anne-Kathrin Peters, Rafael Capilla, Vlad Constantin Coroamă, Rogardt Heldal, Patricia Lago, Ola Leifler, Ana Moreira, João Paulo Fernandes, Birgit Penzenstadler, Jari Porras, and Colin C. Venters. 2024. Sustainability in Computing Education: A Systematic Literature Review. *ACM Transactions on Computing Education* (Jan. 2024), 3639060.

[38] Ulrich Rüde, Karen Willcox, Lois Curfman McInnes, and Hans De Sterck. 2018. Research and Education in Computational Science and Engineering. *SIAM Rev.* 60, 3 (Jan. 2018), 707–754.

[39] M. Sanchez. 2024. Students Harness Power of New Kestrel Supercomputer for Cutting-Edge Energy Research and Innovation. https://www.nrel.gov/news/program/2024/students-harness-the-power-of-new-kestrel-supercomputer-for-cutting-edge-energy-research-and-innovation.html

[40] Angela B. Shiflet. 2002. Computer science with the sciences: an emphasis in computational science. *ACM SIGCSE Bulletin* 34, 4 (Dec. 2002), 40–43.

[41] Winona Snapp-Childs, Claudia M. Costa, Daniel Olds, Addison Snell, Julie A. Wernert, and Craig A. Stewart. 2025. Economic value of HPC experience for new STEM professionals: Insights from STEM hiring managers. *Frontiers in Research Metrics and Analytics* 9 (Jan. 2025), 1–17.

[42] Jenett Tillotson. 2017. A Summary of the Workshop on Training and Sustaining Research Computing Systems Professionals: A Path to a Profession. In *Proceedings of the HPC Systems Professionals Workshop*. ACM, Denver CO USA, 1–6.

[43] TOP500.org. 2024. Top 500 The List, November 2024, top500.org/lists/top500/2024/11/. https://top500.org/statistics/overtime/

[44] U.S. Department of Education. 2024. Eligibility Designations for Higher Education Programs, www.ed.gov/grants-and-programs/grants-higher-education/eligibility-designations-higher-education-programs. https://www.ed.gov/grants-and-programs/grants-higher-education/eligibility-designations-higher-education-programs

[45] Gregor Verbič, Chanaka Keerthisinghe, and Archie C. Chapman. 2017. A Project-Based Cooperative Approach to Teaching Sustainable Energy Systems. *IEEE Transactions on Education* 60, 3 (Aug. 2017), 221–228.

[46] Joy Watson and Jed Lyons. 2011. Aligning Academic Preparation of Engineering Ph.D. Programs with the Needs of Industry. *International Journal of Engineering Education* 27, 6 (2011), 1394–1411.

[47] Lucas A. Wilson and S. Charlie Dey. 2016. Computational Science Education Focused on Future Domain Scientists. In *2016 Workshop on Education for High-Performance Computing (EduHPC)*. IEEE, Salt Lake City, UT, USA, 19–24.

[48] Remco Zwetsloot and Jack Corrigan. 2022. AI Faculty Shortages: Are U.S. Universities Meeting the Growing Demand for AI Skills? (Jan. 2022). https://doi.org/10.51593/20190049