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Challenges and opportunities to build quantitative self-confidence in biologists

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Abstract

New graduate students in biology programs may lack the quantitative skills necessary for their research and professional careers. The acquisition of these skills may be impeded by teaching and mentoring experiences that decrease rather than increase students' beliefs in their ability to learn and apply quantitative approaches. In this opinion piece, we argue that revising instructional experiences to ensure that both student confidence and quantitative skills are enhanced may improve both educational outcomes and professional success. A few studies suggest that explicitly addressing productive failure in an instructional setting and ensuring effective mentoring may be the most effective routes to simultaneously increasing both quantitative self-efficacy and quantitative skills. However, there is little work that specifically addresses graduate student needs, and more research is required to reach evidence-backed conclusions.

Keywords: self-efficacy, mathematics, statistics, computation, education, failure, mentoring

Quantitative skills, defined as tools and reasoning from mathematics, statistics, and computing, are increasingly critical for biological research, but they may not be developed during graduate studies in biology programs (Barraquand et al. 2014, Touchon and McCoy 2016, Juavinett 2022). Although there is little documentation in the literature, the reasons for this gap may include a combination of factors, such as a lack of quantitative training opportunities (Touchon and McCoy 2016, LaTourrette et al. 2021, Juavinett 2022), the failure of mentors to direct students to seek training, insufficient graduate student background to develop skills independently, or barriers to students fully engaging with available resources. In this opinion piece, we discuss how a lack of self-confidence is one such barrier for biology graduate students learning quantitative skills.

We suggest that a lack of confidence in using quantitative techniques may cause an avoidance of both learning and applying these methods in research. We will argue that we need to build confidence in parallel with quantitative skills through enhanced teaching and mentoring techniques and further argue that research on the efficacy of quantitative training of biology graduate students on both of these axes is needed. This change in approach to include a focus on confidence in using quantitative tools when evaluating both pedagogy and mentoring may be essential to training biologists who can both use mathematical, statistical, and computational methods effectively and collaborate easily with their more quantitatively trained colleagues.

The importance of quantitative education for biology graduate students

Dramatic developments in biology over the past 20 years increasingly require researchers to use advanced quantitative skills. Although the progress of biology and our ability to formulate theories that explain the natural world have always depended on such methods (Cohen 2004), the need for researchers able to use quantitative approaches is becoming more urgent. Researchers are now awash in enormous data streams generated by genetic analysis and automated environmental sensors (Hack and Kendall

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2005, Farley et al. 2018). As the anthropogenic footprint weighs more heavily, biologists are also being asked to predict future conditions and to assess the risks relating to epidemics (Lloyd-Smith et al. 2015), contaminants (Murphy et al. 2018), managed species (Walters and Martell 2005), biodiversity (Rossberg et al. 2019), and ecosystem function (Schmitz and Leroux 2020). Although we are unaware of any comprehensive reviews, there is evidence that the demand for quantitative skills to address these research needs is growing, as is reflected in the competencies requested for entry level positions in some biology disciplines. For example, Feng and colleagues (2020) analyzed how often programming skills were listed as prerequisites for entry positions in ecology, on the basis of approximately 56,000 job descriptions for postdoctoral fellows and PhD students on the ECOLOG-L listserv between 2006 and 2018. They found that, in 2018, more than 36% of the postdoc positions required programming skills and that the demand for these skills had more than tripled over those 12 years.

At the same time, self-assessment studies suggest that researchers in biology are not receiving needed training in quantitative skills (e.g., Attwood et al. 2019). A study of 704 National Science Foundation principal investigators in the Biological Sciences Directorate indicated that 90% of those surveyed were going to use big data in their research but saw their quantitative training as the most important limiting factor to best use this data (Barone et al. 2017). Similarly, in a survey of early career ecologists, Barraquand and colleagues (2014) found that 75% were unsatisfied with their understanding of mathematics and statistics, and 95% thought more statistics courses should be available.

The need for relevant training of biologists in quantitative skills at the undergraduate level has been noted repeatedly over the past 20 years (e.g., National Research Council 2003), and there is general consensus about this need (Marshall and Durán 2018). However, although most biology undergraduates are required to take an introductory class in calculus, statistics, or computational literacy, the relationship between these quantitative techniques and biological concepts may not be obvious (Eaton and Highlander 2017). In spite of recommendations (National Research Council 2003), biology courses usually have little integrated quantitative material (with exceptions, e.g., Speth et al. 2010), and in many cases, the institutions or departments lack faculty expertise in the relevant areas (Williams et al. 2019).

The rapidly increasing quantitative sophistication of biological research, coupled with slow-moving undergraduate education reform, means that graduate students may enter their programs without an adequate understanding of the quantitative skills necessary for their chosen research area. Certainly, the need and current lack of quantitative training at a graduate level has been acknowledged in a wide range of biology subdisciplines, such as biomedical sciences (National Research Council 2011), neurosciences (Akil et al. 2016, Goldman and Fee 2017), plant biology (Friesner et al. 2017), ecosystem sciences (Farrell et al. 2021), and the environmental sciences more generally (Theobold and Hancock 2019 and the references within it). For example, Goldman and Fee (2017) conducted an informal poll of a range of leaders in computational neuroscience education and found that both theoretical and experimental neuroscientists thought that students from the life sciences lacked training in quantitative approaches. In this open-ended questionnaire, some of the survey respondents emphasized the need for quantitative courses at both the undergraduate and graduate levels. However, such training is still not widely available or required. In ecology, Touchon and McCoy (2016) reviewed course listings for 154 US doctoral programs and found that only one-quarter required their students to take a biostatistics course, while one-third did not even list a statistics course in their catalog. Similarly, Juavinett (2022) noted that only 15% of neuroscience PhD programs require a programming course, and only 55% even include programming as an elective.

Why self-confidence?

It is widely believed that undergraduate and graduate biology students may have an aversion to mathematics and statistics (e.g., Pan and Tang 2005) although evidence on this point is ambiguous (cf., Andrews and Aikens 2018). However, even low-level reluctance, when coupled with the time demands of their research, the lack of program requirements, the fear of failure (Henry et al. 2019), and poor mentoring (e.g., Martin and Dowson 2009, Olson et al. 2020), could lead to little investment in further studies on quantitative topics. We suspect that such reluctance does exist, on average, and that it is related to a lack of confidence in using quantitative techniques.

Self-confidence differs from basic skills and self-image. We will use the term *generalized self-confidence* to refer to a person's belief in their ability to influence outcomes in their life (for a review of various literature uses of *self-confidence*, see Oney and Oksuzoglu-Guven 2015). In the psychology literature, such generalized beliefs are distinguished from more a specific mindset of *self-efficacy*, which refers to a belief in one's ability to perform a specific task in a given setting to attain a goal (Bandura 1997), such as creating a simulation model in order to complete thesis research in a biology subdiscipline. Beliefs of both types can influence learning outcomes. For example, Pajares and Miller (1994) found that math self-efficacy had a stronger positive impact on mathematics problem solving than prior experience. However, individuals that underestimate their ability to perform quantitative tasks may develop learning aversion or anxiety (Onwuegbuzie and Wilson 2003). Ideally, graduate education and mentoring would develop the opposite tendency, which we will call *quantitative self-efficacy*. We define this phrase as an individual's belief that they can learn and use a variety of quantitative skills to achieve goals related to scientific research.

The acquisition of new quantitative skills is largely a matter of practice, so greater quantitative self-efficacy could lead to a positive feedback loop between a willingness to exercise those skills, greater mastery, and application (figure 1). We know that quantitatively confident students experience less anxiety when using quantitative methods (Onwuegbuzie and Wilson 2003). Moreover, there is some evidence that initially anxious graduate students required to take a quantitative course have less anxiety and more interest in these methods after completion and are even more likely to have plans to obtain more quantitative training after exposure (for an example with social science graduate students and an introductory statistics class, see Huang 2018). We might therefore expect that greater quantitative self-efficacy associated with exposure and practice can help biology graduate students become more ambitious and adventurous in both their acquisition of more quantitative skills and the use of these skills in research (figure 1).

On the other hand, the relationship between increasing quantitative self-efficacy and learning quantitative methods is not linear. Pushing the boundaries of one's skills can trigger feelings of imposter syndrome that can erode both generalized self-confidence (Tao and Gloria 2019) and quantitative self-efficacy. Students will require appropriate supports and pedagogical interventions to overcome such barriers (figure 2). Those with high quantitative self-efficacy may overestimate their abilities and fail to exert sufficient effort or use external resources, leading

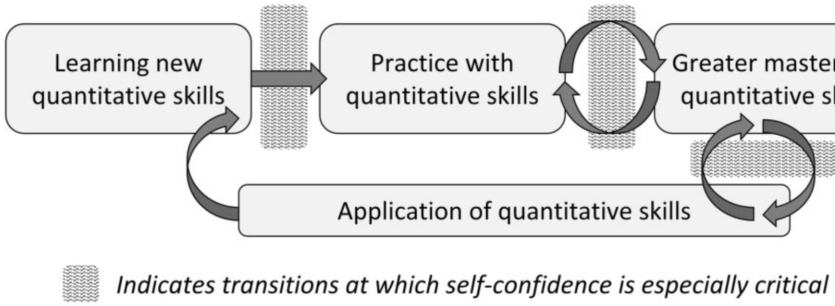

Figure 1. Positive feedback loops among practice, mastery, application, and development of new quantitative skills. A lack of quantitative self-efficacy can serve as a barrier among the stages (cross-hatching), particularly the step between achieving greater mastery and application. If the students receive supports to overcome these barriers, they are more likely to begin the process of learning and applying new quantitative skills again (see the loop between the application of quantitative skills and learning new quantitative skills). This iteration could improve both generalized self-confidence and quantitative self-efficacy.

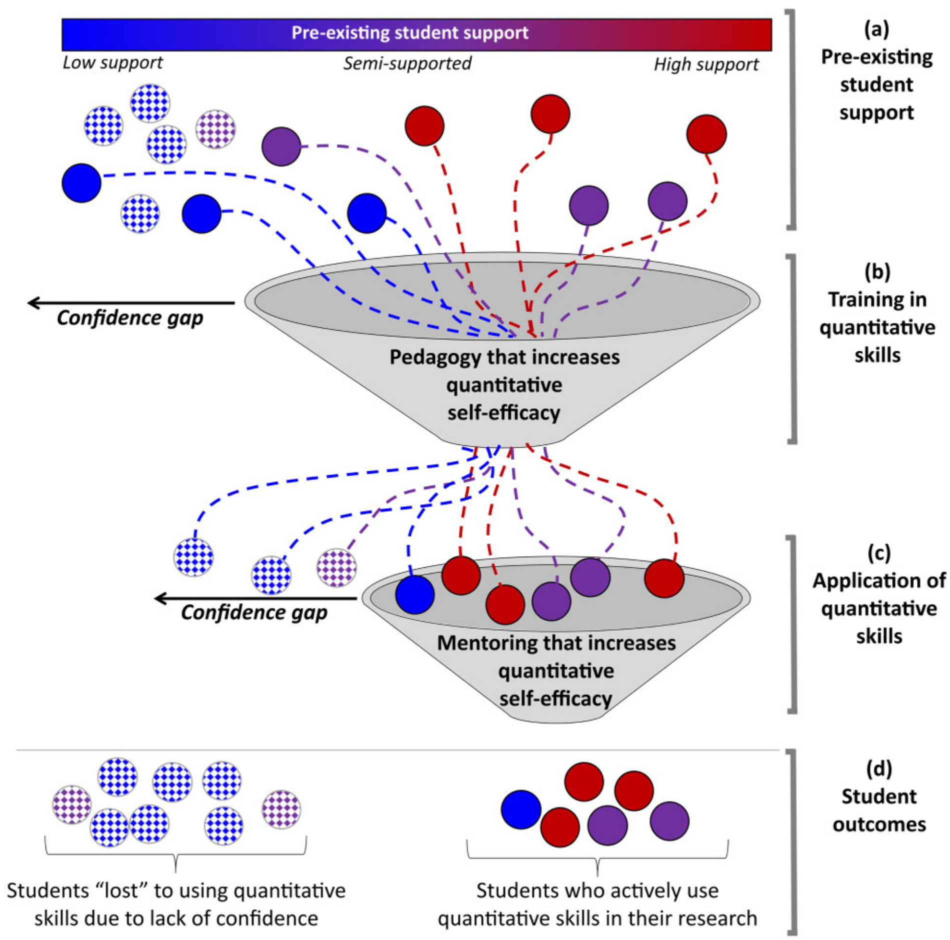

Figure 2. Program requirements, mentor quality and quantitative self-efficacy are important factors that affect which graduate students have low (blue), medium (purple), or high (red) levels of preexisting support with respect to quantitative training (a). These support levels in turn affect which students participate in training programs (b) and how students benefit from mentoring in the application and practical use of quantitative skills (c; the solid balls). Training and quantitative self-efficacy interact to affect which students are likely to actively use quantitative skills in their own research (d; the solid balls). In comparison, the students lacking quantitative self-efficacy because of previous experiences, a lack of effective pedagogy, or poor mentoring may be lost to training opportunities or the active use of quantitative skills in their own research (the patterned balls).

to poorer performance (Jensen and Moore 2008). Interventions, such as freshman orientation courses, have been shown to calibrate these beliefs, leading to better outcomes later because of higher resource allocation to academic work in undergraduates (Wheeler and Wischusen 2014). Accurately calibrated quantitative self-efficacy may therefore be a key element in quantitative skills acquisition of biology graduate students.

It seems likely that there is a connection between quantitative self-efficacy and generalized self-confidence. One study showed that self-efficacy related to scientific skills makes undergraduate students more likely to engage in science roles, which reinforces their identity as scientists (Brenner et al. 2018) and enables them to envision themselves as leaders (Sobieraj and Krämer 2019). There is evidence that generalized self-confidence and persistence are important for graduate students (Carlson 1999) as they transition from mostly coursework to mostly research (Geraniou 2010). We expect self-confident graduate students to bounce back more easily from research setbacks, unfavorable manuscript reviews, and grant application rejections. Graduate students with quantitative skills may even be more likely to be at the forefront of scientific advances. On the other hand, a lack of self-confidence can undermine attempts to address inequalities in STEM training (Chemers et al. 2011, Sobieraj and Krämer 2019), and a failure to address this problem in graduate programs may have negative consequences in other areas, such as timely degree completion (Bostwick and Weinberg 2018). The reciprocal relationships among generalized self-confidence, quantitative skill development, and role identity suggest that training which develops quantitative self-efficacy has far more to offer biology graduates than might be expected (Aikens and Dolan 2014).

Generalized self-confidence, quantitative self-efficacy, and historically excluded groups

The need for both generalized self-confidence and quantitative self-efficacy is particularly important for women, PEER (persons historically excluded because of ethnicity or race; see Asai 2020), LGBTQ+, those with disabilities, and others whose identity is not well represented in STEM, across all academic levels, from undergraduates to those who have received a PhD (Chemers et al. 2011). Gaps between PEERs and White or Asian students in opportunities to learn quantitative skills exist across educational levels (Berry et al. 2014). In particular, quantitative skills are often tied to stereotypes related to gender and race, and this can create a difficult barrier even for otherwise confident students (Flanagan and Einarson 2017). Other factors that can threaten the confidence of students from historically excluded groups then arise, such as low expectations from faculty, a lack of mentorship, and a lack of representation (González 2006).

When addressing these issues, it is important not to fall into a deficit mindset (Milner 2012), in which we focus on the perceived shortcomings of students, rather than remembering that a student's quantitative self-efficacy is mediated by a complex classroom environment. The quantitative self-efficacy of African-American PhDs in computing and mathematics was strongly affected by interactions with peers, verbal encouragement, and a social community (Charleston and Leon 2016). These findings were echoed in a separate study on the experience of female PEER graduate students (Guy and Boards 2019). Therefore, identifying and interrupting the institutional structures and faculty biases that undermine quantitative self-efficacy in students from historically excluded groups is critical, not only for fostering a diverse workforce but for preserving the civil rights of the students (Henderson 2014).

Moreover, recent research has shown that generalized self-confidence tends to be particularly unstable for students from historically excluded groups, highlighting the need for our educational systems to increase support for such students (Litson et al. 2021). Although representation correlates with increased generalized self-confidence in graduate students (Tao and Gloria 2019), underrepresentation negatively correlates with confidence and ultimate career success (e.g., McAllister et al. 2019, Tao and Gloria 2019). More generally, retention and achievement are elevated in students with a sense of agency (Berry et al. 2014) and belonging (Curry and DeBoer 2020). For example, women in graduate departments with mostly male faculty report more of a negative academic self-concept, lower confidence in their abilities, lower on-time doctoral completion rates (Bostwick and Weinberg 2018), and a weaker commitment to completing their PhD and pursuing a career in their field of study than do male students and women in departments with more gender-balanced faculty (Ulku-Steiner et al. 2000). Similarly, imposter syndrome, although it is common in many, disproportionately affects students from historically excluded groups and can reduce retention (Peteet et al. 2015).

Diversifying biology requires intentional, directed work that goes well beyond what we discuss in the present article, but we emphasize that efforts to build self-confidence in all students may contribute to agency, growth, and a sense of belonging in students from historically excluded groups specifically (Theobald et al. 2020). Indeed, the fact that biology graduate students vary widely in their quantitative preparation requires the development of pedagogical systems that accommodate disparities in prior educational opportunities and access (Lee and Clinedinst 2020). For example, in subdisciplines such as ecology that historically emphasize fieldwork, stronger support for quantitative training may serve to broaden participation by students with physical disabilities. In this way, quantitative training of biology graduate students presents a natural opportunity to fix the system (in part; again, we recognize that this is but one piece of a complex problem) rather than endeavoring to diversify by "fixing the student."

Educational research on building quantitative self-efficacy

Research on self-efficacy in various quantitative skills has largely been focused on undergraduate, secondary, and elementary school students. In addition, in light of big data accessibility, there has been an emphasis on the need for computing skills in biology education. We found very few studies that address graduate student needs specifically, and rather too many that discuss computing. As a result, we cite the few available studies on the topic of quantitative education of graduate students, but we also include relevant studies from other academic stages. In addition, the preponderance of examples focused on computing should not be taken as evidence of the importance of this area over skills in mathematics and statistics. We note that the lack of research at the graduate level proscribes our ability to draw firm conclusions. Our interpretations of the existing research should be read as opinions and opportunities for research rather than a comprehensive review.

Some classroom engagement strategies have been found to work well at both the undergraduate and the graduate level, such as inquiry-based learning (Beck and Blumer 2012). A small study of graduate students learning quantitative skills for the first time showed that taking an inquiry-based course led to gains in confidence (Dale et al. 2020). Other engagement techniques, such as interactive think–pair–share activities and team-based learning techniques, have greater positive effects on undergraduate students' self-confidence and problem-solving skills than traditional lectures and should translate well to a graduate setting. Similarly, research at the undergraduate level suggests that mathematical modeling to build quantitative self-efficacy (Czocher et al. 2020) must emphasize the relationship between modeling and the

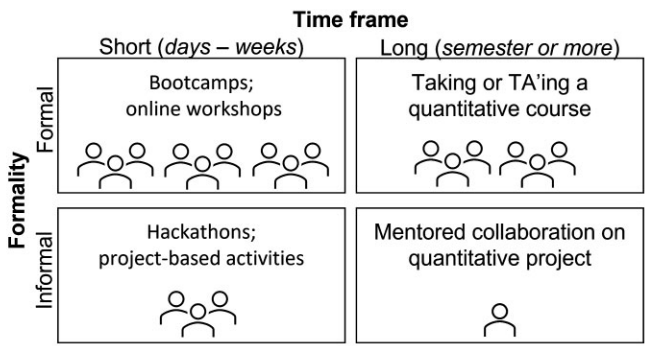

Figure 3. Common methods for training graduate students in quantitative skills, showing the time commitments and level of formality (whether organized top-down in a formalized program or bottom-up and led by the student). Each approach also differs in its social context (depicted by the number of people). The approaches, in addition, vary in their effectiveness, with quality mentoring being perhaps the best for improvement on both axes of skill acquisition and quantitative self-efficacy.

real-world system it represents, and it seems likely that this may be true for graduate students in biology.

Some methods that are successful at the undergraduate level may have different effects on some graduate students. In particular, graduate programs may trigger mental states that have implications for pedagogy. For example, some graduate student survey respondents suffering from imposter syndrome felt anxious at the prospect of "flipped classroom" activities often used in an undergraduate setting (Chakraverty 2020). Similarly, graduate students in education scored higher on a harm avoidance scale than undergraduates (Illovsky 2010), suggesting they may be less comfortable with teaching methods that involve risk and potential failure. Given such possible obstacles in transferring undergraduate level pedagogy to graduate level education and the lack of studies addressing graduate student needs, we suggest that techniques for teaching quantitative self-efficacy be explicitly tested and studied at the graduate level. Moreover, graduate education can include a range of learning activities, each of which possess a range of possibilities and obstacles for building quantitative skills and confidence (figure 3).

Outside the classroom, collaborative opportunities for graduate students can increase confidence (Tao and Gloria 2019). In addition, there is abundant evidence that good mentoring is important for graduate student success and generalized self-confidence. Effective mentoring can promote graduate students' academic achievement, engagement (Martin and Dowson 2009), and quantitative self-efficacy (Olson et al. 2020), and may have positive influences on timely completion of graduate studies (Green and Bowden 2012, Ndayambaje 2018). Regular performance-based assessments, such as individual development plans, improved generalized self-confidence of graduate students, and reduced feelings of imposter syndrome, particularly for students from historically excluded groups (Sowell et al. 2015, Chakraverty 2020). Good mentoring relationships can build women's generalized self-confidence (Paglis et al. 2006), whereas inadequate mentoring is an important factor in students' from historically excluded groups decisions to not pursue graduate studies in STEM (Stachl and Baranger 2020). Mentor qualities such as representation (Charleston and Leon 2016, Tao and Gloria 2019), approachability, and posing challenging problems (Carlson 1999) had strong positive impacts on student success. We suggest that mentoring relationships are particularly important in programs with minimal course requirements for quantitative topics for which the mentor or supervisor becomes the main source of guidance. Collaboration and mentoring are generally already in place in graduate programs; therefore, we recommend an expansion of emphasis on these relationships with respect to quantitative self-efficacy, as well as additional training for mentors to improve student outcomes.

Productive failure, quantitative self-efficacy, and skill acquisition

The role of failure in acquiring quantitative skills may need special attention. Many graduate students may enter graduate school with very little experience in academic failure (Ward-Penny et al. 2011). The model they may have internalized for being a "good student" places a high value on working a problem quickly and comfortably to get to the right answer. Research indicates that this model is both unrealistic and counterproductive. Johnston-Wilder and Lee (2010) described *mathematical resilience* as a skill set that involves persistence and an ability to continue learning despite challenges and setbacks. Kooken and colleagues (2016) included struggle as one of three correlated factors in their measurement of mathematical resilience (along with value and growth). *Struggle* refers to a respondent's belief that experiencing challenges and difficulties is a normal part of learning mathematics and includes multiple components, such as the ideas that making mistakes is necessary to get good at math, that struggle is a normal part of working on math, and people who work in math-related fields sometimes find math challenging. New biology graduate students who have been exposed to far more memorization than problem-solving in undergraduate courses may be unfamiliar with concepts such as these, which emphasize the importance of challenge and failure in learning.

Learning quantitative methods at the undergraduate level is best addressed using active approaches (Freeman et al. 2014, Farmus et al. 2020, Ng et al. 2020), especially those in which students engage with problems and fail to solve them at first. In particular, the role of productive failure, in which the instruction is designed to produce short-term failure but long-term success, is recognized as an important learning tool (e.g., Schwartz and Martin 2004, Kapur 2010, Chowrira et al. 2019). As students began the process of familiarizing themselves with, practicing, and applying quantitative skills, it is essential that early failures do not undermine their confidence so much that efforts to learn are abandoned.

At the graduate-level, well-designed instructional activities can help students develop a resilience to failure that builds on the recognition that it is a normal part of acquiring new skills. Lessons in which the instructors write code live in class, with the inevitable resulting mistakes, can help to normalize failure (Johnston et al. 2019). Commentary from both instructors and peers about statistics or mathematics anxiety and failure also have been identified as helpful in increasing quantitative self-efficacy (e.g., McGrath et al. 2015), and we suggest that anecdotes from mentors could also be helpful in introducing the idea of productive failure, or failure that prepares one for better learning or research outcomes. Normalizing failure is also an important part of inclusivity and retention, because students from historically excluded groups may opt to leave STEM if the real or perceived expectations placed on them are unrealistically high (Noel et al. 2022).

Science is particularly prone to obscuring lessons about productive failure because much of the review process takes place before publication. Students reading published papers may not realize that several quantitative analyses were implemented improperly and redone or failed to answer the research question and were abandoned (also see Rickly and Cook 2017). Even the most sophisticated quantitative methods by the most distinguished researchers might fail on a student's problem, and students need the quantitative self-efficacy to recognize when the method or its implementation is at fault rather than engaging in self-criticism when a particular approach doesn't work. More broadly, for students who enter graduate school with little experience in failure, it is important for faculty members to normalize the struggle associated with research. Feedback from faculty that helps a student reframe challenging situations as opportunities for learning can have a long-lasting influence on the student (Posselt 2018). An essay by Schwartz (2008) titled "The importance of stupidity in scientific research" suggests that PhD programs need to do better at two things: helping students understand that doing research is difficult and teaching students to be comfortable with productive failure.

Failure can also be used to motivate students to acquire new quantitative skills in coursework. In this model, students experience the need for knowledge in some areas after failing to solve a problem, and consequently, there is a better learning outcome. Meta-analysis of studies from junior to undergraduate educational levels suggests that learning from failure as an instructional strategy has moderate success (Darabi et al. 2018). Similarly, although learning challenges among students at the secondary level have been associated with insufficient scaffolding (Kirschner et al. 2006, Hmelo-Silver et al. 2007), ill-posed problems and insufficient scaffolding may also lead to greater benefits (Sinha et al. 2020) as students develop reasoning processes and perceive the need to seek out new skills.

Productive failure could be introduced very naturally in course-based research. In this course design, whole classes of students address a research question that is of interest to other scientists or community members (Auchincloss et al. 2014). These courses were developed at an undergraduate level to allow scaling of the usual mentor-based research experiences to the large enrolments typical in some STEM programs such as biology. Dolan (2016) described several potential advantages of this course structure, including increased self-efficacy in scientific work, increased motivation because of the involvement with a real research problem, and the aspect of iteration in which students learn by trying, failing, and trying again. However, this design is primarily used at an undergraduate level, and assessments of its merit are still emerging (Dolan 2016). Although it does seem likely that a variety of experiences like these, where students realize they do not currently have needed skills, can lead to acceptance of the view that initially failing to solve a problem is part of the learning and research process rather than a commentary on self-identity.

Evaluating techniques for the quantitative education of biology graduate students

We have argued that we must carefully consider the role of quantitative self-efficacy in the classroom and nonclassroom activities in order to build quantitative skills and that the most important component of any training exercise in quantitative skills may be teaching biology graduate students to deal with failure productively. However, all learning opportunities include a social context that affects both generalized self-confidence and quantitative self-efficacy that must be managed for maximum benefit. Types of training or experiences in quantitative skills vary along several dimensions: the time frame over which the experience takes place, the formality of the organization or oversight of the experience, the number of students that each experience can scale to reach, the student to professor or mentor ratio, and the overall effectiveness of each kind of experience. We can divide the many types of quantitative training opportunities into four general categories (figure 3): short-term formally organized events such as bootcamps and workshops, short-term informal collaborations with particular objectives such as coding clubs or hackathons, long-term formal coursework, and long-term collaborations such as mentoring relationships. Most research on the efficacy of these methods is focused on skill-building rather than on the positive effects on quantitative self-efficacy; however, previous research on that topic can be used to inform these activities. Strategies that maximize the acquisition of quantitative skills by increasing quantitative self-efficacy can be considered when structuring a course, group projects, or mentoring activities.

Short-term formally organized events

Organized short-format retreats, workshops, online courses, or bootcamps are used to train graduate students in critical quantitative skills. Bootcamps are intensive learning events, often scheduled just prior to the start of the student's first semester of graduate school. However, evidence of the efficacy of bootcamp training is mixed. Some research has shown that short format instruction experiences can increase the statistics knowledge and quantitative self-efficacy scores of graduate students compared with those of their peers who did not experience the bootcamp (Leventhal et al. 2018). Undergraduate orientation courses can perform the useful function of calibrating beliefs about quantitative skills (Wheeler and Wischusen 2014), and similar functions could be performed at the graduate level. However, other research has shown that graduate-level bootcamps do not appreciably increase long-term student skill development, scholarly productivity, or socialization into the academic community (Feldon et al. 2017).

The short time frame of these experiences is likely to be a factor in their effectiveness: Multiple studies have demonstrated that longer time frames promote improved uptake and retention of complex new quantitative skills (Budé et al. 2011, Rohrer 2015). Short-term learning opportunities may not be the tool of choice for acquiring quantitative skills or self-efficacy, but in the absence of other opportunities, well designed experiences may be quite beneficial (Word et al. 2017). Of course, short-term learning opportunities can serve different purposes as well. Bridging events, such as intensive review courses that occur immediately prior to longer-term courses can have beneficial impacts at the graduate level (Leventhal et al. 2018). An ideal introductory bootcamp would emphasize inclusion and bring together a diverse set of students in order to expose them to the need for quantitative training in biological research, provide early success in using quantitative skills in well scaffolded exercises, calibrate quantitative self-efficacy, increase a sense of identity through peer interaction, and introduce potential mentors in quantitative fields. However, poorly designed bootcamps can establish a pattern of inappropriate responses to failure, create a sense of inadequacy in less prepared students, or reinforce divisions among students with different backgrounds.

Short-term informal collaborations

In short-term, informal, and goal-oriented collaborations (e.g., coding hackathons), small groups of students work together on a specific problem. Other forms of short-term collaborative learning can include coding clubs (Hagan et al. 2020), informal study groups, online discussion groups, student-run workshops (LaTourrette et al. 2021), and project-based activities (Killion et al. 2018). These types of activities can present low risk and fun avenues for students to build and apply their quantitative skills. For example, in 2020, one of the authors (ERW) led a research derby event focused on quantitative skills for 12 graduate students at the University of Vermont. Over 2 days, three teams moved from project idea to data cleaning, modeling, and write-up. One project has now been accepted in a peer-reviewed journal. The team members were from different disciplines and the collaboration would not have happened without the initial short-term informal meeting. The collaboration across disciplines allowed nonquantitative biologists to learn from those with a more quantitative background in a low stakes setting. In addition, the compressed nature of the collaboration allowed the students to see a project from start to finish, potentially increasing their quantitative self-efficacy.

Short-term collaborations can increase student quantitative self-efficacy by providing opportunities to engage in quantitative work related to research and can result in tangible success through publications or presentations (Tao and Gloria 2019). Providing students with the opportunity to work in peer groups before working alone can ease the transfer challenges students face when applying quantitative skills to a new problem. However, students may have widely differing levels of quantitative skills that can lead to a lack of engagement with the quantitative aspects of goal-oriented exercises or even reinforcement of beliefs about low self-efficacy in these areas. For example, in a professional level biology hackathon, observers noted that the learning curve in using GitHub prevented many participants from using it to share code (Trainer et al. 2016). More generally, low self-confidence and unwelcoming environments can lead to low rates of self-selection for activities such as hackathons or coding clubs in women and other members of historically excluded groups (Hardin 2021). Similarly, peer-to-peer relationships established on such a short time frame may not necessarily provide an environment in which students are comfortable working or asking for help when their skill levels are quite different from those of others (Trainer et al. 2016). Preparatory information regarding quantitative materials, as well as opportunities to build pre-event relationships, may ease the difficulties associated with uneven skill levels and poor peer-to-peer dynamics.

Long-term quantitative course work

In traditional graduate courses, good lesson planning can accommodate diverse student interests, increasing student motivation, which, in turn, promotes quantitative self-efficacy (see the “Educational research on building quantitative self-efficacy” section). However, there is evidence that poorly designed undergraduate courses can decrease self-confidence in quantitative skills (Everingham et al. 2013). At an undergraduate level, application approaches that build on previous lessons in biology and math can improve students’ quantitative self-efficacy (Dale et al. 2020). Too often, quantitative education is focused solely on techniques, decontextualized from disciplinary usage (Fennell et al. 2020), which can decrease motivation (e.g., Everingham et al. 2013, McGrath et al. 2015). In particular, too early an emphasis on rigor or details of computation in an abstract approach may decrease engagement (Everingham et al. 2013). In-class coding exercises that fit dynamical models to data, for instance, provide a concrete starting point for students’ future independent research in biology. Application exercises such as this also have the advantage of illustrating the trial and error process of applying quantitative methods in a supportive environment (see the “Productive failure, quantitative self-efficacy, and skill acquisition” section). Approaches for emphasizing the benefits to overcoming the barriers posed by mathematical notation and unfamiliar computing environments include showing how math brings clarity to biological problems, and emphasizing how reproducible code facilitates alternate applications (Johnston et al. 2019).

Given the role of self-efficacy in learning quantitative skills, close attention must be paid to classroom culture. During instruction, the use of humor in undergraduate level courses can reduce student’s negative attitudes toward quantitative topics (Neumann et al. 2009). An inclusive and welcoming environment is also vital, because a lack of quantitative self-efficacy is related to stereotype threat and pressure to conform (Dowker et al. 2016). Similarly, successful group work will require attention to the confidence levels of the group members. Brief code of conduct discussions can be used to avoid self-selection away from quantitative tasks, particularly when the class contains both biology graduate students and those from disciplines such as mathematics, statistics, or computing. Finally, graduate students in biology can also, themselves, serve as mentors for quantitative skills: for example, to undergraduate students and peers with less training in these areas. TAing an undergraduate course in quantitative methods can give graduate students the opportunity to use these newly developed skills and to build confidence as they help others who are even newer to those skills.

Some graduate programs that accept students from both quantitative and life science backgrounds intentionally scaffold coursework in both biology and math (e.g., Noble et al. 2016) to allow for cross-disciplinary communication and collaboration among students with positive outcomes. Few, however, describe the development of educational materials specifically designed for cross-disciplinary education (Noble et al. 2016, Dale et al. 2020). If a goal is to incorporate quantitative skills training into graduate biology education in general, collating existing educational material is needed. With appropriate investments (e.g., funding and preparation time), these could be archived in an online repository similar to that of the Quantitative Undergraduate Biology Education and Synthesis, which is focused at the undergraduate level. However, we contend that in addition to standard pedagogical tools, material focused on addressing quantitative self-efficacy is needed. The curation and management of these materials by a professional society, such as the Ecological Society of America or the Society for Mathematical Biology, would ensure quality and longevity of the resource.

Long-term mentored collaboration

Mentoring and collaboration lie at the heart of graduate education and will often be one of the primary methods by which biology graduate students are introduced to new quantitative methods. An important aspect of mentorship is its psychological support function, in which a graduate student not only develops an identity as scientist but also grows the confidence to apply advanced techniques to their research. Mentorship problems can therefore have a highly detrimental effect (see the “Educational research on building quantitative self-efficacy” section). A recent report from the National Academies presents nine sets of recommendations to encourage a shift away from a culture of ad hoc mentorship to a more intentional approach (National Academies of Sciences, Engineering, and Medicine 2020). Intentional rather than ad hoc mentoring structures may also be necessary to avoid gaps in the effective mentorship of PEERs (Zambrana et al. 2017). Ideally, long-term mentoring (either as mentor or mentee) increases generalized student confidence by providing opportunities to engage in meaningful research, builds relationships with other researchers, and provides tangible evidence of success through publication (Tao and Gloria 2019).

Quantitative self-efficacy might be best enhanced through a cognitive apprenticeship framework (Maher et al. 2013) that follows the use–modify–create process (Lee et al. 2011), with more hands-on involvement of the mentor early in the collaboration and students gaining independence during the process. In a modeling and fading approach (Schoenfeld 1985), mentors explicitly guide early quantitative efforts and fade out as students gain skills and confidence. Early instruction efforts should include events in which, in the process of analyzing, coding, or solving problems on the board, the mentor models appropriate learning responses to their own errors or failures. Similarly, as a mentor to undergraduate students in classroom and laboratory settings, a graduate student can use the quantitative skills they are developing to help others who are even newer to those skills, thereby reinforcing the graduate student's training and increasing quantitative self-efficacy.

Bridging across training types

To recruit, train, and build quantitatively self-confident biologists, multiple points of contact and types of training may be required. A balance of classroom and cocurricular learning experiences will ensure that students are explicitly made aware of expert practices, heuristics, and modes of thinking associated with quantitative methods in their discipline and related areas. Repeat exposure to quantitative techniques increased confidence in math graduate students (Carlson 1999), and similarly, we expect multiple training events will have the greatest payoff for biology graduate students. By incorporating multiple types of training into a graduate program, students will gain desensitizing exposure to quantitative methods and will experience a natural scaffolding for skills development.

Evaluation of quantitative self-efficacy, skill acquisition, and directions for future research

What is not measured cannot be measurably improved. Therefore, educational reform for quantitative training of graduate students requires meaningful evaluation tools. Standard practice for evaluation usually involves survey instruments with self-reporting of understanding and skill acquisition for participants (e.g., Stefan et al. 2015), but this approach may not be accurate. For example, bootcamps are generally well rated by participants for these metrics, but a longitudinal study on graduate student bootcamps suggests that they have no long-term impact on statistical or computational skills (Feldon et al. 2017). It may be that students are conflating their engagement with the bootcamp experience and its actual effectiveness. As a result, we suggest that evaluation instruments should not solely rely on self-reported metrics of learning outcomes. Furthermore, our goal is to train biologists who have the ability to use and understand quantitative skills in their research; therefore, longer-term evaluations with objective metrics, such as how quantitative material is used in published papers by the training's participants, as was pioneered by Feldon and colleagues (2017), seem particularly valuable.

As we argue in the present article, even if quantitative skills acquisition is achieved, it may be that future learning or research use is inhibited by practices that erode student quantitative self-efficacy. By evaluating both skills and self-efficacy beliefs in both the short and long term following learning events, we can begin to understand how these factors are related and how we might modify our approaches to achieve better outcomes. As was noted by Aikens and Dolan (2014), most available instruments for evaluating attitudes toward quantitative work are for general audiences rather than biologists specifically. There have been some efforts to develop discipline-specific evaluation tools to track attitudes and self-evaluation for undergraduates (e.g., Andrews et al. 2017), and similar efforts are needed for graduate students. Aikens and Dolan (2014) suggested that evaluation instruments could measure more positive attitudes toward quantitative work, such as reduced anxiety, greater self-efficacy, increased interest, and a better sense of the relevance and importance of mathematics, statistics, and computation to biological research. In addition, instruments could also document desired side effects, such as the sense of belonging to the cadre of researchers in a subdiscipline (e.g., Perceived Cohesion Scale or Sense of Belonging Scale) (Bollen and Hoyle 1990) and the Academic and Intellectual Development Subscale (Weidman and Stein 2003). Finally, an additional perspective on the impacts of learning events could be obtained through the analysis of individual development plans of quantitative learning participants (Hobin et al. 2012) that considers how a plan incorporates quantitative skills and how they connect to the values assessment parts of such a plan.

The effective reform of quantitative education for graduate biology students therefore requires evaluation tools that will allow us to document our success or failure with the implemented interventions in terms of skills, attitudes and, of course, professional outcomes. The topics to be investigated include the transferability of self-efficacy beliefs from one context to another in graduate education and the efficacy of quantitative skills acquisition in different educational contexts (traditional programs, bootcamps, etc.). As these evaluation tools are applied, careful attention must be paid to differential success based on students' racial, ethic, and gender identity, sexual orientation, and disability status, so that biases in the approaches taken can be identified and addressed. In this way, we will develop a suite of evidence-based practices that will help graduate students to improve both their quantitative skills and their confidence in using and further developing these skills.

Conclusions

Educational research supports the view that a lack of confidence in one's abilities is a barrier for learning and applying quantitative skills. Because undergraduate programs in biology may not provide much exposure to mathematics, statistics, and computing, new graduate students may be unaware of the need for these skills in research and of fruitful approaches for acquiring them. In particular, biology graduate students may be unfamiliar and uncomfortable with the process of repeatedly failing while practicing quantitative methods and may, therefore, incorrectly attribute these failures to personal inadequacies.

A variety of instructional approaches can be used to increase both quantitative skills and confidence regarding these skills during training opportunities, whereas some approaches should be avoided (e.g., an excessive emphasis on rigor) or carefully managed (e.g., group work). Perhaps the most important of approaches is where mentors demonstrate both the use of quantitative methods and the productive failure of this use in a specific disciplinary context. Furthermore, given the role of generalized self-confidence in learning these skills, attention must be paid to the social environment of training experiences and mitigation must be applied when poor outcomes seem likely for those from historically excluded groups. Whatever methods are used, their evaluation should include not only metrics for new knowledge of quantitative methods but also effects on quantitative self-efficacy, diversity, and inclusion, as well as longer-term outcomes, such as application in research.

Although we offer suggestions in the present article based on previously published research, we note that quantitative graduate education is comparatively understudied. A move toward more evidence-based design of training opportunities in quantitative skills for biologists may have much larger benefits on graduate student retention, professional identity, and research contributions, given the important role of self-efficacy in this area, and therefore, more research is merited.

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