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## Expertise in STEM Disciplines

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### Abstract and Keywords

Enhancing expertise in science, technology, engineering, and mathematics (STEM) is vital to promoting both the intellectual and economic development of a modern society. This chapter synthesizes relevant studies on the acquisition and development of STEM expertise from different areas of research, including cognitive psychology, the psychology of science, sociology and anthropology, and educational research. Specifically, first, the structure of relevant STEM disciplines in conceptualizing the domain of expertise are discussed. Then the fundamental mechanisms of thinking and problem-solving practices in science and engineering that underlie expert performance within these disciplines are presented. Issues pertaining to assessment and recognition of expertise in STEM fields are also examined. Lastly, evidence pertaining to the impact of training and education on the development of STEM expertise is reviewed. The chapter closes with a critical analysis of STEM expertise research to date and identifies unanswered critical questions and new directions for future research.

Keywords: research training, science, engineering, discipline, psychology of science, socialization, graduate education, innovation

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### Introduction

The development of expertise in science, technology, engineering, and mathematics (STEM) is a topic of great interest in modern policy contexts. Enhancing STEM workforce capacity expands the potential of these fields to both enhance human knowledge about the natural world and drive the development of new technologies that provide strong economic benefits (Rothwell, 2013). However, despite broad consensus that STEM expertise is necessary for the realization of these benefits, empirical evidence of how the development of such expertise can be supported and enhanced is limited. In part, this is due to a bifurcated view of the indicators and mechanisms of expertise development in these fields. On the one hand, research into individuals' development of research skills

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and the practices of STEM experts has existed largely within the cognitive and psychological sciences. On the other, the training, evaluation, and consumption of research does not occur separately from disciplinary and academic communities of practice that are social in nature. As such, the broader social and cultural contexts of universities—especially their graduate programs—and of the STEM disciplines themselves play a major role in the development of experts' identities, expectations, and beliefs as they relate to the definition of expertise and expert performance (Gardner, 2010; Holley, 2009). Thus, for the purposes of this chapter, we define expertise in STEM as the mastery of the knowledge and skills necessary to produce new knowledge that meets or exceeds the standards of rigor appropriate to the disciplinary context in which it is situated.

This chapter describes the major areas of research targeting expertise in STEM disciplines, with a specific emphasis on science and engineering. These emphases reflect the relative proportion of literature developed on expertise within the specific disciplines, although some of the literature described engages samples that draw participants from across STEM disciplines. In synthesizing relevant studies, the chapter draws from four major types of research: cognitive psychology, the psychology of science, sociology and anthropology, and educational research. As such, there is an active attempt to interweave the psychological framing of expertise as a property of individuals who possess an extensive base of knowledge and skills with the social framing of expertise as a transactive recognition of valued attainment and stature in relevant fields. To this end, we first address the role that disciplines and fields play in defining the domain of expertise. Second, we discuss cognitive models and mechanisms of reasoning in science and engineering. Third, we examine the criteria by which expertise is identified within STEM fields from anthropological and sociological perspectives. Fourth, we discuss research on the factors that specifically influence the development of STEM expertise by focusing on both educational findings related to learning progressions and the process of socialization that engages the interactions between graduate students and faculty in the modern university context. We close the chapter with a summary of unresolved issues in the study of STEM expertise and specific questions for future research.

## Importance of Recognizing Distinct STEM Disciplines

By definition, expertise is domain specific (Ericsson & Smith, 1991). Thus, meaningfully engaging expertise in STEM disciplines requires recognition of discipline as an essential component of domain. Disciplinary identity establishes which skills, knowledge, assumptions, and evaluative criteria are central to the recognition and development of expertise. Secondly, field of study or practice also contributes to the establishment of domain boundaries by anchoring disciplinary work to a specific phenomenon around which knowledge has accumulated. For example, one individual may be described as an expert chemist (i.e., discipline) whose research focuses on pollution in the atmosphere

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(i.e., field), and another may be an expert mathematician with research in the same field. While each would apply their own disciplinary tools and frameworks, they might each call upon overlapping bases of knowledge stemming from past research on atmospheric pollution.

STEM disciplines bear both similarities and differences to one another. For example, in science, as in engineering, empirical (typically quantitative) evidence and logical inference are used and valued as the primary basis for conducting their work. However, each of these disciplines has its own goals (Feldon, Hurst, Rates, & Elliott, 2013). For instance, scientists attempt to generate empirically supported principles that provide generalizable and parsimonious explanations for an entire class of phenomena (Blackburn, 1999). In contrast, engineers attempt to design targeted solutions to specific problems within localized constraints that span both physical and social parameters (Koen, 1985), such that optimal solutions are unlikely to be universally generalizable. Thus, solving the nature of outstanding performance or achievement differs by discipline, because “maximal adaptation to task constraints” (Ericsson & Lehmann, 1996, p. 273) will manifest differently.

The definition of discipline traditionally engages both structural and cultural components (Lattuca, 2001). Structurally, becoming an expert entails mastering the norms and practices that describe a discipline’s subject matter and its accepted methodologies. Both are inherently grounded in the discipline’s view of knowledge or *epistemic culture* (Knorr-Cetina, 1997), which cannot be separated from the social and historical dimensions of the disciplinary community and its norms. A group of scholars organized around a domain of expertise share research questions, inquiry methods, and problem-solving approaches that configure the intellectual undertakings of that discipline (Chubin, 1983; Kuhn, 1962; Price, 1965). For example, epistemological assumptions in cellular and molecular biology heavily favor experimental designs that require nuanced implementations of control conditions (e.g., use of both positive and negative controls; Gross & Mantel, 1967; Rates & Feldon, 2014). These differ from other disciplines in which positive and negative controls may not be differentiated (e.g., physics; Galison, 1997) or in which controlled experiments may not be considered viable for contributing meaningful knowledge contributions (e.g., climatology; Navarra, Kinter, & Tribbia, 2010).

In many cases, disciplinary knowledge and experience allow for the creation of solutions to novel problems. However, there are cases in which the solution to a given problem lies beyond the search space established by a single discipline’s task constraints. In some cases, Lattuca (2001) described such interdisciplinarity as outreach from one discipline to others (i.e., informed disciplinarity) or as a convergence between different disciplines around a common problem (i.e., synthetic interdisciplinarity). In other cases, questions inherently cross traditional disciplinary lines (i.e., transdisciplinarity), or arise independent of an established disciplinary context (i.e., conceptual interdisciplinarity). Although such efforts are challenging and not always successful, results can realize major gains in understanding complex problems (Rhoten & Parker, 2004). For example, interdisciplinary work including physicists, chemists, and engineers at the Joint Institute

for Laboratory Astrophysics produced the Bose-Einstein condensate (originally theorized in the 1920s), for which they earned a Nobel Prize in 2001 (Aldhous, 2003; Cech & Rubin, 2004). Notwithstanding, it is currently unclear how domains of expertise might be conceptualized within an interdisciplinary context.

## Mechanisms of Reasoning in STEM Disciplines

The psychology of science has a long history of studying the mechanisms of reasoning that are common to various STEM disciplines. Efforts to characterize these mechanisms have primarily focused on two levels of analysis: fundamental cognitive processes and central tasks that meet disciplinary criteria for building disciplinary knowledge. The basic cognitive processes include mental simulation, analogical reasoning, causal thinking, and generating inductive and deductive inferences (Dunbar & Fugelsang, 2005), which occur in the context of critical disciplinary tasks for developing knowledge claims such as formulating productive research questions, generating testable hypotheses, making observations, collecting and analyzing data, presenting findings, drawing conclusions, and building models and theories (Zimmerman, 2000).

Mental simulation serves as a form of forward reasoning (cf. Chi, Feltovich, & Glaser, 1981) that is documented across many STEM disciplines (Anzai & Yokoyama, 1984; Ball & Christensen, 2009; Brown, 2011). Leveraging their extensive knowledge of relevant prior research, findings, principles, and theories, experts draw inferences about the necessary properties of an unknown component necessary to the solution of a problem, reasoning through likely outcomes when encountering uncertainty or ambiguity (Christensen & Schunn, 2009). Studies have documented such strategies with scientists when designing experiments where established protocols are not known (Dhillon, 1998; Schraagen, 1993) and analyzing data when the results obtained are unclear or inconsistent with expectations (Trickett & Trafton, 2007). Similarly, during product development, engineers are likely to mentally simulate the functions or features of a developing product and the interactions that end-users might have with them to reduce the extent of uncertainty in making subsequent design decisions (Christensen & Schunn, 2009).

To identify the role of mental simulation under uncertainty in engineering design, Christensen and Schunn (2009) captured five months of a professional design team's meetings on video as they worked to develop new features for a product. Reflecting about nine hours of conversation, the transcripts of these meetings were analyzed by identifying verb phrases that reflected mental operations pertinent to the design effort. The researchers then classified all segments ( $n = 6,171$ ) according to whether they reflected mental simulation. If segments were determined to indicate mental simulation, they were also coded according to whether simulation was applied to the functional aspects of the product or end-user behaviors. Segments were also coded for indicators of uncertainty on the part of the speaker (e.g., "maybe," "not certain"). Statistical analyses indicated that mental simulation occurred significantly more often immediately following an expression of uncertainty (17 percent) than the base rate for expressions of uncertainty (8 percent).

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Further, the frequency of segments indicating uncertainty were significantly higher than the base rate of uncertainty before (17 percent) and during (13 percent) mental simulation than following the completion of a simulation event (11 percent; not significantly different than base rate).

Analogical reasoning is another core mental strategy used in both scientific investigation and engineering problem-solving (Ball & Christensen, 2009; Chan & Schunn, 2015; Clement 1988; Holyoak, 2005; Nersessian, 1984; Robinson, 1998). For example, when constructing new hypotheses or designing experiments, scientists retrieve prior relevant knowledge or experience from long-term memory. They then evaluate the similarities between hypotheses or experiments previously used in other studies (i.e., source) and those currently targeted by analogical mapping (Dunbar, 1997; Holyoak, 2005; Klahr & Simon, 1999). Due to the association between knowledge base (past experiences and domain knowledge) and analogical thinking, expert scientists tend to make more extensive use of analogies during scientific problem-solving than novice scientists (Dunbar, 2000; Hmelo-Silver, Nagarajan, & Day, 2002). In addition, scientists frequently use analogies when they explain or present a certain concept or result to others. However, these explanatory analogies tend to be made to relatively different areas or domains (i.e., distant analogies) compared to analogies used in the phases of hypothesis formation and experiment design.

In engineering design contexts, three types of analogies are typically used during design problem-solving: *explanation*, *problem identification*, and *solution generation* (Ball & Christensen, 2009). Specifically, explanatory analogies play a critical role for engineering designers to explain their ideas and solutions to others, and the distance between the target and the source of these analogies is relatively larger than with the other two types of analogies. In addition, when finding potential problems in a novel design or generating particular design solutions, engineers use previous designs or existing exemplars as analogous sources (Christensen & Schunn, 2009).

## Dual Space Framework for Scientific Discovery

According to general theories of human problem-solving, a problem space is composed of a set of initial problem states, a goal state (i.e., target solution), and operators for moving from one state to another in the navigation from initial to goal state (Newell & Simon, 1972). Problem-solving thus refers to an activity that occurs by search in a problem space to seek a route successfully connecting the initial state to the goal state. Employing this metaphor, Klahr and Dunbar (1988) proposed “a general model of scientific reasoning, that can be applied to any context in which hypotheses are proposed and data is collected,” known as “scientific discovery as dual search (SDDS)” (p. 32).

Klahr and Dunbar (1988; Klahr, 2000) consider hypothesis formation and experimental design to be the two major aspects of scientific discovery as a complex problem-solving process. To solve problems, scientists thus engage heuristic searches in two distinct but interacting problem spaces. Hypothesis formation is the construction and validation of

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theory through obtained findings, and experimental design is the design of empirical procedures to generate data capable of supporting or disconfirming hypotheses.

The SDDS model specifies that the hypothesis space includes the current knowledge base related to the relationships among the variables in the domain and all possible hypotheses generated either from that knowledge or from prospective experimental findings. Similarly, the experiment space includes the current hypotheses and all possible experiments that can be carried out to test the hypotheses. Scientific investigation is then conducted by simultaneously searching these two spaces. The SDDS framework also distinguishes three primary components that direct search in these two problem spaces: *search hypothesis space* (i.e., formulating a completely specified hypothesis that yields the most likely explanation or prediction), *test hypothesis* (i.e., evaluating the obtained hypotheses through experiments), and *evaluate evidence* (i.e., determining the appropriateness of the cumulative data to accept or reject the hypotheses). As such, progress in navigating the hypothesis problem space entails successful navigation of the experiment problem space to yield valuable evidence to determine the viability of a hypothesis. Likewise, progress in navigating the experiment space is dependent upon solutions from the hypothesis space to target variables for isolation and inform decisions about optimal methods for generating informative data.

## Decision-Based Design in Engineering

Although varying definitions of engineering thinking and practice exist, many researchers characterize engineering design as a deliberate decision-making process constrained by both physical and social constraints (Chen & Wassenaar, 2003; Dym, Agogino, Eris, Frey, & Leifer, 2005; Koen, 1985; National Research Council, 2001). The *decision-based design* (DBD) framework, originally coined by Hazelrigg (1998), assumes that engineering design is a rational process of selecting design alternatives against highly situated criteria, which follows “the rule that the preferred decision is the option whose expectation has the highest value” (p. 656). This DBD process basically involves two major phases: *alternative generation* (i.e., creating all potential product design options) and *alternative selection* (i.e., selecting the best optimal one) (Chen & Wassenaar, 2003).

In terms of generating alternatives, the set of potential design options is inherently extremely large or infinite, because the set of possible design configurations and dimensions for each configuration is unlimited (Hazelrigg, 1998). Engineers might use different strategies to create possible design alternatives during this phase, such as analogies (Keeney, 2004; Keller & Ho, 1988). In addition, when evaluating and choosing optimal alternatives, engineers encounter situations of uncertainty and risk, because they cannot exactly foresee how their designs will be actually implemented as products. Thus, engineers often use modeling or simulation to approximate the functions and behavior of their designs (Christensen & Schunn, 2009; Koen, 1985).

# Recognition of Expert Performance in STEM Fields

Ericsson and Smith (1991) suggested that expertise can be defined as superior performance that is shown to be consistent and reproducible for particular skills or knowledge of a domain. However, studies of expert physicists have found widely discrepant and inconsistent applications of domain knowledge to problem solving (Cooke & Breedin, 1994; Reif & Allen, 1992). Further, expertise is often operationalized in terms of the attainment of credentials and the number of years of training or work experience in the domain. This experience-based approach tends to depend largely on peer evaluation or social recognition as a way of identifying experts in a particular discipline (Ericsson & Towne, 2010). The identification of experts is, thus, challenging because experience-based judgments of expertise do not always correspond to both field knowledge and problem-solving performance (Ericsson & Lehmann, 1996). In addition, “criteria may differ from one field to another, and they may be loosely and even inconsistently applied from one case to another” (Sternberg, 1997, p. 158).

Scientists’ activities are verified and judged by fellow researchers in their disciplines via peer-reviewed conference papers and journal publications. Indeed, Latour and Woolgar (1979) argued that developing skills in laboratory work “is only a means to the end of publishing a paper” (p. 71), and it is the paper that is the ultimate contribution to the scientific community. Through the peer review process, work products deemed to be of high quality allow the scientists to receive peer recognition that leads to various benefits for their further work (Allison, Long, & Krauze, 1982). Specifically, scientific recognition

of one’s contributions and consequent collegiate reputation ... is the key currency of the open science reward system. To this are tied the academic researcher’s material rewards, such as salary and job tenure, and access to the human resources and physical facilities that scientists typically need to produce published results.

(David, 1994, p. 70; see also Ehrenberg, Zuckerman, Groen, & Brucker, 2009)

Yet, the social recognition that scientists achieve may not precisely reflect their actual performance or contributions, especially in a team science environment (Feldon, Maher, & Timmerman, 2010). Different factors other than a scientist’s actual skills are involved in the process of how scientists gain recognition and reputation over the course of their careers within the scientific fields.

## The Matthew Effect

Merton (1968, 1988) originally developed the idea of cumulative advantage in the career development of scientists, in which early recognition of scientific accomplishments leads disproportionately to future recognition. Analyzing interview data from Nobel Prize laureates, he found a considerably skewed distribution of recognition and credit for

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scholarly accomplishments in science that favored those who published earliest on a topic, regardless of the actual significance of the contribution to the collective knowledge of the field. This Matthew effect posits that “eminent scientists get disproportionately great credit for their contributions to science while relatively unknown scientists tend to get disproportionately little credit for comparable contributions” (Merton, 1968, p. 57). For example, the better recognized scientist will get most of the credit for collaborative work (e.g., co-authored papers) irrespective of his or her actual contribution to the work. Similarly, if two scientists generate the same scientific discovery independently, the more established of the two scientists will get more recognition for the discovery. Zuckerman (1992) also confirmed this inequality in recognition and evaluation for scientific achievement by demonstrating that Nobel Prize recipients are more likely to become major candidates for other awards, because the Nobel Prize seems to increase the reputation of those awards and reduce the likelihood of making the wrong choice of award winners. Thus, advantage (e.g., invitations to collaborate, access to research grant dollars) accumulates over time for those who are initially successful, resulting in both greater opportunities to publish and greater recognition. Such processes account for a robust underlying social stratification in science (Allison, Long, & Krauze, 1982; Allison & Stewart, 1974; Cole & Cole, 1973) that undercut Ericsson and Smith’s (1991) requirement that domains of expertise appropriate for rigorous study must provide equitable access to demonstrate outstanding performance.

A similar effect can be found in the career trajectories of early career scientists. Many studies have examined the effects of the institutions where scientists are trained and the eminence of their advisors on their academic careers, including productivity and recognition (e.g., Sheltzer & Smith, 2014; Zuckerman, 1992). Crane (1965), for instance, found that scientists who received their graduate training at a more prestigious university were likely to be more productive than those trained at a less prestigious university. The eminence of the graduate school from which a doctoral degree was obtained was a stronger predictor of a scientist’s later productivity than that of their current academic affiliation. In addition, scientists who were formerly students of prestigious advisors are likely to be more productive than those who were students of lesser known advisors. Further, obtaining a postdoctoral research position at one of a very limited number of highly prestigious laboratories yields a higher rate of entry into faculty positions within major research universities (Sheltzer & Smith, 2014).

Such a correlation between young scientists’ home laboratories and their high performance and recognition can be accounted for by a “joint process of self-selection and selective recruitment” (Zuckerman, 1992, p. 157). That is, talented students interested in becoming scientists are discriminating in choosing prominent universities and elite advisors conducting significant work in the field. Simultaneously, prominent universities and advisors also select these talented individuals as their trainees. Further, because high prestige graduate schools tend to have relatively greater material and human resources, students in these schools are better positioned to demonstrate early success as a scientist (Merton, 1988). Similarly, the elite advisors transfer to their students not only their knowledge and skills but also the scientific standards, values,

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social connections, and self-confidence that are necessary to make significant advances in science (Gopaul, 2016). These students are, therefore, prepared well for elite status throughout their training and demonstrate higher rates of publication in excess of the small initial advantages they may demonstrate (Green & Bauer, 1995; Paglis, Green, & Bauer, 2006). Unfortunately, such conditions create a challenging environment for establishing expertise in absolute comparative terms (cf. Ericsson & Smith, 1991).

### Bibliometric Analysis

Bibliometric analyses provide a means for assessing product-based, rather than reputational, indicators of expertise using publication and citation analyses to more objectively assess scientists' scholarly performance (Long, Plucker, Yu, Ding, & Kaufman, 2014). Using this approach, Simonton (1997, 2004) proposed the model of creative productivity, which is based on a Darwinian perspective that views the generation of human creative thinking and products as a *blind-variation-and-selective-retention process* (Campbell, 1960; Simonton, 1999). The variation–selection process implies that the ultimate impact or success of a new scientific discovery is more likely to be assessed retrospectively than prospectively due to the substantially blind nature of the variation–selection process. In other words, individual scientists cannot necessarily predict which combinations of ideas and information will have greater impact over time, so stronger and weaker variations in individual scientific outputs are randomly distributed among scientists and within the careers of individual scientists (Simonton, 1997). Further, the selection process is also considered to be blind because it typically runs at multiple levels simultaneously, with authors selecting publication outlets, reviewers examining scholarly merits, and editors prioritizing areas of scientific work without prior knowledge of the decisions others in each category will make. For example, individual scientists who select which of their articles to submit to a given journal or conference cannot foresee what topics or how many rival articles will be submitted. Similarly, reviewers offer their comments independently of one another, such that one reviewer's opinion cannot influence that of another. Moreover, emerging technologies and findings in the field enhance the unpredictability of scientific products or articles that will ultimately have a high impact in the future.

Using bibliometric analysis, Simonton (1997, 2004) argues that scientific awards or honors may not predict the recipients' later success or the impact of their work, because the award process is a type of a variation–selection process that is blind and random. Rather, a scientist's productivity (i.e., total number of published articles) is the strongest predictor of the ultimate influence (i.e., citation rate) of a certain article. The variation–selection model assumes that if the distribution of quality across publications (as judged by citation rate) is random, the probability of large numbers of citations is constant across all publications. Therefore, the only way to increase the number of widely cited publications is to increase the total number of publications produced.

Conceptualizing expertise in this framework indicates that the bibliometric strength of a given scholar is a marker of their expertise. However, Simonton's (1997, 2004) model does not link directly to cognitive processes that would tie it to most of the literature on expertise. Prior scholarship on creativity by Campbell (1960) and Sweller (2009; Sweller & Sweller, 2006) suggests that, similar to Simonton's model, creative cognitive processes represent a random generate-and-test model, in which navigation of a problem space occurs as a random walk. Under this assumption, the likelihood of obtaining a goal state is thus dependent on the size of the problem space, with the probability of attaining the goal state increasing as the possible search space decreases. If knowledge of relevant scientific concepts, principles, and strategies constrains the realm of possible solutions and solution paths, then experts with more extensive or more optimally organized knowledge in relation to the problem would be searching smaller problem spaces. As such, an expert advantage would be maintained, even within a context of stochastic processes driving scientific discovery (Feldon et al., 2013).

## Factors Contributing to the Development of Expertise in Scientific Research

Educational interventions that can facilitate the development of expertise in STEM disciplines have been extensively studied at multiple levels of schooling. Yet, few efforts have directly linked childhood experiences specifically to expertise attainment. Retrospective studies of STEM professionals indicate that the presence of role models and early interest play an important role (e.g., Chakraverty & Tai, 2013). Likewise, schooling experiences tend to shape trajectories toward or away from advanced study of STEM topics based on both the extent to which students perceive themselves as compatible with a STEM identity (e.g., Archer et al., 2010, 2012) and the quality of academic preparation for advanced study in relevant topics, including mathematics (e.g., Arcidiacono, Aucejo, & Hotz, 2016, Wang, 2013).

### Progressions of Learning

Recent attention to longitudinal progressions of science learning has focused efforts in K-12 research around the identification of optimized sequences of content instruction that are most likely to yield successively more sophisticated ways of thinking about central disciplinary concepts (Duncan & Hmelo-Silver, 2009; Wilson, 2009). These learning progressions facilitate students' development of frameworks that can sustain complex tasks such as extended hypothesis testing and modeling relevant data (National Research Council, 2007). For example, Schwarz and colleagues (2009) developed a scientific learning progression for elementary through middle grades that builds fundamentals of scientific practice, encompassing two dimensions: (1) modeling as a generative process to aggregate and synthesize information into scientific knowledge and (2) modeling as a dynamic, iterative process of revision and modification as new data and understandings are obtained. Beginning at the middle school level, other progressions develop science

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argumentation skills. These deepen the emphasis on domain-specific argumentation skills and critical analysis to begin the transition to authentic scientific practices that entail using understanding of theoretical concepts to shape novel inquiry (Berland & McNeill, 2010; Osborne et al., 2016).

Research to understand and support progressions of scientific knowledge and skills has also emerged at the level of graduate training. Through extensive interviews with faculty supervisors of graduate students, Kiley (2009; Kiley & Wisker, 2009) identified several foundational concepts that commonly served as substantial barriers to further progress until mastered. These threshold concepts are such that, “once grasped, [they] lead to a qualitatively different view of the subject matter” (Kiley & Wisker, 2009, p. 432). Threshold concepts are, therefore, likely to be transformative, integrative, irreversible, troublesome, and bounded (Meyer & Land, 2003, 2005). Given these characteristics, threshold concepts entail a sequential structure in which each serves as a barrier to further expertise development until that threshold is crossed (Roberts, 2016). With each threshold crossed, it becomes possible to conceptualize and develop skills that target more nuanced aspects of disciplinary practice in ways that would not be accessible to a student who had not yet crossed (Urquhart, Maher, Feldon, & Gilmore, 2016).

Overall, these threshold concepts center around major competencies for advancing disciplinarily acceptable arguments and knowledge claims. These include the full comprehension and effective use of theoretical frameworks, constructing coherent arguments or theses, and developing conceptual models as coherent representations of findings. Theoretical frameworks appropriate a research study or argument within the broader context of the field and discipline. Theses present research evidence with explicit links to the significance or implications of the research findings. Conceptual models synthesize empirical findings with prior results from the primary literature to present coherent, supported hypotheses around the phenomenon of interest.

Through analysis of STEM graduate students’ scholarly writing over time, Timmerman, Feldon, Maher, Strickland, and Gilmore (2013) similarly found that the effective use of primary literature (as entailed in Kiley & Wisker’s (2009) threshold concepts of theoretical framework and conceptual model) and the ability to generate disciplinarily appropriate testable hypotheses (as entailed in Kiley & Wisker’s threshold concept of constructing a disciplinary argument or thesis) systematically preceded the development of other research skills. Only when students’ scores in these areas reached a certain level of proficiency did scores in other areas (e.g., data analysis, identifying limitations of a study design) increase.

Further data suggest that these progressions of skill development are nonlinear in nature. As with the Matthew effect (Merton, 1968) described previously, small initial differences in STEM graduate students’ skill levels at the beginning of an academic year increase over time, creating a widening gap in research skills (Feldon, Maher, Roksa, & Peugh, 2016). The mechanisms driving this trend are not yet clear. It is possible that small initial advantages over other students attract the notice of supervising faculty,

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leading to greater recognition and increased access to mentoring and research opportunities (Green & Bauer, 1995). However, Feldon and colleagues documented only very minor differences in the reported experiences of participants (e.g., quality of relationship with faculty advisor, participation in supervised research, publishing opportunities) in both the stronger and weaker skill groups. A possible alternative explanation with support from their data suggests that students in the stronger group may be more proactive in constructing extended meaning from their experiences and more inclined to reinvest effort as tasks become easier (cf. Bereiter & Scardamalia, 1993).

## Socialization

Socialization theory posits that graduate students training to become a researcher undergo a process of acculturation into their discipline as they join their research teams and academic departments (Gardner, 2010; Weidman, 2010). It means that students establish both formal and informal interactions with those in the disciplinary and graduate communities and, as a result, start understanding their dynamics and incorporating their values and practices in an active and self-evaluative manner (Weidman et al., 2001).

One way in which socialization occurs is through the interactions of a graduate student and his or her faculty mentor. Cognitive apprenticeship is such a pervasive pedagogical approach that it has been labeled a signature feature of doctoral training (Golde, Conklin Bueschel, Jones, & Walker, 2009). For example, a study exploring doctoral students' motivation to graduate showed that the more collegial the relationship with their faculty advisor, the higher students' satisfaction and motivation (Mason, 2012). Further, it is through engaging in supervised research activities that students build their self-efficacy beliefs and identity as science researchers (Holley, 2009). However, Maher, Gilmore, Feldon, and Davis (2013) found that in contrast to ideal mentoring practice, which assumes progression in the complexity of assignments and subsequent feedback over time, students tended to report a constant level of heavy cognitive demands related to research productivity with limited quantity and depth of feedback (for more information on cognitive apprenticeship and other examples of mentoring, see Chapter 44, "Learning at the Edge: The Role of Mentors, Coaches, and Their Surrogates in Developing Expertise," by Petushek et al., this volume).

Heavy reliance on the mentorship model assumes that advisors occupy an ideal position from which to view students' performance in STEM research, provide feedback, and craft opportunities to help students develop their expertise through deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993). Unfortunately, empirical tests of this assumption do not endorse its full acceptance. In a study of intact pairs of STEM graduate students and their faculty mentors, students' written research proposals were scored and compared against mentors' statements about the skill strengths and weaknesses they observed in their students. These perspectives predicted student performance at no better than chance and often were unrelated to or directly

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contradicted students' self-perceptions of strengths and weaknesses (Feldon, Maher, Hurst, & Timmerman, 2015).

This study (Feldon et al., 2015) recruited 81 students pursuing research-intensive graduate degrees in STEM disciplines and elicited from them sole-authored research proposals early in the fall semester. These students were then asked to revise and resubmit their proposals (again as sole authors) late in the following spring semester. Pairs of domain experts trained in the use of a previously validated rubric scored these research proposals, with focal aspects including students' abilities to set the proposed research in the context of the field, frame productive research questions and testable hypotheses (as appropriate), design valid and appropriate studies, and identify the limitations and delimitations of prospective findings (Feldon et al., 2011).

In addition to the scores from the rubrics, the research team interviewed all participants late in both the fall and spring semesters and asked them to identify their strengths and weaknesses as a researcher. Independently, the researchers also interviewed the faculty whom participating students identified as their research mentors shortly after the fall and spring student interviews. In the faculty mentor interviews, each individual was asked to articulate the strengths and weaknesses of the identifying student in terms of their research skills. For both students and their faculty mentors, researchers kept the interview prompts intentionally vague to avoid biasing participant responses by focusing them on specific skills for which they may or may not have held specific assessments for the student in question.

Emergent themes from all interviews yielded sixteen codes related to research knowledge and skills. Of those, nine aligned directly to skills assessed by the rubric used to score research proposals. Statements of matched faculty-student pairs were compared to assess levels of agreement across all themes. In turn, statements from student and faculty interviews, respectively, that aligned with one or more of the nine rubric-identified skills were compared to scores attained on those skills for each submission of the research proposal. For statements describing a specific skill as a strength by one member of the student-faculty pair, researchers compared the statement to the assessment offered by the other member of the pair as well as the scores attained through rubric scoring. For each skill, a score at or above the sample mean was considered to be a strength, and a score below the sample mean was considered to be a weakness.

Results from these analyses indicated that in more than 75 percent of cases, students and their faculty mentors were focused on completely unrelated skills. However, when both members of a pair identified the same skill, they disagreed on whether it was a strength or weakness in approximately half of those cases. Further, for most skills, neither the student nor the faculty mentor was able to predict performance as assessed by the rubric scores at a rate greater than chance. The one exception to this trend was graduate students' self-assessments of their ability to utilize primary literature to frame a study, which concurred with rubric scores in 67 percent of cases from the spring proposals and interviews.

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These findings reflecting limited insight by faculty mentors into the skill development of their students may be attributable to the evolution of university-based STEM research practices, in which the pace and volume of work required of faculty is increasing (Anderson et al., 2011; Austin & McDaniels, 2006; Johnson, Lee, & Green, 2000). It is also increasingly common for such endeavors to be team-based (Charlesworth, Farrall, Stokes, & Turnbull, 1989; Delamont & Atkinson, 2001; Knorr-Cetina, 1999; Parry, 2007). These conditions have given rise to a model of cascading mentorship (Golde et al., 2009), in which supervising faculty work most extensively with postdoctoral researchers, who in turn mentor senior graduate students. These senior students then support junior graduate students, who become primarily responsible for supervising undergraduate researchers. As such, faculty mentors may directly observe a students' work only rarely.

The lack of mentorship guidance and feedback requires successful STEM students to be independent learners. In this context, it is likely that academic self-regulation—i.e., “the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning processes” (Zimmerman, 2013, p. 137)—becomes important to the development of graduate students' success, because the system within which graduate students develop expertise offers little direct externally imposed regulation. Even though research in self-regulated learning (SRL) has not heavily targeted graduate students, some studies do indicate that higher levels of expertise are accompanied by higher levels of self-regulation (Artino & Stephens, 2009; Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002). Further, Zimmerman and Campillo (2003, p. 238) affirm that novices and experts have very different profiles of self-regulation competency, in that “experts display greater use of hierarchical knowledge when formulating strategic solutions, greater use and self-monitoring of strategies, more accurate self-evaluation, and greater motivation than novices.”

## Future Directions

This chapter highlights a number of the major areas of research in efforts to understand how expertise manifests and develops in STEM disciplines. Due to the dependence of expert performance on both the cultural dimensions of scholarly productivity within disciplines and the ability of individuals and teams to solve complex problems, understanding the ways in which experts realize their contributions is highly challenging and defies some of the long-established criteria for the empirical study of expertise. For example, to contribute to a general theory of expertise, Ericsson and Smith (1991) specify that individual experts suitable for study must demonstrate stability in the characteristics that lead to outstanding performance. In this regard, they specifically state that this criterion excludes those who excel in games of chance. However, the most prestigious forms of social recognition of outstanding performance in science, such as a Nobel Prize, can be awarded for a single major discovery that builds on the accumulated work of many scholars and may have required the participation of experts from many domains. Further, the bibliometric analyses offered by Simonton (1997, 2004) and the model of cognitive creativity established by Campbell (1960) and Sweller (2009; Sweller & Sweller, 2006)

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explicitly rely on stochastic processes to generate scientific achievements that impact the progress of the field. In addition, substantial research has documented gender biases favoring men that skew the relationship between the scholarly contributions made and the recognition of those contributions (Feldon, Peugh, Maher, Roksa, & Tofel-Grehl, 2017; Lincoln, Pincus, Koster, & Leboy, 2012).

Another challenge pertains to the availability of “a larger group of other individuals (a ‘control’ group of sorts) who have experienced similar opportunities to make contributions or to achieve” (Ericsson & Smith, 1991, p. 2). Given the documented social advantages of individuals based on early, minor contributions to an area of research (Merton, 1968), demonstration of small advantages over peers in skill at an early stage of training (Gopaul, 2016; Green & Bauer, 1995), and receiving initial training from more prestigious university faculty (Crane, 1965; Sheltzer & Smith, 2014; Zuckerman, 1992), it becomes difficult to argue that all scientists receive “similar opportunities.” It is likewise difficult to establish consistent definitions of domains of expertise as fields evolve and interdisciplinarity becomes a more prominent mechanism for solving challenging scientific problems (Lattuca, 2001; Rhoten & Parker, 2004).

Further, it is typically considered necessary to be able to “account for the acquisition of the characteristics and cognitive structures and processes that have been found to mediate the superior performances of experts” (Ericsson & Smith, 1991, p. 12). Nonetheless, the conventional mechanisms by which expertise is assumed to be developed during graduate training have failed to yield consistent results. For example, the mentoring practices employed by university faculty supervising graduate students in STEM are frequently documented to be subpar (Maher et al., 2013) and students whose research skills develop at faster and slower rates report largely identical mentoring experiences (Feldon et al., 2016). Likewise, with the rise of team science models, tracking the flows of mentorship becomes even more challenging for a cascading model of mentorship from senior peers (Golde et al., 2009). As pointed out previously, these phenomena suggest that increased attention to the role of self-regulated learning in the preparation of STEM experts may be warranted.

While addressing these issues with understanding the development and function of expertise in STEM disciplines will prove challenging, they are not necessarily intractable. Substantial progress has been made in parsing out the sequence of development for necessary skills (Kiley & Wisker, 2009; Timmerman et al., 2013), as well as in identifying discrete interventions and activities that lead to demonstrably greater research skill development during graduate training (e.g., coupling teaching and research experiences, Feldon et al., 2011; coauthoring research publications between students and faculty, Feldon, Shukla, & Maher, 2016). While such findings are encouraging, they represent only one aspect of the social and cognitive duality of STEM expertise, and it is understanding this complex dynamic that may ultimately yield the most complete picture of the phenomenon.

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We recommend several practices that have the potential to substantially advance the field. First, insofar as it is possible, we suggest evaluating developing expertise using performance-based metrics (e.g., rubric-assessed, sole-authored samples of scholarly writing). While this is not practical for gathering data from leading experts in the field due to publishing norms in team science environments, it can be successfully applied at the level of graduate training. Such data may provide a mechanism for longitudinal modeling in which skill acquisition patterns during training may be predictive of subsequent bibliometric indicators of field influence. Further, assessments that do not rely on written products would also be informative for those individuals who are developing STEM expertise outside of an academic context (e.g., industry). Second, comprehensive studies that link performance and experiential data from individuals, programmatic and instructional practices at their training institutions and laboratories, and subsequent bibliometric performance data are likely to draw more informative conclusions about the constellations of factors that lead to the development of both demonstrable and socially recognized expertise in the field. Third, the dynamic nature of STEM disciplines and interdisciplinarity must be accounted for in two ways: (1) as domains in which performance across multiple individuals can be compared, and (2) as social contexts that drive productivity choices (e.g., valuing holding patents over publishing journal articles) such that bibliographic analyses may not fully credit the expertise or level of influence on a field.

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