Interdisciplinarities in Action: Cognitive Ethnography of Bioengineering Sciences Research Laboratories

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The paper frames interdisciplinary research as creating complex, distributed cognitive-cultural systems. It introduces and elaborates on the method of cognitive ethnography as a primary means for investigating interdisciplinary cognitive and learning practices in situ. *The analysis draws from findings of nearly 20 years of investigating such practices in research laboratories in pioneering bioengineering sciences. It examines goals and challenges of two quite different kinds of integrative problem-solving practices: biomedical engineering (hybridization) and integrative systems biology (collaborative interdependence). Practical lessons for facilitating research and learning in these specific fields are discussed and a preliminary set of interdisciplinary epistemic virtues are proposed as candidates for cultivation in interdisciplinary practices of these kinds more widely.*

1. Introduction

Interdisciplinarity is widely cast as a hallmark of frontier twenty-first century research in the sciences and engineering. Interdisciplinary research is customarily characterized as "integrative" and "innovative," yet difficult to

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achieve. The difficulty lies in the complexity of the problems posed, the need to develop novel cognitive practices, and the fact that interdisciplinary collaboration is fraught with difficulties that increase with the distances between the collaborating disciplines. Although there are a broad range of empirical methods used to investigate these dimensions, studies of the dynamic processes of interdisciplinarity practices, that is, how interdisciplinarity is enacted in situations of scientific research and the challenges posed for researchers are scant.[1] Further, although detailed taxonomies of different kinds of interdisciplinarity have been elaborated in the abstract since 1972 (Klein 2010), richly nuanced accounts of interdisciplinary practices are needed when it comes to thinking about learning and facilitating a specific kind of research. Ethnography has long been a method used by anthropologists to study and interpret cultural practices situated in naturalistic settings. Most importantly, ethnographic research enables examining both the insider ("emic") perspective of the participants and developing the ethnographer outsider ("etic") interpretation of practices of interest. Recently, within the cognitive sciences and philosophy of science, "cognitive" ethnography has emerged as a method specifically for studying problem-solving practices situated in real-world science environments.

Cognitive ethnography is particularly well-suited to examining the conceptual, reasoning, and learning dimensions of interdisciplinary problem-solving, where differing and often incompatible epistemic practices and values are in play. The method is perhaps uniquely suited to investigating the processes of integration because it enables collecting fine-grained data as researchers attempt to solve interdisciplinary problems within a complex context of cognitive, social, material, and cultural resources and constraints. Cognitive ethnography provides nuanced findings about specific interdisciplinary practices—how they come to be as well as how they are used—that not only enhance our understanding of interdisciplinarity but also can help faculty and policy makers figure out how best to facilitate research, especially as they develop programs to educate the twenty-first century scientist. The NSF-funded research program my co-PI, Wendy Newstetter, and I embarked on fifteen years ago took up both the challenge of a nuanced examination of interdisciplinary practices and of using

1. Notable exceptions in philosophy and cognitive science, most of them recent, include Brigandt 2013; Dunbar [1995] 1999; Goodwin 1995; Hall, Stevens, and Torralba 2002; Hall, Wieckert, and Wright 2010; Andersen and Wagenknecht 2013; Christensen and Schunn 2007; O'Malley, Calvert, and Dupré 2007; O'Malley and Soyer 2012. Additionally philosophers have begun to attend specifically to what interdisciplinary "integration" means in cases of contemporary and historical science (see for instance Griesemer 2013; Leonelli 2013; Love and Lugar 2013).

our findings to determine ways to facilitate research and learning in emerging fields in the bioengineering sciences. We decided at the outset that our research group would conduct cognitive ethnographies to capture interdisciplinarity in action. I begin with a discussion of what is "cognitive" ethnography and why it is an important method for investigating interdisciplinary research practices and proceeded to a description of the research we conducted across four labs, ending with discussion of some significant findings about research practices and learning in these different interdisciplinary settings.

2. What Is "Cognitive Ethnography"?

Cognitive ethnography utilizes standard ethnographic methods for collecting (field observations, participant observation, interviews) and analyzing (grounded coding, thematic analysis, case study, and so forth) data. What makes it "cognitive" is primarily the focus of the research questions on problem solving, which has long been held by cognitive science to play a central role in cognitive processes such as learning, creativity, insight, and cognitive/conceptual change. In keeping with the traditional cognitive science framing, cognitive ethnography conceives of problem solving as a form of information processing that uses representations and reasoning in pursuit of goals. Where it diverges from the traditional framing is maintaining that the relevant representations and reasoning are not only "in the head" of an individual, but also situated in the problem-solving environment and distributed across one or more individuals and select artifacts. Cognitive ethnography emerged as the methodological choice of "environmental perspectives" (Nersessian 2005) that have been seeking an understanding of cognition as an embodied, artifact-using, situated, and socio-cultural process in which the environment does not simply scaffold, but is integral in the process. Proponents of this perspective—here I focus on the pioneering cognitive anthropologists Edwin Hutchins and Jean Lave—have been utilizing cognitive ethnography to move the study of human problem solving out of the psychology lab, with its use of artificial problems, and into real-world settings with problems of everyday life, ranging from ordinary activities to sophisticated work practices.[2]

Although Lave and Hutchins took their research in different directions, they were both equally critical of the overly linguistic and thing-oriented

2. There are several threads of pioneering, mutually influential contributions that came together at that time—largely by researchers spanning departments at UC San Diego that I cannot discuss here (see for instance, Lynch 1985; Norman 1988; and Engeström 1987). I came to appropriate and develop the method from the research I discuss and only later discovered the confluence of what had become by then separate endeavors.

construal of culture of cognitive anthropology and of the context-free, body-independent "functionalist" construal of cognition of cognitive psychology and AI. These construals together led to the notion within cognitive science that culture provides representations ("content," "ideas," see, e.g., D'Andrade 1987) that cognitive processes or mechanisms operate on, and thus the cognitive processes could be investigated separately and removed from the contexts in which they are customarily exercised. This divide led to the paradigm of studying cognitive processes—memory, reasoning, representation, learning, and so forth—in the artificial situations of psychology experiments and AI modeling. Lave (Lave 1988) rooted her critique in the problem of why it is that people are generally more competent at various reasoning and problem-solving skills in real-world contexts—such as arithmetic practices in grocery stores, in monetary practices among Brazilian street children, and in Liberian tailoring—than in experimental settings or traditional school settings where educational practices are influenced by the view that cognition is all "in the head." These findings led her to argue that the "more appropriate unit of analysis is the whole person in action, acting with the settings of that activity" (Lave 1988, p. 17). "Cognition" is to be understood as "stretched across mind, body, activity, and setting" (Lave 1988, p. 18). Lave's initial research used cognitive ethnography as a method to investigate the reasoning and problem-solving practices of "just plain folks," for instance, people grocery shopping for the best buy. Later she and followers extended it to a range of "communities of practice" (Lave and Wenger 1991).

Hutchins began studying "human cognition in its natural habitat," (Hutchins 1995, p. xiii) in his research on inferential practices of Trobriand Islanders regarding land tenure, which established that, seen in context, their so-called "primitive thought" processes use the same logical operations as Western thought (Hutchins 1980). His most influential research, though, has focused on problem solving in technologically rich and well-defined problem environments: piloting planes and ships, where "natural" is extended to comprise not only ordinary settings but also work contexts, i.e., "naturally occurring culturally constituted human activity" (Hutchins 1995, p. xiii). In this research he articulated the analytical framework of distributed cognition[3] and the method of cognitive ethnography as a means for systematically studying cognitive processes that are "distributed" across complex systems of interacting humans and artifacts in real-world problem solving practices. Hutchins' main theses underlying

3. It is important to underscore that Hutchins' position is that distributed cognition is an analytical framework and not an ontological claim as advanced by Andy Clark with his "extended mind thesis" (Hutchins 2011).

this approach are that: 1) culture needs to be reconceptualized as a process, not content to be added to cognitive mechanisms, determined independently, and 2) cognition is a cultural process in which "people create cognitive powers by creating the environments in which they exercise those powers" (Hutchins 1995, 169). The dynamics of these "cultural practices account for much of what is needed to account for the origin of human cognitive systems" (Hutchins 2011, p. 445). Thus, cognition and culture are integral to one another. Cognitive ethnography, therefore, provides a method for studying the origins, development, and enactment of the situated problem-solving practices of complex evolving distributed cognitive-cultural systems, such as those created by interdisciplinary researchers (Nersessian 2006; Nersessian et al. 2003; Nersessian et al. 2002; Chandrasekharan and Nersessian 2015). Cognitive ethnography, of course, can be used to study disciplinary practices, but it is an especially useful method for gaining insight into the nuances of different kinds of interdisciplinary practices, for instance, what "integration" means, how it is to be achieved, and the challenges it poses in a specific problem-solving context. In particular, it enables focusing on how researchers negotiate disparate and often conflicting modes of practice and epistemic norms and values in the processes of problem solving (MacLeod and Nersessian 2016; Osbeck and Nersessian 2017).

Research in the distributed cognition framework largely consists of detailed observational case studies employing ethnographic methods. The overarching objective, however, differs from socio-cultural studies that aim mainly to ferret out the social, cultural, and material facets of a case. As cognitive science accounts, cognitive ethnographies need to move beyond just creating the requisite "thick description" (Geertz 1973) of ethnographic analysis, with richly nuanced details of the specific case, to also providing a more general, abstract account of cognition. The aim of the cognitive science research is to understand the nature of the regularities of cognition in human activity. We aim to do likewise in investigating interdisciplinary scientific practices.

The conceptual and methodological framing of our research project was designed to advance an account in which cognition and culture are mutually implicative in authentic scientific practices. We chose the method of cognitive ethnography since it offered the possibility to analyze interdisciplinary problem-solving practices as situated in evolving distributed cognitive-cultural systems (Nersessian 2006; Nersessian et al. 2003). We aimed to capture in detail the dynamics of interdisciplinary integration in the day-to-day struggles of the researchers as they made decisions about how best to scope a complex problem, what resources (conceptual, methodological, material) to bring to bear on solving it though building models, and how to justify the compromises (e.g., abstractions, restrictions, and so forth) they made in the process. In several cases we were able to develop studies of individual researchers or groups as they worked on solving a problem over months and even years.

3. Project and Methods Overview

The bioengineering sciences use a range of engineering and biosciences resources to conduct basic biological research in the context of application. For instance, the tissue engineering lab we investigated has been carrying out ground-breaking research on basic endothelial cell biology to understand the effects of forces on these cells as blood flows through the vessel, while having as a major objective to create living tissue substitutes for diseased arteries. The bioengineering sciences occupy a major position in twenty-first century science, are inherently interdisciplinary, and are complex: cognitively, technologically, and collaboratively. They self-consciously seek to "integrate" concepts, methods, theories, and materials from engineering, biology, and medicine. The impetus for this kind of research has come primarily from engineering. This movement of engineering into biology has given rise to a multifaceted interplay of quite disparate conceptual frameworks, methodological approaches, and epistemic values. Innovation in methodological practices is required to tackle the novel, largely engineering-directed research problems being formulated concerning complex biological systems. A signature practice of these fields is investigating biological phenomena through designing, building, and experimenting with surrogate in vitro physical simulation models (comprising biological and engineering materials) or computational simulation models. The focus of our research has been examining the dynamics of these problem-solving practices, specifically, the challenges around development, use, and learning.

Our investigations comprise four pioneering interdisciplinary university research laboratories: two in biomedical engineering (BME): tissue engineering and neural engineering and two in integrative systems biology (ISB): one solely computational, the other a combined computational and wet experimentation lab. We chose university labs because they are largely populated by graduate students who are simultaneously pioneers in research and learners. Our investigations have established that the forms of interdisciplinarity practiced in BME and in ISB are quite different, leading to different challenges for problem solving. The BME labs are populated by graduate students in an educational program (that we were using our research to help design) aimed at moving beyond collaboration between engineers and biologists through producing hybrid bio-medical-engineering researchers. In both labs, the researchers tackle problems of bringing together cells and tissues and engineered materials in processes of designing, building, and experimenting with dynamical living hybrid models to simulate in vivo biological phenomena. The ISB labs aim to understand, intervene on, and control biological systems comprising integrated, interacting, complex networks of genes, proteins, and biochemical reactions. Solutions to the problems posed require constructing computational simulation models in need of rich experimental data, which creates an essential epistemic interdependence among the participating fields: computational sciences, engineering sciences, and biological sciences. The nature of the problems posed in ISB requires both a high degree of specialization and collaboration. The computational lab comprises primarily engineers of various kinds, but all conversant with systems engineering, and applied mathematicians who collaborate with bioscientists external to the lab. The combined lab is attempting to develop modelers (predominantly engineers), who conduct their own experiments in the service of building computational models ("bimodal researchers"; MacLeod and Nersessian 2013a), but also collaborate with external bioscientists.

3.1. Data Collection and Analysis

Our objective in data collection can be summarized as: starting from an open and broad stance about what might be relevant to our research questions, to conduct a systematic long-term investigation involving numerous scientists across a broad range of perspectives, problems, and lab organizations so as to collect a range of different data from which to triangulate the analyses. Although there were variations in our research questions for the two fields, they took the general form of: 1) what are the cognitive practices used in problem solving and the challenges these present? 2) what supports and facilitates learning? and 3) how is interdisciplinary integration manifested in the lab research and learning processes? For the ISB study, our preliminary research brought to the fore questions of identity, so we added 4) what are the implications for interdisciplinary identity in the appropriation of different cognitive resources?

Each lab was investigated for approximately five years. Data collection in all labs comprised: audio-taped open and semi-structured interviews; participant field observation with note-taking; lab tours (initially those given for us, then for visitors); arranged demonstrations of experimental procedures and technologies involved in their data collection and analysis; video and audio recorded lab meetings; journal club meetings; photographs of white boards and lab space evolution; and artifact collection: grant proposals, paper drafts, powerpoint presentations, dissertation proposals, emails, diagrams/sketches, and so forth. The extent of our interview and observational data is summarized in Table 1. All interviews and some meetings have been transcribed.

Table 1. Data summary.

Laboratory	Interviews	Meetings	Field Observations (Hours)
BME A	72	15	~300
BME D	75	40 (plus 16 journal club)	~500
ISB G	44	7	~20
ISB C	62	15 (plus 2 joint C and G)	~250

3.2. Research Sites

To understand better the different challenges of interdisciplinary problem solving faced by researchers as they attempt to integrate engineering and biology in these environments, I provide a brief overview of the kinds of problems addressed in each lab. All the labs we investigated were pioneers, conducting research for which there was little or no precedent when they began. In the BME labs we conducted intensive data collection over the first two years and followed-up selected dissertation projects through to completion, including additional interviews, for a total of five years.[4] Both labs designed, built, and conducted experiments on living physical models, locally called "devices."

Lab A's overarching research problems were to understand mechanical dimensions of cell biology, such as the effects of the forces of blood flow on gene expression in endothelial cells, and to engineer living substitute blood vessels for implantation in the human cardiovascular system. The dual objectives of this lab explicate further the notion of an engineering scientist as having both traditional engineering and scientific research goals. Examples of intermediate problems that contributed to the daily work included designing and building living tissue models—"constructs"—that mimic properties of natural blood vessels; using biomechanical forces to create endothelial cells from adult stem cells and progenitor cells; designing and building environments for mechanically conditioning constructs; and designing means for testing their mechanical strength.

Lab D's overarching research problems were to understand the mechanisms through which neurons learn in the brain and, potentially, to use this knowledge to develop aids for neurological deficits and "to make people smarter" (director). Examples of intermediate problems that contributed

4. I discuss these labs in the past tense because both are now closed.

to the daily work included: developing ways to culture, stimulate, control, record, and image neuron arrays; designing and constructing feedback environments (robotic and simulated) in which the "dish" of cultured neurons could learn; and using electrophysiology and optical imaging to study "plasticity." One researcher developed a computational model of the dish model-system that played an unanticipated pivotal role in the research.

In the ISB study we had fewer resources and researchers, so we conducted intensive data collection in each lab over the first year and followed selected dissertation projects through to completion for a total of five years. Both labs built and experimented with computational simulation models.

Lab G's research problems focus on computational and mathematical modeling of biological systems at the genetic, metabolic, and cellular levels. The focus of the modeling is on the interactions among different components of biological systems (such as metabolic and signaling pathways), rather than on structural properties of specific components (such as DNA, Ribosome). The problems addressed are wide-ranging. For instance, one of the problems tackled by the lab was developing a model of the production and transport of dopamine and of how this system is affected in Parkinson's disease. In this research the lab worked with experimental data provided by a medical research group specializing in neurodegenerative disorders. Another problem was developing a model of ethanol production using algae, based on data provided by researchers at a biofuel company. In general, the domain-driven problems are provided by bioscience researchers of various kinds who approach the lab to model their data. The overarching focus of the lab's own agenda is on methodological problems in modeling, especially developing mathematical techniques to improve the estimation of model parameters, and the optimization of these parameters.

Lab C's research is guided by an overarching problem: to understand the impact of redox (reduction-oxidation) environment on proteins through systems modeling approaches. Cells maintain a reduced internal environment under normal physiological conditions. However, oxidizing molecules and free radicals that are produced in the cell as a part of physiological processes or that enter it can react with cellular components such as DNA, cell membranes, and proteins. Such reactions have physiological consequences and have been implicated in several diseases. Lab C's research focus is on the impact of alterations made by oxidants on proteins, which are part of signaling pathways, and on the dynamics and outcomes of these pathways. Based on her own training, the director has been developing some graduate researchers with the ability to do biological experimentation in the service of building and testing their computational models. One student also engaged in engineering design through collaborating in developing a microfluidic device ("lab-on-a-chip") to produce single cell and population data that are more amenable to quantitative investigation (Aurigemma et al. 2013). The lab's broad overarching problem translates into research projects as varied as modeling chemotherapeutic drug resistance in acute lymphoblastic leukemia cells and modeling senescence in T cells.

3.3. Data Analysis

We used a variety of complimentary qualitative methods; specifically, qualitative data coding, case study analysis, thematic analysis, and cognitive-historical analysis. The qualitative data coding methods we have been using comprise: systematic, fine-grained open coding and "grounded theory" development. There is an extensive range of qualitative methods that have been developed and critiqued over the last half-century, especially in psychology and sociology (for overview see Patton 2002). Qualitative methods applications are not formulaic or recipe-like, so we have needed to tailor and innovate in data analysis with respect to our research goals and questions, while adhering to the canons of what constitutes "trustworthy" (Lincoln and Guba 1985) and "validated" (especially the American Psychological Association standards; see Eisner 2003) data collection and analysis procedures. These canons require systematically collecting a range of different data sufficient for triangulating data from multiple sources from which to corroborate and determine the referential adequacy of interpretations. Our research conducted long-term studies that provided longitudinal data consisting of persistent observations, multiple interviews of each participant, and the kinds of archival data previously mentioned. Since I want to focus the remainder of the paper on findings pertaining to interdisciplinarity, here I briefly mention only a few of our data analysis procedures relating to grounded coding (Corbin and Strauss 2008; Glaser and Strauss 1967) since the codes provide the basis for our interpretations.

We practiced what we dubbed "team ethnography." More than one ethnographer had responsibility for observations and interviews in a given lab, and the more senior members of our group worked across the labs. Our weekly research group meetings provided the venue for discussing the ethnographic work with one another as it unfolded and for reaching consensus on coding, theme development, and other forms of data interpretation as we were relating our findings to appropriate cognitive, socio-cultural, and philosophical theoretical frameworks. Our research group varied in size and composition over time, but remained highly interdisciplinary and thus provided multiple lenses through which we could "theorize" the data.[5]

5. In qualitative research, the researchers are considered the "instruments" of data collection and analysis. Each of us already had an interdisciplinary background when we joined the project. Our group brought a wide range of perspectives to the project: philosophy and

Coding development took place in several stages. During open coding, coding pairs from different backgrounds in our research group worked collaboratively on each transcript. Interviews were analyzed progressively, line by line, from beginning to end, with the aim of providing an initial description for as many textual passages or "meaning units" as seemed appropriate to both researchers. Coders consulted with the entire research group on the clarity, fit, and logic of the codes assigned. Feedback was used to make adjustments. Consistent with the goals of analytic induction (codes emerging from data) and constant comparison (Lincoln and Guba 1985; Corbin and Strauss 2008), the coders resumed coding of additional interviews, revisiting previous coding, and assessing descriptions for adequacy and fit throughout the process. Research group meetings reviewed all codes and further grouped and arranged codes into superordinate categories and subcategories. We then related codes and developed the categories/concepts as a start towards building "theory." In this context, theorizing is understood, broadly, as formulating "a set of well-developed categories (themes, concepts) that are systematically interrelated through statements of relationship to form a theoretical framework that explains some phenomenon" (Corbin and Strauss 2008, p. 55).

We have been using the codes and categories to analyze the data further and to examine them through various theoretical lenses. Our case study analyses take the form of "thick descriptions" (Geertz 1973). The case studies follow practices of a specific researcher, or small group, as they worked on solving a complex problem. The thematic analyses develop descriptions and interpretations of various dimensions of the evolving cognitive-cultural systems of the labs, including interrelated trajectories of problems, technologies, models, researchers, learning, and development of practices, especially methods. The cognitive-historical analyses (Nersessian [1987] 2008) focus on examining the development and use of investigative and learning practices through the lens of pertinent cognitive science research, as well as using findings to extend and critique cognitive research.

4. Interdisciplinarities in Action: Selected Findings

It is widely agreed that the chief characteristic of interdisciplinary research is integration.[6] Integration is what promotes creativity and innovation.

history of science (physics, biology, psychology), cognitive science (AI, cognitive psychology, philosophy), linguistic anthropology, learning science, human-centered computing, theoretical psychology, psychoanalysis, architecture, and industrial design.

6. A broad characterization of interdisciplinary research has been proposed by the US National Research Council: "a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding

What is needed is both a more nuanced understanding of what "integration" means in the problem-solving practices of quite different interdisciplinary "epistemic communities" (Cetina 1999) and the specific challenges encountered in trying to achieve it. Although it is not possible to provide extended analyses here, cognitive ethnography enabled us to examine in fine detail how our researchers determined how to reconceive a complex biological system with the engineering and computational resources at hand so as to be able to solve—at least partially—the target problem. This process often required adapting concepts and methods they transferred from engineering as well as creating new ones specifically arising from the bio-engineering integration they were attempting.

As one can imagine, the findings from long-term investigations are rich and varied. We do not claim to have captured all the nuances of the range of interdisciplinary practices in either BME or ISB. An important goal of ethnographic research of multiple sites is to assess transferability: to ascertain what abstracted insights might be in common across sites and possibly extended to the broader field, and which are unique to a site. Many of our findings of the challenges of integrating engineering and biology in BME transferred robustly across the two labs. The ISB labs were different as described earlier and various aspects of the modeling process differed. However, our major insights about the challenges of integrating biology, engineering, and computation in ISB problem-solving practices did transfer. We have presented our findings to audiences of researchers outside of our studies in each field and have done sufficient broad sampling of each of the fields to feel confident that our research provides significant insights relevant to the practices and challenges of interdisciplinary research and training across the fields. Section 4.1 will provide an overview of our analysis of cognitive practices and challenges in BME problem-solving and Section 4.2, in ISB. Section 4.3 will focus on some the challenges of collaboration in ISB.

4.1. BME Problem-Solving

The overarching problems BME poses are directed towards using engineering design methods and principles to create interventions for specific medical disorders. Examples include constructing living implants that can perform normal functions of arteries and developing brain-controlled prosthetic devices that neurons can learn to control. The kind of biomedical engineering we investigated developed programs of in vitro research using physical simulations models (called "devices" in our labs) to investigate

or to solve problems whose solutions are beyond the scope of a single discipline or field of research practice" (NAS, NAE, and IM 2005, p. 26).

both selected aspects of the biology of in vivo systems and create novel artifacts and technologies for medical application. Devices are hybrid artifacts where cells or cellular systems interface with nonliving materials in model-based simulations run under various experimental conditions (Nersessian [2008] 2009; Nersessian and Patton 2009). This kind of research program was developed by engineers who wanted to investigate problems such as the effects of shear stresses on endothelial cells in arteries, but found it difficult to interest biologists in the problems. The in vitro research approach was developed because many of the problems the field poses either require a level of control not possible to achieve in animal research or would be unethical. In each BME lab there was one or more devices central to the evolving research program. Because the devices are created to address the specific research problems of a lab, they are usually designed, constructed, and redesigned in-house through several iterations. The devices participate in experimental research in various configurations of hybrid "model-systems." As one researcher explained, they *"use that {notion} as the integrated nature, the biological aspect coming together with the engineering aspect, so it's a multifaceted model-system."*[7] Cognitive ethnography enabled focusing on the nature of the on-going challenges faced by researchers as they figured out how to design, build, and experiment with these hybrid "multifaceted model-systems" so as to replicate the in vivo phenomena at the right level of abstraction to provide useful information about specific processes in a complex biological phenomenon, while also keeping the cells and tissues alive over extended periods. The "dish" model-system of Lab D provides a brief exemplar of these challenges.

The main research problem of Lab D was to understand learning in networks of living neurons, which they operationalized in terms of the network's ability to form connections and reorganize itself ("plasticity"). As with most engineering, understanding of the phenomenon is related to the ability to control it, in this case, to create supervised learning in neuron cultures. Prior to setting up his own lab, the director did postdoctoral research in another lab to help develop a platform for stimulating and recording neuron cultures, the "multi-electrode array" (MEA). The construction of the dish model-system requires breeding rats with neural cells expressing green fluorescent protein (for optical imaging) and techniques for dissociation and plating of neural and supporting glia cells onto the MEA (electrodes poking up for recording and stimulation). The MEA has been constructed so as to enable the cells to form a long-lasting (months to years) living culture. The dish comprises only a monolayer of cells both because of the design of the electrodes and because it is more likely to live

7. All italicized quotes are from interviews with lab members.

longer. The researchers rationalized that complexity-reducing choice by arguing that if learning can be produced in a monolayer of cortical neurons, then they would have a highly significant result (which they did within four years). They designed an environmental chamber to house the dish so that both optical imaging and electrophysiological investigations were possible. Recording, simulating, and analyzing the data required lab members to build a special set of software tools; likewise, for visualizing dish electrical activity. Finally, for building out this "open-loop" model-system into an embodied model-system that would provide feedback to the dish, a number of computational "animats" and real-world robots ("hybrots") needed to be designed to interface with the dish though programs that appropriately model such things as muscle movement.

As mentioned previously, this kind of in vitro research was initiated by engineers who either could not recruit bioscience collaborators or who found such collaborations inherently difficult because biologists lack the requisite quantitative and engineering knowledge to facilitate collaboration (Nersessian 2017a). Thus, the senior BME researchers in our setting enlisted our assistance in devising an educational program that aimed at developing their graduate students into hybrid researchers to meet the goals and challenges of twenty-first century BME. The stated aim was to create "interdisciplinary integration" at the level of the individual researchers.[8] We coded this integration as we saw it enacted in the labs as "hybridization"—hybrid bio-medical-engineering researchers capable of carrying out individual projects with hybrid devices and with the ability to collaborate fluidly with disciplinary colleagues in their work beyond the labs (what we call "boundary agents").

In the BME context then, integration as hybridization takes on the meaning of fitting together, blending or fusing into an inseparable whole, which creates something genuinely novel. One way in which we analyzed the nature of the fusing and its challenges for problem solving was through expanding an emergent category from our coding, "interlocking models," into a major analytical theme. Interlocking models is a multidimensional system-level notion that serves to articulate how components of the lab construed as a distributed cognitive-cultural system are fitted together.

8. They later adopted the characterization of "interdiscipline" meaning "interdisciplinary discipline" for their field. "Many educational programs in BME might be described as 'engineering with a little biology thrown in.' We maintain that practitioners for the twenty-first century need to be trained in a truly integrative fashion. BME is best understood as an 'interdiscipline'; that is, a field that is inherently interdisciplinary. BME is situated at the intersection of three disciplines: biology, engineering, and medicine. All three are essential to the practice of a biomedical engineer" (from proposal submitted for State of Georgia Regents' Award for Best Educational Program, which they were awarded).

Dimensions pertaining to the challenges of interdisciplinary facets of the cognitive practice of model-based simulation with hybrid devices include conceptual ("mental models") and artifactual integration. Model-systems are designed and constructed to comply with interlocking biological and engineering constraints. The daily challenges of both research and learning center on determining the appropriate, selective interlocking of biology and engineering concepts, methods, and materials for the problem at hand.

With respect to interdisciplinary integration, the interlocking models required for conceiving, designing, and experimenting with dish model-systems (as developed through our codes) comprise at least those in Table 2.

The BME kind of interdisciplinary problem-solving requires the researcher to interlock the relevant biological and engineering constraints for creating, experimenting, and reasoning by means of physical simulation models. Throughout the research, problem-solving processes require

Table 2. "Interlocking models" category.

Interlocking Models
Biological and engineering models in the wider community
(as detailed in journals, textbooks, and so forth)
cell biology
biochemistry
neuroscience
electrical engineering
neural engineering
mechanical engineering
Bioengineered in vitro artifact models
dish
animat
hybrot
MEArt
etc.
Researcher mental models of
in vivo and in vitro phenomena
devices qua in vitro models
devices qua engineered models

using various abstractive and evaluative procedures to select and merge relevant constraints. This selectivity enables focusing on features relevant to the problem-solving process while bracketing potentially irrelevant features. For instance, the choice of using only a monolayer of cortical neurons would be revisited if more elements were determined to be relevant epistemically, and the MEA would then also need to be redesigned to accommodate those changes.

4.2. ISB Problem-Solving

ISB is a young field, though it shares objectives with an older systems biology philosophy. A major goal is to develop analyses of complex nonlinear biological phenomena at the system level. The traditional approach of well-controlled experimentation focused on characterizing select components or processes is necessary but not sufficient for investigating how higher-level functionality emerges from myriad interactions at lower levels. The confluence of new kinds of data production and collection (high-throughput) technologies, computational resources (e.g., high-performance computing and novel parameterization algorithms), and the development of curated biological data bases and internet search engines for seeking biological literature has made it possible to bring quantitative and computational methods to bear on the problem of developing an integrative analysis of the behavior of complex biological systems at all levels, from intracellular interactions to ecosystem processes. Finding solutions to the problems the field is posing creates an essential epistemic interdependence (MacLeod and Nersessian 2016; Andersen and Wagenknecht 2013) among the participating fields: various engineering fields, computational sciences, biological sciences. ISB at present does not have a unified vision of what a researcher needs to learn/know to be an effective problem solver. The nature of the problem-solving requires both specialization and collaboration.[9] As with Lab C there are some attempts to develop hybrid modeler-experimentalists, however, in the present situation modelers (mainly engineers, applied mathematicians, and physicists) and experimentalists (mainly molecular biologists and biochemists) need to collaborate. As will be discussed in section 4.3, with little knowledge of one

9. We have been characterizing this kind of interdisciplinary field loosely as a "transdiscipline" but definitions of "transdisciplinary" in taxonomies are vague and often contradictory, and do not quite capture the nuances of ISB. The kind of interdisciplinary integration we witnessed has features of what Peter Galison (Galison 1997) calls "intercalation" where fields keep separate identities and practices while possibly transforming one another in significant ways. But the need for working partly in the field of the other seems not captured by his analysis. "Symbiosis" is perhaps a better characterization of the nature of ISB interdisciplinarity.

another's fields, collaboration is fraught with difficulties. In the present state of the field our research indicates the onus is on the modeler to be the boundary agent, stepping into the biological arena to build their models.

Constructing computational simulation models of complex biological systems is the overarching problem posed by ISB. Interdisciplinary "integration" in the labs we studied is largely achieved by infusing experimental data gathered from a range of disparate sources into the computational models that are built in iterative processes. Ideally, the model output provides both insight and understanding into the system phenomena and hypotheses to guide experimentation. Model-building requires transferring and adapting concepts and methods developed mainly for modeling engineering systems to modeling biological systems, such as modifying wave smoothing techniques from signal processes in telecommunications to smooth noisy biological data. "Integration" at the conceptual level means, as one researcher noted: *"the tasks of this new frontier require thinking beyond linear chains of causes and effects: thinking in terms of integrated functional entities; thinking in systems, networks, and models."* The kinds of modeling problems researchers tackled during our research included response of cancer cells to chemotherapy drugs, sustainable biofuel production, arteriosclerosis as an inflammatory process, and yeast metabolism. The same modeler could be working on cancer today and yeast tomorrow. The Lab G director maintains that modelers can tackle a range of biological problems because they have *"flexibility to recognize shared features of control/regulation across disparate domains,"* which comes from experience with engineering systems. But their understanding of control/regulation needs to be adapted to biological systems. Because the domain is continually shifting, our modelers all maintain that deep knowledge of a specific biological field would not be helpful. Thus, collaboration with experimentalists with deep knowledge of the biology of the problem at hand is critical to the objective of system-level analysis. Since Lab G is the predominant way of working at present, I briefly overview its practices.

Lab G uses laptop computers and builds ordinary differential equation (ODE) models primarily of gene regulatory, cellular, metabolic, and cell-signaling networks. The researchers bring whatever concepts, methods, and bits of theory from systems engineering they find useful to bear on building models of biological systems for which they were not designed. Additionally, these researchers also work on developing new parameterization algorithms in order to overcome the problem of inadequate data. They address problems presented to the lab director by outside collaborators from academia and industry. These collaborators have little grasp of modeling and usually have insufficient data or data of the wrong kind (e.g., steady state instead of time series) to build robust and informative models. The burden is on the modeler to derive the needed data from the literature, but most often they are left with many undetermined parameters. Often it is impossible to get timely new experiments done to check the predictive hypotheses their models yield. The problem-solving processes of one modeler whose goal was to produce a model of lignin production in alfalfa provides a brief exemplar.

Industry bioscientists had been working on converting alfalfa to a biofuel and had created several transgenic species, but these were "recalcitrant" in producing a biofuel. They approached Lab G with a problem: to model the lignin pathway of alfalfa to determine if it is possible to "tweak" it and break down lignin so as to better optimize current transgenic biomass-producing species to produce a biofuel. The modeler's chief target was to build a model that would connect concentration levels of the building blocks of lignin and the key reactions known to be important in the generation of sugars. The researchers would not provide him with all their data since they had not published them (which took another six months) and seemed not to realize the modeler both needed the data to build the model and would not publish them himself. A search of the literature provided data too sparse to model alfalfa, so while he waited the modeler decided to model a closely related woody species, poplar, for which there were more data. He hoped some of what he produced would transfer to the alfalfa model, but this only worked at steady-state (wild-type equilibrium) not for the transgenic species. Building out the alfalfa model now using the collaborator data from seven transgenic species left him with twenty-seven open parameters. He did model optimization for only a few "significant parameters," determined as those that correlated maximally over thousands of model instantiations with changes in the targeted ratio of monomers. The remaining parameters were set to values the modeler deemed "biologically reasonable." In the end, five optimized models that converged on similar math relations for the target variables were found to test well and gave similar predictions (with no guarantee a global optimal was found). With a consistent convergence, he argued the outcome of five well-performing models provided "model validation." What is remarkable is that in the process of getting the model to fit, the modeler needed to hypothesize major changes to the long-established lignin biological pathway. In particular he hypothesized that an unknown factor outside the current pathway is having a significant regulatory effect on it. Lacking biological knowledge, he called the factor "X." This hypothesis piqued the interests of his nonresponsive biological collaborators, who then determined experimentally what that factor was, and together they published these results—a major biological finding.

As witnessed in both our labs, without effective collaborations, lack of biological knowledge and insufficient data increase complexity of the modeling work. The complexity of biological networks includes frequent feed-forward and feedback effects and many elements play multiple roles in a network. Every problem requires modelers to adapt or tailor methodological strategies to transform it into one they have the potential to solve. They are required, themselves, to search through the available biological literature and data bases to build out the biological metabolic and signaling pathway diagrams of the system under investigation sufficiently to inform the modeling process. Usually the researcher starts from a small piece of a pathway provided by a collaborator or found in the literature and then fills it out making "guesses" about "what is reasonable" to add/alter in conjunction with running simulations, with and without pieces, as they build the model. They need to predict what effects a modification of the biological pathway representation will have, and locate where a modification needs to happen to solve the problem. They try to check their guesses with their collaborators, but often find them unresponsive. Further, what resources are to be used in building the model are largely at the discretion of the modeler. Systems biology lacks the established domain theories that in physics-based sciences provide representational resources and methods for building reliable simulation models. In our analysis, we developed the superordinate category "managing complexity" to capture a range of codes that emerged with respect to the challenges researchers face in building simulation models. We expanded this category into a major theme for analyzing, in particular, the cognitive challenges for problem-solving via simulation model-building (Chandrasekharan and Nersessian 2015; MacLeod and Nersessian 2013b; MacLeod and Nersessian 2015). Every model is a strategic adaptation to a set of constraints ranging from those of the complexity of the biological problem to the fact that simulation experiments and real-world experiments take place on vastly different time scales to the human cognitive constraints to the challenges of collaboration. Most of these constraints cannot be mitigated, but our interviews with modelers and experimentalists led to insights into small learning interventions we thought could be useful to enhancing collaboration.

4.3. Challenges and Strategies for Collaboration in ISB

Across interdisciplinary fields generally, the dilemma is whether to educate researchers as specialists or polymaths to meet their problem-solving demands. Our investigations have led us to see the response to the "specialists or polymaths dilemma" as lying in compromises that are adapted to the specific situation of the research. Cognitive ethnography provides a unique means to investigate the details of these compromises and adaptations as they are made in the problem-solving process. In ISB problem-solving, modelers and experimental collaborators both have the objective of producing a computational model/simulation that should be biologically informative, especially with respect to providing experimental guidance. Our focus has been on modelers but our analyses also have been directed towards the interdependence with experimentalists and what makes for effective collaborative problem-solving (cognitive and cultural dimensions). Although the requirements for effective problem solving in these contexts lie more towards the specialist end of the spectrum for both, we found that effective collaboration requires more than cursory acquaintance with the collaborating field. Yet what we witnessed in the labs we investigated (and have been told by numerous other researchers is the current state of the field more globally) is that modelers have little understanding of the possibilities and constraints of experimental practices and experimentalists have little understanding of the nature and requirements of model building—and neither has an understanding of the epistemic values of the other. Although the bimodal route of Lab C, where modelers learn to conduct their own experiments in the service of model building might seem the way to go, the Lab G director pointed out that there is a "*philosophical divide among system biologists*" as to whether modelers should conduct their own experiments. Each, as he said, is a "*full time job, and if you don't want to do two full time jobs, something will suffer from it*." Even the bimodal researchers in our study, while recognizing the advantages of creating their own experimental data, expressed that concern, and some said they envisioned having students in their labs focused on one or the other.

Our strategy was to determine, from the nature and challenges of the problem-solving practices we witnessed and from those discussed in interviews, what, at a meta-level, are some learning requirements for effective research. Then, because each side stressed the limited time available to spend on work that was not strictly modeling or experimenting, we needed to determine how such learning might be achieved using a "small interventions, big payoff" approach. The problem-solving practices around the theme of managing complexity, collaboration, and many others that could be noted, entail significant demands for participating in the cognitive-cultural systems of ISB research. Our analyses identified interrelated characteristics that lead to effective collaboration and problem solving: 1) cognitive flexibility, 2) interactional expertise, and 3) epistemic awareness. From an epistemological perspective, these characteristics are epistemic virtues for conducting good interdisciplinary science, that is, interdisciplinary virtues. According to Linda Zagzebski, a virtue is "a deep and enduring acquired excellence" motivated by and reliably successful at achieving intellectual ends (Zagzebski 1996, p. 137). She asserts, following Aristotle, who first introduced the notion that there are intellectual as well as moral virtues, that virtues are acquired by practicing them. What we are calling interdisciplinary virtues have socio-cultural as well as cognitive dimensions in that cultivating them promotes the development of collaborative communities of researchers. We proposed to investigate if these specific interdisciplinary virtues could be cultivated through targeted learning experiences.[10]

Cognitive flexibility, in this case, is the ability to see or understand a problem from different perspectives, which facilitates both the kinds of adaptation needed to transform a complex problem into one that can be solved, as well as collaboration. Strictly speaking in developmental psychology cognitive flexibility is an executive function that develops as the prefrontal cortex develops and not through learning. However, in educational fields the term is being used broadly in relation to learning as we use it (see, e.g., Spiro et al. 1994). Interactional expertise is a notion introduced by Harry Collins and Robert Evans (Collins and Evans 2002) to characterize the nature of the expertise required of sociologists doing fieldwork. It marks a division between the development of conceptual understanding of the practices of collaborators, which enables each to engage linguistically with the practices, and the ability to perform the practice. Collins, Evans, and Michael Gorman extended the notion to interdisciplinary collaboration, and stress, additionally, that it is also "tacit knowledge-laden and context specific," (Collins, Evans, and Gorman 2007, p. 661).[11] "Epistemic awareness" is a term we introduced to capture the epistemological dimension of problem solving (Osbeck and Nersessian 2017; Nersessian 2017b). It comprises a metacognitive awareness of epistemic identity and epistemic values and the role these play in the research. Epistemic awareness is the ability to reflect both on the epistemic dimensions of one's own discipline and research practices and on those of the collaborators.

These virtues are not normally emphasized in disciplinary contexts. Generally, the skills associated with them are not easily acquired on one's own. The development of a full "hybrid" curriculum in BME cultivates all of these interdisciplinary virtues (and more) through processes of learning domain knowledge, methods, concepts, and epistemic dimensions of the participating fields, and using these in problem solving over a number

10. These are not a complete set of interdisciplinary virtues, just what we found to be the most important for promoting effective research collaboration. For instance, resilience in the face of impasses is another we identified, since in the kind of pioneering science we witnessed failure and impasses are ever-present. Another is methodological versatility, having multiple methods in one's toolkit. Further, although I discuss the ISB case here, we found that these characteristics promoted good interdisciplinary research in both BME and ISB. The differences lie in the ways in which they are cultivated given the current states and aims of the fields.

11. How to distinguish the notions of interactional and contributory expertise has been the subject of an extensive debate in the literature that we need not consider for our purposes (see, e.g., Andersen 2016; Collins and Evans 2015; Collins, Evans, and Weinel 2016; Goddiksen 2014).

of years. These researchers can be independent BME investigators, as we saw in our studies, but also can act as boundary agents in collaborations with experimentalists, medical researchers, and engineers who are not BMEs. At least in the current state of ISB (and quite possibly a necessary feature of this kind of research), the "hybrid" curriculum is not desired as modelers and experimentalists need deep training in one discipline, i.e. sufficient to be solely a computational scientist (engineer, applied mathematician) or an experimentalist (bioscientist, medical researcher). But to realize the full potential of ISB requires some degree of penetration of each kind of researcher into the field of the other. At a minimum this means modelers learn to adapt what they know to complex biological problems across a range of areas, as well as learning to know what biological information they need and how to seek it, and experimentalists learn to know enough about the nature and potential of modeling biological systems to produce the kind of data needed and to know, as one experimentalist put it, "*the right kinds of questions*" to ask in furthering a collaboration. Within our project we experimented with some minimalist learning interventions aimed at developing the noted characteristics early in order to mitigate some of the struggle of collaboration.

Because the model is central in ISB problem solving, the engineers/computational scientists are taking the lead in moving the field forward. As we saw, modelers do more than just feed biological data into a model and provide predictive outcomes to experimentalists. They have to understand how to search the literature to find relevant data and build out the biological pathway, both of which require discernment and judgment about biological phenomena, what it is feasible to do in experimentation, and the reliability and relevance of the data, as well as the ability to discuss problems with experimentalists as they are developing the models. On the other side, sophisticated biological experimentation requires equally specialized training, but to be able to collaborate effectively with modelers, we found that experimentalists need to understand the basics about how a model is constructed so as to, at the very least, devise experiments to produce the kind of data modelers need to construct and test, experimentally, informative models.

I can only report briefly on two interventions we undertook with the newer researchers in our labs that proved quite successful. On the modeling side, as we saw, modelers develop cognitive flexibility not through taking numerous biology classes, but through efforts to recast phenomena from disparate biological domains in terms of features of engineering systems, especially control and regulation. What biology classes they do take are usually more theoretical or bioinformatics classes without labs, so they have little understanding of how biological data are produced, which creates a major impediment to collaboration. We were told that a full semester rotation in a biology research lab would take too much time away from modeling work. We proposed an intensive "experimental summer camp" experience for modelers, in which they spend a month in an experimental lab collaborating with them engaged in a real piece of research to learn hands-on what it takes to design and execute experiments, as well as something of the way experimentalists think about biological phenomena. The modelers were not absolute novices to biology since they had been conducting the literature searches and building the pathways as we discussed above. However, they had no idea of the complex environment of the biological lab or sense of the nature and costs (time and financial) of the experimental practices through which data are collected and analyzed. The students described the following gains: increased self-confidence, comfort with experiments, and knowledge of experimental procedure; enhanced ability to anticipate the needs and questions of experimentalists, to understand experimentalist reasoning processes, and to evaluate experimental literature; and new appreciation for the difficulties/constraints of experimentation and, interestingly, for why their advisor kept telling them to model trends, not every data point—data can be noisy.

On the experimentalist side, learning about model-building cannot be achieved by visiting a modeling lab. Hands-on experience requires a more structured approach. Fortunately, the department was interested in developing a new introductory graduate course in biosystems modeling in which students from the biological sciences would develop conceptual understanding of modeling and basic modeling skills while working on systems biology problems with engineering/computational students, who would be learning to adapt their knowledge and skills to modeling biological systems. We worked with both lab directors through several iterations of the course (Voit et al. 2012). Although several biology students have taken the course, during our study only one was from our labs. Notably, she had had an early, unsuccessful research collaboration with a modeler. She described a new awareness of the affordances of models and a new understanding of math as a flexible tool for "*actual real world application*." She reported being a "*changed woman*," with respect to her attitudes about modeling after the class. Notably, she explained that now she understood "*what he needed*" and not only "*what questions she should have been asking*" but "*what questions he should have been asking*" her.

Although only a start, our findings suggest the value of specific, time-limited learning experiences for increasing cognitive flexibility, epistemic awareness, and interactional expertise, which contribute to more effective collaborations, better reasoning, greater awareness of the affordances of methods, and enhanced ability to reflect on one's own perspective and that of the other. In sum, even small, targeted learning interventions can have big payoffs to benefit collaboration and thus problem-solving potential in the ISB research space.

5. Conclusion

The goals of our project were multifaceted, but a major one was to investigate emerging interdisciplinary cognitive and learning practices around problem-solving in frontier research laboratories in the bioengineering sciences. Cognitive ethnography was necessary to fathoming how interdisciplinary problem-solving is enacted *in situ*. We had no hypothesis about the nature of the inderdisciplinarity we would encounter when we entered the BME labs. What we learned from our initial interviews, observations, and discussions with faculty constructing the fledgling BME program was that: 1) in these labs engineers were tasked with conducting basic biological research through constructing living physical simulation models, part cells and cellular materials and part engineered materials, and 2) faculty wanted to build an educational program that would require students to "integrate" all three dimensions of BME from the outset. Section 4.1 discussed briefly how hybridization is achieved through the conceptual, methodological, and material integration required to design and construct physical model-systems and conduct experiments by simulating selected biological processes. Based on our analyses we argued that this form of interdisciplinary problem-solving requires learning to build interlocking models along many dimensions. We participated in developing a novel curriculum to foster this kind of problem solving.

We began our investigation of the ISB laboratories with preliminary research for preparing the grant proposal, which led to a hypothesis that problem solving in these labs could not be characterized as hybridization of the sort in BME. In ISB we needed to investigate the implications of importing systems engineering concepts and high-level computational and mathematical methods developed for other purposes into the biological sciences. We found that the nature of the systems-level problems formulated in the emerging ISB field creates an epistemic interdependence among the collaborating members of the fields: engineering, applied mathematics, and biosciences. Problem-solving requires both collaboration and that at least some participants operate beyond their disciplinary practices and within those of another participating field with little training to do either in the present state. Section 4.2 discussed briefly how it falls on the modeler to manage the complexity of the problem-solving process, including determining how to adapt engineering concepts and methods to biological problems and how to find the biological data necessary to build, simulate, and test their models, as well as finding ways to help experimentalists understand their models, which at this point in time are seen as "black boxes," and understand the data needs for building and testing them. Section 4.3 discussed the chief interdisciplinary virtues we determined from our investigation to be required for effective collaboration and our minimalist strategies for fostering more effective collaboration in ISB.

Our cognitive ethnographic research establishes that a method that was pioneered for examining cognitive practices in areas where problem-solving tasks and goals are largely well-defined can be extended fruitfully to the open-ended problem-solving environments of emerging interdisciplinary sciences and engineering. Indeed, cognitive ethnography provides the primary means for developing fine-structured analyses of varieties of interdisciplinary as they are enacted in real-world, real-time situations of practice. It provides a unique level of granularity for understanding the nature and challenges of these exploratory, incremental, and nonlinear problem-solving practices, their development, and the epistemic principles guiding them. Insights gleaned from intensive case studies can be used to develop strategies for facilitating specific varieties of interdisciplinary learning, integration, and collaboration. Findings from cognitive ethnography can also be used to enrich and validate findings from more global methods of studying interdisciplinary such as bibliometric analyses of patterns of interaction and influence (see, e.g., Roessner et al. 2013).

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