

WORKING ALONE TOGETHER: COORDINATION IN COLLABORATION ACROSS DOMAINS OF EXPERTISE

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This study develops theory on how coordination occurs in collaboration across multiple expert domains. Ethnographic fieldwork at two top U.S. universities explored the emerging field of systems biology cancer research, an extreme case of cross-functional work. Scientists make diverse contributions compatible by engaging in the coordination practices of joint assessment and consultation and in the collaborative practices of counterprojection and alignment. The study advances a process model of coordination as an ensemble of different types of practices that drive collaboration across domains. Insights into how experts coordinate work within domains and how this affects temporal dynamics of collective work have implications for the literature on cross-functional coordination, innovation, and practice.

Coordinating specialized work that is carried out in different divisions of labor represents one of a firm's most formidable challenges. Cross-domain collaboration is often the source of innovation and knowledge development; for example, cross-functional teams that pull diverse specializations together develop unique capabilities to address complex tasks. An increase of complex tasks (Spitz-Oener, 2006) and specialization (Alvesson, 1993; Becker & Murphy, 1992) make the question of how coordination occurs in teams of diverse experts particularly relevant to the study of organizations. Complexity and expertise diversity make coordination both more necessary and more precarious. Complex tasks often imply novelty that undermines analysis and foresight; and diverse perspectives invite contestation about how to accomplish tasks. To coordinate this type of collective work, traditional means such as protocols, schedules, and routines become largely inadequate because they rely on standardization. Instead, coordination may be more accurately represented as an ongoing process of addressing emerging and potentially unprecedented circumstances.

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Scholarly conversation on such coordination of collective work across specializations is built on survey- and simulation-based studies of why and how coordination matters in cross-functional tasks and practice-based research into how experts navigate domain interfaces. In short, coordination is critical for integrating diverse contributions, but costly because it requires extra work at the boundary between domains. What has escaped scholars' attention is that experts often spend considerably more time conducting specialized work apart from each other than they spend together with their collaborators from other domains. Consequently, current understanding of cross-functional collaboration is inadequate and incomplete inasmuch as it does not include coordinative efforts that experts might make during domain-specific work to align contributions and how these efforts complement the coordination process. Because even "small differences in efficiencies can generate significant variations in profitability and survival" (Kogut & Zander, 1992: 393), new insights into cross-domain collaboration are needed. Yet practitioners often do not know how to support such collaboration (Hansen & Nohria, 2004; Holland, Gaston, & Gomes, 2000).

This study draws from ethnographic fieldwork in systems biology, a newly emerging approach in the biomedical sciences to areas such as cancer research, to explore how scientists bring forth specialized contributions and make them compatible across disciplines. Systems biology takes the challenge of cross-domain collaboration to the extreme as a high degree of domain diversity, novelty, and complexity make the problem of coordination salient. I develop a theoretical framework of expertise and practice to conceptualize diverse specialization before describing my setting and fieldwork.

My findings are that scientists work consecutively and iteratively on projects and employ a set of shared practices to link emerging contributions across temporal and domain differences. As a key insight, this study highlights ways in which experts realize collaboration through coordinating what they do when working apart from each other. Coordination is modeled as an ensemble of different types of practices that drive the process of cross-domain collaboration. This study showcases the extraordinary sophistication, dedication, and technology that knowledge workers bring to bear upon extraordinarily complex problems that are some of the most vexing in society.

COORDINATION AND THE DIVERSITY OF EXPERTISE AND PRACTICES

Collaboration among diversely specialized parties is appropriate for tasks requiring unique types of knowledge that one party could not develop alone (Cummings & Kiesler, 2007). Coordination—managing interdependencies among activities (Malone & Crowston, 1994)—is essential to collaboration (Jassawalla & Sashittal, 1998) and teams (McGrath & Argote, 2001). For example, without sufficient coordination, specialists may be unable to leverage their expertise (Bunderson & Sutcliffe, 2002). Differences in understandings of how a problem should be solved, which are naturally present in cross-domain work, may lead to incompatible actions by collaborators (Cronin & Weingart, 2007). Two streams of inquiry in the literature have addressed the relationship between coordination and diverse expertise: studies of cross-functional teams and practice-based studies of coordination.

The first stream of inquiry, which is based on surveys and simulations, supports the central role of coordination for collaboration in cross-functional teams. Coordination improves team performance in innovative tasks (Hoegl & Gemuenden, 2001) through informal and participative mechanisms (Olson, Walker, & Ruekert, 1995) and through timely dispersion of project-related information (Hauptman & Hirji, 1999). Coordination is less effective in diversely specialized teams than in multifunctional teams (Lafond, Jobidon, Aube, & Tremblay, 2011). Diversity in functional backgrounds implies nonoverlapping knowledge and expertise (Bunderson & Sutcliffe, 2002), making coordination at once more necessary and more difficult. Expertise is the “specialized skills and knowledge that people bring to the team’s task” (Faraj & Sproull, 2000: 1555). Diversity in expertise raises coordination needs above and beyond administrative concerns such as scheduling (Faraj & Sproull,

2000). For example, collaboration between scientific disciplines incurs considerable coordination costs (Cummings & Kiesler, 2007).

Surveys and simulations may not be able to adequately capture coordination in diverse teams, however. Measures of coordination used in previous research have been straightforward; they include measures of information technology and the power of project leaders (Hauptman & Hirji, 1999), structure and synchronization of individual efforts within teams (Hoegl & Gemuenden, 2001), cross-domain exchange and shared resources and activities (Cummings & Kiesler, 2007), and timely satisfaction of intertask dependencies (Lafond et al., 2011). Although such measures confirm that coordination occurred, they cannot explain how it was accomplished (Okhuysen & Bechky, 2009). Since coordination is more adequately understood as the ongoing accomplishment of managing interdependencies in collective work (Faraj & Xiao, 2006; Malone & Crowston, 1994; McGrath & Argote, 2001), retrospective and snapshot measurements do not provide rich enough data to sufficiently explain how the process unfolds.

The second stream of enquiry in the literature employs direct observations with a focus on occupational practice to further illuminate coordination in cross-functional work. Studies of how diversely specialized groups deliver automotive parts (Carlile, 2002, 2004), machines (Bechky, 2003), online advertising (Kellogg, Orlikowski, & Yates, 2006), and emergency care (Faraj & Xiao, 2006) have shown that actors use special approaches to bring diverse contributions together. Examples are cross-boundary intervention, representing domain-specific knowledge, and breaking protocols that no longer correspond to a situation (e.g., Faraj & Xiao, 2006). These findings suggest that collaborating across domains requires, in addition to specialized work, labor in the form of coordination practices (Faraj & Xiao, 2006; Kellogg et al., 2006). Coordination work consists of making relevant domain-specific details transparent and arranging empirical manifestations of contributions according to a shared objective.

Collectively, these studies emphasize the navigation of domain interfaces in the form of boundary objects (Carlile, 2002), product hand-offs (Bechky, 2003), trading zones for contributions (Kellogg et al., 2006), and expertise management among communities of practice (Faraj & Xiao, 2006). Less attention has been paid to how experts collaborate when working in their specialized domains. Both Bechky (2003) and Carlile (2002) suggested that experts have to adjust their work, but they did not further examine these adjustments. Considering

changes that experts introduce in their work when collaborating with others is critical for more fully understanding how coordination occurs in collective work. Such an examination elucidates experts' endeavors to collaborate that stand apart from the specialized work they conduct in their own domains. Lastly, this consideration could also provide further clues as to the role of individuals in making collaboration across domains of specialization more or less likely to succeed.

The present study builds on the stream of practice-based coordination. It recognizes practice as an observable phenomenon, an approach that enables closing a gap in research between theory and real-world occurrence (Orlikowski, 2010). Practice describes the specialized activities that professionals pursue in their occupations (Clancey, 2006; Cook & Brown, 1999). A group of practitioners share practice in a number of dimensions, such as apprenticeship and evaluation standards (Cook & Brown, 1999), purposefulness (Sandberg & Dall'Alba, 2009; Schatzki, 2006), terminology (Orr, 1996), and artifacts, including technology (Hutchins, 1990; Orlikowski, 2000). These elements become more prominent with increasing specialization. For example, science studies describe training, specificity of research outcomes, discipline-specific languages, and costly laboratory equipment (Fujimura, 1996; Knorr-Cetina, 1981, 1999; Latour & Woolgar, 1986). Scientists are specialized to a degree that qualifies the sciences as systems of experts (Knorr-Cetina, 1999). I use the term "expert practice" for the specialized and continuously evolving ways of task accomplishment that are particular to any domain and shared in a community. The term additionally serves to identify forms of work that are not domain specific but are as important as domain-specific work for reaching collective goals.

This article advances a process view of coordination in collective work that highlights efforts in the form of changes experts make to expert practice in response to requirements of collaborators. Collaboration denotes collective work in which coordination is not simply nominal, but integral; that is, coordination not only informs whether and when, but also *how* specialized work takes place. Labor that goes above and beyond the expert practice that actors conduct in a noncollaborative setting results in collaboration work. I argue that novel work that warrants a tight integration of highly diverse contributions gives rise to "collaborative practices" that experts share across domains. "Counterprojection" and "alignment" enable scientists to direct their expert practice so as to create correspondence between

contributions-in-the-making. Collaborative practices, in contrast to expert practice, are not based on domain-specific expertise and are therefore harder to track. The notion resonates with Swidler's (2001: 86) proposition of a type of practice that anchors others, structures social domains, and coordinates actors' actions.

As a corollary, this study develops a process model that captures the interplay of different types of practices that accomplishes coordination, and associated temporal repercussions for collective work. Expert practice takes longer as scientists build novel expertise by learning how to make contributions that will match those from other disciplines. Scientists from diverse disciplines take turns contributing to a collective task, building on insights from collaborators. As phases of specialized work alternate between domains, collaboration unfolds in asynchronous intervals so that scientists have to connect emerging contributions not only across disciplines, but also over time. Coordination occurs through the combination and arrangement of three types of practices: expert practice that yields specialized contributions, coordination practice that arranges contributions across domain boundaries, and collaborative practice that modifies expert practice so contributions become compatible. Evidence from my fieldwork helps me tease apart these practices and track their interaction and distribution over time.

METHODS

A steady increase in scientific teamwork over the past four decades (Wuchty, Jones, & Uzzi, 2007) and calls for research into team science (Börner et al., 2010; Robertson, Martin, & Singer, 2003) make cancer research a compelling setting in which to study coordination in teams of experts, particularly because systems biology constitutes an extreme case of cross-functional work. Efforts toward theory development rely on theoretical sampling (Eisenhardt & Graebner, 2007)—that is, a setting is selected to fit a described problem. Extreme settings make a phenomenon "transparently observable" (Pettigrew, 1990) in that they exhibit the properties of interest more *richly* than other settings (Weick, 2007). A pattern out of the ordinary helps place into perspective data that average across large, generalizable categories (Starbuck, 1992). For example, asked about the generalizability of his academic setting, Bourdieu maintained that generality derives from particularity inasmuch as it plots the possible in a given setting (Bourdieu & Wacquant, 1992). Cutting-edge scientific research offers an op-

portunity to extend understanding of collective work across highly diverse domains of expertise.

Systems biology constitutes an extreme case of cross-domain collaboration that presents a challenge to coordination in three ways. First, experiments and computational models require a high degree of expertise. The scientists studied here pursued or had pursued doctoral training of four to six years and at least one but not infrequently two postdoctorate trainings of two to three years each. Systems biology cancer research requires a finely tuned integration of experimental data and models, but very few scientists master both. This polarization emphasizes domain diversity (Harrison & Klein, 2007) that increases the need for coordination (Cummings & Kiesler, 2007). Second, measuring and modeling cellular processes in systems biology is a complex task (Weng, Bhalla, & Iyengar, 1999), and coordinating for complexity is very difficult (Carlile, 2004). Third, emerging insights from collaborators and publications keep performance requirements in flux and force scientists to continuously reassess their ways of working as they inch forward into uncharted territory. Task novelty calls into question what everybody has to contribute (Carlile, 2004), but coordination depends precisely on the ability to anticipate work (Okhuysen & Bechky, 2009). The scientists in this study operated in a highly competitive environment in which rates of acceptance for publication in top-tier journals were below 8 percent and funding rates at the NIH between 5 and 15 percent. Yet their work has appeared in *Cell*, *Nature*, and *Science* and is NIH funded, suggesting that they do something right regarding cross-domain collaboration.

Research Setting

The study took place at two top universities in the northeastern U.S. that each ran a systems biology research program spanning four laboratories and one lab at a pharmaceutical company. The programs had won prestigious NIH grants of \$10 and \$18 million respectively, both of which were renewed in the same amount. Their aim was to understand and predict cancer evolution by measuring and modeling cell signaling, a problem of significant complexity. Human cells contain well over 30,000 proteins that are thought to govern cell behavior such as growth or death through signaling pathways. Cell death (apoptosis) is desirable when a cell malfunctions, but cancerous cells avoid it and continue to divide and proliferate. Signaling pathways are measurable when activated but may take alternative trajectories, intersect, and coincide with other activated pathways. Many interacting

variables that behave erratically create *disorganized complexity*, and only a large enough quantity of data allows predictions of the overall system (Weaver, 1948; Weng et al., 1999). High-throughput technology is necessary to measure many data points, as are computational techniques to analyze and model the data. The prospect, which still may be decades away, is to reliably predict cancer development and customize treatment to individual patients.

Two to seven scientists collaborated on 12 projects that formed the core of my research. They had backgrounds in chemistry, engineering, mathematics, computer sciences, physics, immunology, and molecular biology. Scientists collecting biological data specialized in one or two experimental techniques and a specific subsystem of the cell. Those analyzing data primarily worked with one type of computational model.¹ Both methodological approaches entail highly refined scientific practices that require a deep knowledge of the literature, a great amount of skill, and great ability to focus. Yet the nature, appearance, and outcomes of experimental and computational work differ significantly, as an analysis will reveal.

Ethnographic Research

Ethnographic fieldwork including observations and interviews has been applied in science studies (e.g., Knorr-Cetina, 1981) and is suitable for several reasons. Ethnography thrives on an in-depth mapping of how things work in organizations (van Maanen, 2011; Watson, 2011). This is accomplished mainly through attention to contextual detail that increases the accuracy and relevance of research (Sandberg & Tsoukas, 2011). Taking an ethnographic approach, I sought to capture how scientists engaged in the “relational whole within which they carry out their tasks” (Sandberg & Tsoukas, 2011: 346). Practices constituted the unit of analysis (Nicolini, 2011) as manifestations of work. The time frame allowed for my immersion into the field together with my learning about two sets of highly refined scientific practices.

I first studied laboratory practices in cancer biology part-time for six months. The next step was gaining access to two research programs in systems biology that involved multiple labs and the disci-

¹ Computationalists also perform experiments when modeling (so-called *in silico* experiments). The differentiation between experimentalists and computationalists in this article refers to wet lab (based on living cells) experimental practice versus modeling practice.

pline of computational science. As my setting expanded, I moved to full-time research for 12 months. My focal lab was relatively large, with more than 25 staff members. This size is uncommon not only because systems biology is quite new, but also because managing a large group of scientists from multiple disciplines taxes the expertise and financial and spatial resources of a principal investigator. The lab was equipped with artifacts consisting of technology and research material (cell lines, enzymes, etc.) approximating \$2 million and \$1 million in value, respectively. I was introduced as a doctoral researcher studying cross-disciplinary collaboration, a topic that was well received as the scientists considered the social aspect of their work important but unaccounted for in the natural sciences. For all practical purposes I was recognized as a lab member. I was given an ID card, a desk in the main office, and access to the lab “wiki” and internal documents such as grant applications. My name was added to the e-mail list and my picture to the photo gallery of staff by the lab entrance. I also went to social gatherings outside the labs with lab staff. At the end of my study, I presented part of my work—a model of cross-domain knowledge development (Bruns, 2012)—at one of the weekly meetings.

Data Sources

Observation. I worked at the main office, among the computationalists. The experimentalists were in an adjoining lab space, allowing me to observe how they conducted their experiments. I took notes on a notepad so that I could follow the scientists moving about the lab. I mostly stayed in the background but occasionally asked questions about details that had caught my attention. I wrote down what individuals said verbatim as much as possible and described in detail what they did. Field notes were transcribed later in the day. At three weekly meetings associated with the two research programs, I connected with scientists from other labs and arranged times for shadowing them. I used my laptop to take notes, as did other attendees, at these meetings, at three regional and national conferences, and at smaller project meetings. Although my attention was initially directed toward understanding systems biology, some terminology, and relevant scientific practices, I became increasingly interested in how scientists moved work forward across two highly diverse disciplines.

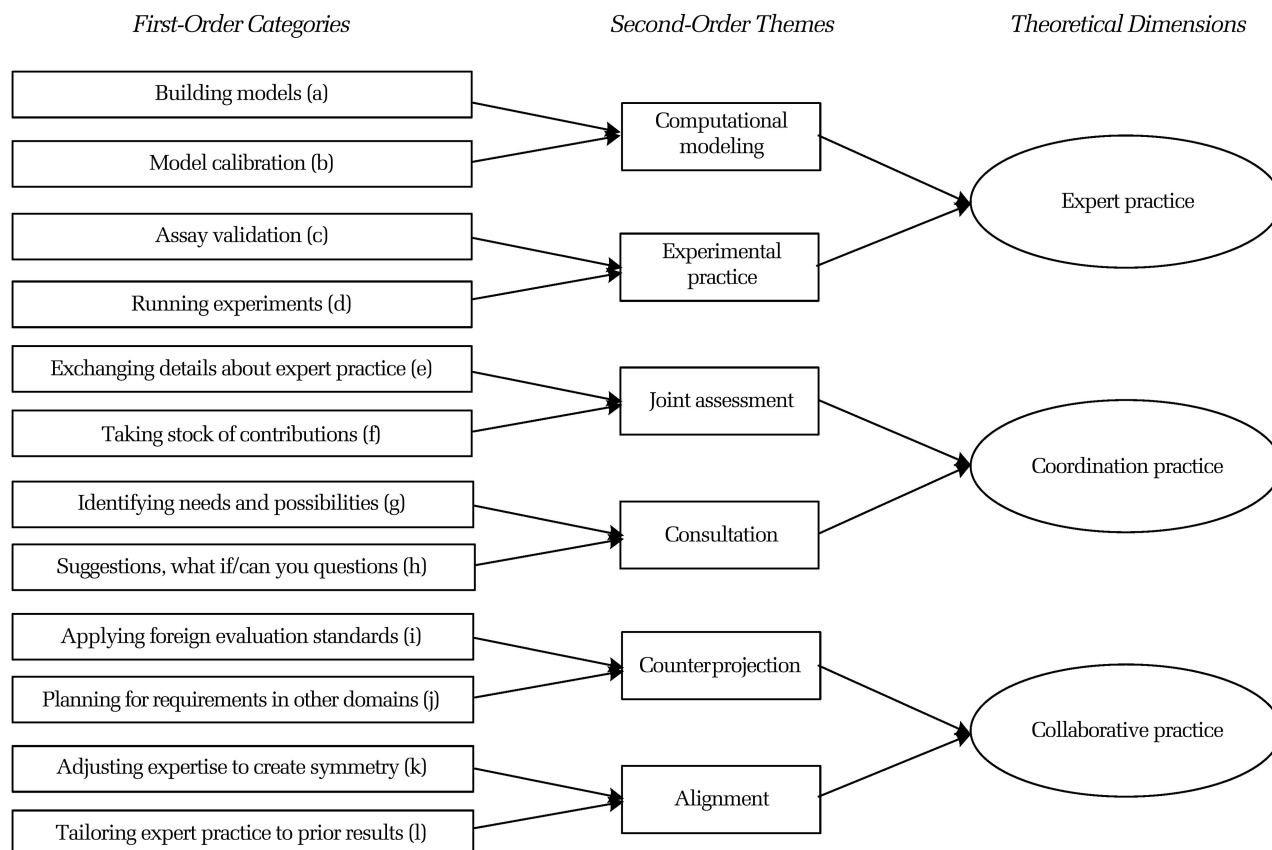
Interviews. I conducted 20 informal and 48 formal interviews most of which took between 60 and 75 minutes. For formal interviews I used small meeting rooms at the university to limit back-

ground noise. I asked scientists to explain their experimental or computational practices, how they became involved in joint projects, how these were moving along, how they evaluated their collaborators’ work, and what topics they discussed in their project meetings. In particular, I was interested in how the work of their collaborators affected their own work. In this fashion, I complemented the observational data I collected relating to the projects. I was able to trace back lines of research to the very beginning of the two research programs. A professional transcribed the interviews.

Analysis. I generated 170 documents totaling over 750 pages of single-spaced text that I uploaded into Atlas.ti, a qualitative data analysis tool. When observations confirmed the pattern of coordination in cross-domain collaboration rather than yielding new insights, I considered data collection complete. I began analyzing my data as they became available to check and refine emerging understandings, using grounded theory (Strauss & Corbin, 1998) and applying line-by-line coding to interview transcripts, observation field notes, meeting reports, and written archival material. I coded for computational and experimental practice, such as technology, assay validation, training, and descriptions of projects and goals. Sorting through records of conversations, I identified patterns and mechanisms that enabled the construction of correspondence across domains. I used disciplines, data sources, and projects to triangulate evidence. Conceptually related codes such as “what if” and “can you” questions led to categories that in turn informed different types of practice.

Figure 1 shows the first-order categories, second-order themes, and their aggregate theoretical dimensions. In my analysis, I distinguished between practices that were discipline specific and those that were shared across disciplines and mapped how they correlated throughout the process of collaboration. After establishing that expert practice occurred in diverse locales and at different times, I examined how scientists endeavored to mend those differences. I identified the coordination practices of joint assessment and consultation, which operate at domain interfaces, and the collaborative practices of counterprojection and alignment, which operate within domains. Counterprojection implies incorporating standards and requirements from another domain into the planning and evaluation of one’s expert practice. Alignment is modifying one’s expert practice to meet the requirements of another domain. These practices are shared across domains and over time. Anecdotal evidence of failed projects further confirmed my argument that these practices supported coordination in cross-domain

FIGURE 1
Model of Data Structure



collaboration. Next, I present findings addressing the fundamental separation in specialized work that scientists conducted in their respective disciplines to make contributions, before turning to the shared practices of bringing contributions together.

FINDINGS

The expert practices of laboratory experiments and computational modeling were so time intensive, exacting, and refined that scientists spent the majority of their time working apart from each other. They worked in the laboratory or at their computer or read up on the relevant literature. The degree of expertise required to operate proficiently in these disciplines largely prohibits a joint application of expert practice. Although a description cannot accurately reflect the many variations in experimental and computational expert practice, a comparison of how the scientists worked within domains (Figure 1, a–d) is necessary to understand their efforts at coordinating their work when collaborating.

Comparing Expert Practices

Laboratory experiments consisted of many repetitive steps, such as administering a stimulant and measuring cellular outcomes several times in dozens of samples in a completely standardized way contrived to control variation. Standardization required establishing an experimental protocol (assay validation) that could take a year or longer, as well as meticulous preparation and ongoing care of living cells and experimental environments. One example is use of the technology Bioplex, which identifies proteins with the help of microscopic beads that are coated with antibodies. Different proteins attach to disparate beads, where they are detected by scientists using a second set of antibodies. A pattern of fluorescent emissions that can be counted to quantify cellular reactions emerges. Over weeks, experimentalists prepared large samples of various cell types with a range of drugs in different concentrations before they could run the experiment that would take another week.

Computationalists wrote programs to mathematically capture biological data in models based on

principal component analysis, partial least squares regression, Boolean logic, and networks of differential equations. Various modeling tools provided desirable model features but were difficult to integrate and required translations across interfaces. The goal of a model is to achieve an acceptable trade-off between fit with the data and model generalizability. Computationalists continuously worked on improving model-data fit (model calibration). For example, they used a portion of the total data to check how well the model predicted the remaining data. Changes to protein relationships to improve fit implied tracing a protein throughout the complete code, for instance. As it was unlikely that one fit described the data set in the best possible fashion, computationalists sought to identify families of fits in order to analyze similarities and differences in how they described the data and concurrently reevaluated the model.

Table 1 illustrates critical discrepancies between expert practices. Laboratory experiments are bounded in time—that is, good practice dictates collection of same-condition, same-time data. Computational models depend on not external but internal timing, such as integrating data collected 30 seconds into an experiment with those collected after a half hour. The scope of control is limited in experiments. For example, the air in a pipette, which cannot be controlled, affects measurement values. Computational models, in contrast, are fully controllable. Here, scientists wrestled with the uncertainty and potential inaccuracy of biological data as well as the question of which experimental details to include to capture characteristic

events without overspecifying the model. I first consider coordination at domain interfaces before returning to expert practice and the question of how scientists made their contributions compatible when working within domains.

Collaborating When Working Together: Joint Assessment and Consultation

Scientists frequently helped peers in their own discipline with expert practice, a regularly occurring phenomenon in science (Knorr-Cetina, 1981). They spent time with experts from other domains during conferences, weekly meetings, and project meetings to discuss findings from expert practice and to solicit feedback. When working together on expert practice and in meetings, scientists would engage in joint assessment and consultation. Joint assessment consisted of establishing a shared interpretation of preliminary contributions. Consultation linked this interpretation to specific possibilities of expert practice. Yet coordination practices yielded a different dynamic during expert practice with peers than they did at meetings with collaborators from another discipline, as the following comparison shows. The first excerpt from my field notes (Table 2) exemplifies how two experimentalists handled the many samples needed for a reading with Bioplex technology. The reading was unexpected, which caused distress: not only did the scientists spend weeks producing the samples, but also this experiment costs \$40,000. Time and money were at stake.

TABLE 1
Comparing Expert Practices

Characteristic	Experimental Practice	Computational Practice
Scope of control	Experiments depend on living matter that is responsive to many variables that cannot be controlled or even identified.	Models are fully controllable.
Failure	Experimental failure may remain inexplicable. Failure requires repeating the entire experiment. For some types of experiments, 30 percent error is normal.	Mistakes can be identified through tests and are traceable in the code of the model. Mistakes are fixable. Mathematics is based on accuracy.
Technology	A host of physical artifacts is needed for laboratory experiments.	Artifacts such as programs are virtual and allow for remote work.
Temporality	Stringent timing of experiments is necessary. Timing is critical for experimental outcome.	Work can be (dis)continued at any time. Timing does not play a role for the outcome of models.
Logic	Internal: Experiments are designed so that it is apparent when they do/do not work. A well-thought-through experiment that works confirms the underlying hypothesis.	External: There is no clear demarcation between an acceptable model and one that should be rejected. A model can always be improved. A model that accurately reflects experimental data does not automatically reveal the causal biological mechanism. Further analysis is necessary to identify the critical parts of the code.

TABLE 2
Joint Assessment and Consultation during Experiments

Field Notes: Experimental Breakdown	Coordination Practice
[1] Steven: "Good?"	Joint assessment [1–4]
[2] Alex [distressed]: "Bad, very bad. There's no beads."	Consultation [4–8]
[3] Steven [looking at screen]: "They're all aggregated. You had way too many before."	Joint assessment [9–15]
[4] Alex: "I don't think it's the instrument. Should I keep reading it?"	Joint assessment [9–15]
[5] Steven: "It just reads one bead, right?"	Consultation [16–19]
[6] Alex: "Yeah."	Joint assessment [25–29]
[7] Steven: "I would just stop it, I guess. Can you ask Max about his reading from last night?"	
[8] Alex goes to get Max. Max and another colleague appear by the Bioplex machine.	
[9] Max: "Did you vortex and sonicate them?" ^a	
[10] Alex: "Yeah."	
[11] Max confirms that the reading worked fine last night: "I think something is amiss here. With your specific assay. Sorry Alex, it went really smoothly last night." [Max and his colleague disappear.]	
[12] Alex: "Do you think the calibration is wrong with the beads?"	
[13] Steven: "But they're aggregated, right?"	
[14] Alex: "Maybe they are calibrated wrong. I'll go check."	
[15] Steven: "But they show up as aggregated. Otherwise it would just be searching for beads."	
[16] Alex: "I'm just gonna prime it."	
[17] Steven: "You can also flush it."	
[18] Alex: "Prime. I'll do the prime first. You see, there is one bead. I think it's a bead problem."	
[19] Steven: "Like I said, I don't know why you had so many. That's a huge amount of beads."	
[20] Alex: "Let's do one more plate. Plate 5."	
[21] Steven: "Is that a different cell?"	
[22] Alex: "Yeah." [he passes Steven the plate]	
[23] Steven: "Where's your book? The big book to the machine?"	
[24] Alex: "Oh, I've never read that."	
[25] Steven: "Ah yeah, there's a whole list of things in the back. [He goes through the troubleshooting guide.] It gave you error messages?"	
[26] Alex: "Yeah, lots: 1, 2, and 4."	
[27] Steven [reading]: "'Aggregated beads are due to a waste reservoir being overfull.' Did you just change it?"	
[28] Alex: "Just now. I hope that that's it, but I doubt it."	
[29] Steven: "'Plate not shaken for 30 seconds before analysis, low or no sheet flow, incompatible buffer used.' All possibilities."	
[30] Alex [relieved]: "Ah! It reads."	

^a Spinning a sample so that the cells collect in pellets, and applying sound to the sample to precipitate certain reactions.

This incident of experimental breakdown elicited deliberation about practice (Sandberg & Tsoukas, 2011) that was articulated because two scientists were involved. Coordination in the form of joint assessment and consultation surfaced next to expert practice. The scientists considered instrument, beads, and samples as the problem source and developed a number of alternative solutions. Notably, their use of terminology such as "sonicate," "prime," "flush," and "vortex" allowed for swift communication, as these terms point to procedures well known to the scientists. Drawing on shared expertise, Alex² and Steven quickly moved back and forth between coordination and expert practice, jointly assessing preliminary results from the experiment and consulting about possible next steps to attain a useful outcome, while Alex

changed the waste reservoir, primed the technology, and ran a reading on another cell line. Joint assessment and consultation served to coordinate diverse inputs and approaches toward completing the experiment.

Scientists also used joint assessment and consultation separately from expert practice during meetings with collaborators. Expertise diversity introduced obstacles to collaboration, such as the absence of a shared terminology and work environment. Scientists pursued expert practice remotely and discussed results and future action in project meetings. Coordination practices were thus decoupled from expert practice. The following excerpt from another project shows how Steven and Sean, a computationalist, examined a model that Sean had built on Steven's latest experimental results. The model showed pathway activation as on (1) or off (0), but experiments captured strong and

² All names are pseudonyms.

weak signals. The model was accompanied by a “heatmap” that portrayed signal strength in colors. Before the meeting, Steven had compared the heatmap to his experimental data.

- (1) Steven: “I noticed another thing too. I went through with a plotting tool that we have and . . . you see a lot more here. . . .”
- (2) Sean: “Because of the time scale here. We’re going to change that.”
- (3) Steven: “Yes, it’s just visual. But here—is that a peak or not?”
- (4) Sean: “Yeah, we can play with different threshold values.”
- (5) Steven [comparing model to written notes]: “There is a modest increase with IL-1beta. These are subjective [pointing to his notes]. I just looked at it and wrote down what I saw. Why are these gray?” [pointing to a row in the heatmap].
- (6) Sean: “Yeah. We are going to switch those.”
- (7) Steven: “So what we need to figure out is where this fits.”
- (8) Sean: “We made a connection to mTor. There is a known effect. Here, we draw a line.” [drawing line in network model on his computer]
- (9) Steven: “Ah, that makes sense. So these guys here, they should be removed.” [pointing to proteins in the network model]
- (10) Sean: “But then we don’t have an effect on tyrosine. Is that ok?”
- (11) Steven: “Yes.”
- (12) Sean: “I think we should change this first [pointing to network model] and then . . . we can do it together. I can do it and you can watch.”

Just as during expert practice, the conversation throughout this meeting moved back and forth between joint assessment and consultation. First, the scientists established a shared interpretation of preliminary contributions. Steven asked for details about the model (quotations 1, 3, and 5), and Sean signaled room for adjustment (2, 4, and 6). The conversation next moved to pending expert practice (7), such as the agreement to remove one protein from the model. Notably, Sean referred to literature in Steven’s domain (“There is a known effect”), which is an example of how cross-domain knowledge supports the integration of diverse contributions. The scientists pointed their fingers and used “this” and “here” as tangible definitions (Bechky, 2003) to communicate across domains. Consultation linked assessment of prior contributions to pending expert practice. Except for a small change in the network model (12), most resolutions relating to expert practice could not immediately be implemented. Rather, during their discussion, Sean e-mailed Steven a figure of the current model-data fit, and Steven made a “to-do” list, noting

“ences for visualization, show 1 and 0 as on/off.” Steven would reconsider the model-data fit and which threshold values between activated and deactivated states in the model would best reflect his experimental data. His next application of expert practice could only be assessed at a later point. Domain diversity caused a delay in expert work.

Joint assessment implied exchanging details about expert practice and taking stock of preliminary contributions (Table 3; e and f in Figure 1). It differs from “sensemaking” that bridges perspectives from diverse domains (Faraj & Xiao, 2006; Weick, Sutcliffe, & Obstfeld, 2005) inasmuch as it can occur separately from expert practice. Scientists imparted discipline-specific knowledge and pointed out the most critical features in their results, while their collaborators asked “why” questions to clarify what they had noticed. For example, patterns in mass spectrometry data on novel proteins that had seemed interesting to a modeler could be explained by a known biological mechanism. Conversely, a research scientist noted how his computationalist colleagues would pick up on details in macrophage signaling data that he had not initially noticed. Details about domain-specific practice helped put results into perspective. Changes in the shared objective also became evident during joint assessment. Preliminary results might indicate that a trajectory was a dead end, no longer relevant, or less interesting than another one. Joint assessment was fundamentally directed toward the past. It helped create a shared understanding of tentative accomplishments and laid the grounds for consultation.

Consultation implied comparing needs in one domain with possibilities in the other and making suggestions for pending expert practice (Table 4; g and h in Figure 1). It is similar to brainstorming, which plays an important role for innovation in organizations (Paulus & Yang, 2000; Sutton & Hargadon, 1996); but it is different inasmuch as it plays a prominent role throughout the entire project rather than only at the beginning. It connects consecutive intervals across domains and over time by matching the immediate need of another party to actual possibilities in expert practice. Weighing what would be useful in one discipline against what could be done in the other made limitations and opportunities of expert practice apparent, as in a project called Macrophage Signaling Pathway. “Can you” questions prompted scientists to consider the technical possibility of a proposed solution. Answering in the negative triggered an explanation and often an idea for alternative action. In the project Cell Death Model, tentative models might not have explained biological data well

TABLE 3
Coordination Practice: Excerpts from Joint Assessment^a

Interviews with Computationalists	Interviews with Experimentalists	Observations
e: “When you just see data, you have no idea what the hell it is. You have this faint idea: oh yeah, it’s this signal—it’s going up and it’s going down. But what you really need to do is find out how are they measuring it, and in the assay, what are the assumptions of the measurement? . . . What’s the processing done on it afterwards? And then you have an idea of how to interpret it.” (Jeff, postdoc, EGF Receptor Model)	e: “I talk him through it and say, ‘Look, we saw this. This is the next thing we tried and here’s what we’re thinking now.’ Like so try and take you through from ‘here’s what we’ve done, here’s what worked and didn’t work, here’s where we’re going. What do you think? What other suggestions would you have for what we should do next?’” (Ellie, postdoc, Gene Expression Model)	Jeff [C]: “What about the effect of single ligands first, before looking at two? Marc has done that. And Bob has done crosstalk. We definitely have to go through that exercise.” Roy [C]: “Definitely. Do we know anything about the heterodimers?” Marc [E]: “No, that’s too hard. They have a rough idea of the affinity of heterodimers.” Luca [C] hands over an article to Marc who takes a quick look. Marc: “Yes, but here they assume that there is 2 binding, but it also could be 2 and 4.” Luca: “I agree, but this is all we have.”
e: “I can explain quite well to them what we’ve done with the data, and why and how, but because they have a richer experience with the biology that they’re studying, they’ll be able to tell me that something that looked interesting in the data in fact is not. They can explain it with some preexisting model or understanding.” (Tom, lead research modeler, Mass Spec Novel Protein)	e: “They [C] just have a very different look at things; again, coming back to these different methodologies and different capabilities—I tend to be more straightforward as far as, ‘Okay, this is what I did, this is what happened,’ and they’re a little more—pulling things out that I don’t pick up on, on first glance.” (Steven, research scientist, Macrophage Signaling Pathway)	Sean [C]: “Do we have the simulations for 0.01?” Bob [E]: “Yes, we do.” Sean: “Let’s do a comparison.” Bob [looks it up] “Right there—it’s identical.” Sean: “Hm.” Bob: “See any differences?” Sean: “No. And the solution itself? The same [looks into paper]. So that would mean that in this case it is not affecting so much what is winning.”
f: “I sit down with a biologist and say, ‘Okay, now this is the system that everyone thinks it is and these are the models that might exist modeling it and none of these are right. Tell me exactly what each of these arrows mean and what arrows are missing, what arrows shouldn’t be there,’ and they’ll tell me and I’ll say, ‘Well, just because of what you’ve told me in Line 5 says that these three models are wrong because that’s not what that is.’” (Duane, research scientist, Cell Death Model)	f: “Let’s say you measure some protein and you see it going up and down. The modeler might say, ‘Wow, that’s really interesting. Look, it’s going up and down, it’s oscillating, there must be some really cool reason for that.’ And I would say, ‘No, that’s just noise, that doesn’t mean anything.’ He’d say, ‘Well, how do you know?’ ‘I’ve done these experiments a hundred times and it’s just noise, look at the axis. The magnitude that’s going up and down is too small. You see big fluxes when it’s real. These small little oscillations are just noise.’” (Marc, postdoc, EGF Receptor Model)	Michael [E]: “So the data were done by . . . assay. Here is the staining of pockets of lipids. You can see it goes away in many of the cells that are unhealthy here. The . . . is exported out of the liver into the organism and then outside the body. This is a marker for overall metabolic health.” Kenneth [C]: “So glutecine positive means healthy.” Michael: “Yes. These halos around mitochondria are healthy. So it’s not apoptotic. . . .” Kenneth: “So these are cells that are dying.” Michael: “It’s not clear. These are all markers of toxicity and correlate with other measures of toxicity, but you can imagine that there is apoptosis that is independent of this.”
f: “I might have a specific question about a specific subset of the data that looks like there’s larger variability than I would have expected and see if he had any thoughts about that or questions about clarifying his experimental protocol or asking him to summarize some of his key observations in the data so that I can get a feel for what the experimentalist thinks is important variation versus not important variation.” (Adam, postdoc, Macrophage Signaling Pathway)	f: “It was kind of a mixing of two people interpreted the things separately then you come together and say, ‘this is what I see,’ ‘this is what I see,’ and from there you get the other person’s perspective and then decide from that how you’re going to go forward.” (Steven, research scientist, Macrophage Signaling Pathway)	

^a “C” in brackets indicates the speaker is a computationalist. “E” indicates an experimentalist. An “e” before an excerpt indicates that it pertains to exchanging details about expert practices, and an “f,” taking stock of contributions.

enough, but they did indicate which experiments would yield data for further improvement. Although not all suggestions from colleagues were viable, some were critical; an example is the com-

putational prediction of a peak in the project ERB Model that was verified in experiments but might have been missed had measurement points been selected at random. Excerpts from meetings illus-

TABLE 4
Coordination Practice: Excerpts from Consultation^a

Interviews with Computationalists	Interviews with Experimentalists	Observations
<p>g, h: "I might present some preliminary modeling results and then he might ask how we can use that or 'can you extend it in this way, can you use it to predict the results of these experiments or to design new experiments.' . . . Also, he might give me some particular modeling goals that would guide my approaches to try and do something that will be more helpful to him." (Adam, postdoc, Macrophage Signaling Pathway)</p> <p>h: "I think a really close understanding and a close working relationship with people deriving the data and, honestly, somebody who—the perfect modeler would be somebody who can then design their experiment, who can even help design the experiments, right, so I think that's really important." (Anne, Ph.D. student, Mass Spec Novel Protein)</p> <p>h: "That was another insight to help them plan the experiment and to pick the right time points [to measure the effect]. If all your time points are at the very beginning where maybe the signal is slightly delayed, then you won't see any signal. But if you spread it out in a way so you catch the late peak, then that's very useful and powerful." (Kyra, research scientist, ERB Model)</p> <p>h: "You start simple and work more complex. If your model's good enough simple, do you necessarily have to make the next step? There's that. Oftentimes, obviously, your models aren't good enough but at least you've learned something, you can suggest experiments and you know where maybe to add on and make it more real." (Duane, research scientist, Cell Death Model)</p>	<p>g: "It's been really easy to talk to him [C]. I don't think there are—sometimes, he asks me if I can do an experiment which is just impossible, or just extremely time consuming, or probably won't give the result we would hope for." (Jane, Ph.D. student, Cell Death Model)</p> <p>g: "I'm trying to adapt and understand what it is that they [C] are trying to get out of the experimental data. There's a lot of back and forth trying to figure out what they need and what I can do with the data that I generate." (Steven, research scientist, Macrophage Signaling Pathway)</p> <p>h: "We'll actually sit down next to each other and talk about how we'd go about this process for searching for parameter values based on the type of experiments that I'm gathering, the data that I'm gathering. . . . Many times we just get together to chat about what he's working as well, so the types of theoretical computational methods that he's trying at the moment. I try to make suggestions about different approaches from the computational end, but that more comes from a biologist, which I think I am more of now. So maybe different types of data that could be used with that mathematical component or maybe naive ways to do the computation." (Donna, Ph.D. student, EGF Receptor Model)</p>	<p>Jeff [C]: "If we could monitor the phosphatases." Marc [E]: "Experimentally?" Jeff: "Yeah." Marc: "That's very difficult. Because they have those . . . with 50 forms of PD8." Steven [E]: "So the next one should be easy—just choosing which one to take for disruption." Sean [C]: "Probably p38, right? It's not affecting too many things." Steven: "But you're not really showing . . . What if we did LPS and turn those two on?" Sean [typing]: "I would do maybe that and then on top p38." Luca [C]: "If we tried different ligands . . . and use the modularity of . . ." Marc [E]: "I feel that's a pie in a sky." Jacob [C]: "How long is that gonna take?" Marc: "How many targets?" Luca: "She [Donna, E] said she can measure all the <i>Erbs, shk, raf, rasp</i>." Jacob: "<i>Rasp</i> does not phosphorylate." Luca: "She can still measure it." Jeff [C]: "No, she doesn't have the assay." Marc: "Six ligands on six targets—it's unclear to me what the benefit is."</p>

^a "C" in brackets indicates the speaker is a computationalist. "E" indicates an experimentalist. A "g" before an excerpt indicates that it pertains to the identification of needs and responsibilities, and an "h," suggestions or "what if"/"can you" questions.

trate how possibilities of expert practice, such as availability of assays and conditions of proteins (PD8, p38), surfaced as scientists vetted plans for expert practice across domains. Suggestions, ideas, and requests entered an inventory of desirable objectives to inform expert practice in the next interval. Consultation was grounded in what scientists had learned in prior expert practice and directed toward future action.

Collaborating When Working Alone: Counterprojection and Alignment

In reviewing outcomes from prior expert practice with their collaborators and planning pending expert practice, the scientists transcended temporal and domain differences in collaboration. Yet they still spent a substantial portion of their time on expert practice during which they were solely re-

sponsible for coordinating their own work. To accomplish collaboration, scientists had to close the feedback loop with the preceding exchange at cross-disciplinary meetings. This section revisits expert practice with an eye on specific efforts to collaborate that scientists made while working apart from each other. The collaborative practices of counterprojection and alignment helped them address domain differences while contributing remotely.

Counterprojection. Using counterprojection, scientists evaluated expert practice from the perspective of the other domain and tailored their plans to foreign requirements. Perspective taking (Boland & Tenkasi, 1995) implies taking knowledge of other domains into account; counterprojection extends this notion by suggesting that the scientists also consider the consequences that their expert practice, such as their experimental or modeling decisions, will have on work in other domains. This collaborative practice provided the foundation for integrating diverse contributions by identifying characteristics of expert practice that would be relevant to the work of collaborators. Duane, a mathematician, explained how his work was different before he started to collaborate extensively:

I always at least think I'm working with a biologist now as opposed to then. Then I might have made a model where I might not have taken into account "Could you prove this experimentally? Could you measure these things? How real is it?" I can read a paper and come up with something and who knows if it's real? It might not—very quickly it could leave reality. But now: "Can I measure these things? Can I change certain things? How would I prove this experimentally?" I want to make it very real and not put too many assumptions up front to oversimplify it because I think in biological systems the complexity and nonlinearity can give rise to synergy or emerging properties that if you're too simple you might not find. So I'm not afraid of complexity and difficulty and I always try to keep it grounded in reality now. Before I didn't. Whether I'm working with biologists or not, I always try to keep those things there.

In planning his work, Duane kept the reality of his experimentalist colleagues in mind by monitoring his contribution-in-the-making from their perspective. Counterprojection alerted scientists to changes they needed to make in expert practice so that their contribution would correspond to those from other domains. Counterprojection reflected back upon consultation. Just as their colleagues had posed "can you" questions, scientists now posed "can I?" questions of their practice. In imagining experiments that could test his models, Duane ap-

plied foreign evaluation standards. His statement suggests two important implications: as a precursor to alignment, counterprojection has consequences for domain-specific work. Duane described how he came to incorporate the complexities of biological systems into his mathematical models. This further alludes to learning that continued to affect his modeling work regardless of whether or not it was for a collaborative project with biologists.

Table 5 substantiates how scientists used counterprojection to evaluate a potential contribution from their colleagues' perspective to anticipate consequences for work in that discipline, and how they planned their work accordingly (i & j in Figure 1). A comment from one NIH official for systems biology reflected this approach: "I truly believe that you need to consider the biology in terms of the model and vice versa." Yet this was easier said than done as it required framing expert practice in terms of the knowledge scientists had acquired about the other domain. Such knowledge was rooted in literature, methodology, symbology, assumptions, and conventions of validity that radically differed from those in their own discipline. For example, a computationalist stated that experimentalists had to assume a quantitative, input-output perspective that is not common in biology. For modelers, an understanding of the experimental limitations should inform design choices. A principal investigator expressed how hard it was for experts to embrace another perspective after years of intense training, admitting, "the deepest challenge has always been getting people to appreciate the strengths and the questions and the perspectives of each other."

Alignment. In alignment, scientists developed novel expertise to modify their expert practice to make a contribution that met requirements in another domain. In contrast to the notion of implicit coordination, which points to nominal adjustments actors make when they work (Rico, Sanchez-Manzanares, Gil, & Gibson, 2008), alignment depends on explicit prior communication and entails a potentially significant learning process. Cross-domain collaboration imposed exigencies on expert practices from two domains: specialized work had to be feasible and meet domain-specific quality standards, and the resulting contribution had to be viable for integration with that of the collaborator. Compatibility of contributions thus required shaping expert practice according to insights developed during the preceding phase of expert practice in the other domain. Choices of laboratory experiments were guided by the usefulness of the anticipated data for computationalists, and important modeling decisions were based on findings from the biological system. The following interview excerpt il-

TABLE 5
Collaborative Practice: Excerpts from Counterprojection^a

Interviews with Computationalists	Interviews with Experimentalists
<p>i: "We all tend to have parochial arrogance, that what we've learned is the most important and useful stuff, and somebody from another discipline—what they know and what their perspective is—is somehow inferior. You've just got to turn that on its head and actually take the stance that you're going to be most productive if you allow them to still consider their perspective as completely worthy of respect and your contribution is to just enhance, complement." (principal investigator)</p>	<p>i: "You have to try and see their point, even though you think you're right, but you have to entertain it because they entertain you when you—so it's give and take." (Marc, postdoc, EGF Receptor Model)</p>
<p>i: "For some experimentalists, the thought of an input/output system just is not—they just haven't been trained to think that way. So to think about a stimulus as an input and the output is that the cell grows or dies—I think thinking about a pathway or a cell as a system rather than as a single protein or two proteins that interact is an important step in understanding what's going on." (Kyra, research scientist, ERB Model)</p>	<p>i: "I feel like we're missing a lot of the important stuff that's going on by thinking about it entirely qualitatively. It's not that nobody ever thinks quantitatively, it's just that we only do so occasionally and when it's convenient. So I feel like an important thing to do is to figure out a way to look at these things quantitatively. I mean it's systems in the sense that it's quantitative." (Paul, postdoc, Mother of All Datasets)</p>
<p>j: "I don't think we do this as much as we should, but taking things at as specified of a level as possible for the experiment when thinking about doing your computations is an important thing. So there are some things you just can't measure experimentally, but we definitely try to say 'Given the experiment that I can do, how can I design the computation, which has a lot more freedom, to map that as closely as possible?'" (Kenneth, Ph.D. student, Drug Toxicity Inflammatory Cytokines)</p>	<p>j: "I've seen experimentalists who work closely with people who do modeling who also shift their thinking in terms of how to plan experiments or what kind of techniques to use, based on what they've learned from the modeler." (Jennifer, postdoc, Mother of All Datasets)</p>
<p>j: "It's very hard to do something that has no perturbations. There's always something that can disturb your cells, whether it's temperature variations, atmospheric, and so it's very hard to control everything. So I think I'm revising how I think about experimental design, because I'm starting to move on to make some of my own experiments, and so I think it's very important for me to keep those sorts of things in mind about how to expect and account for biological variation." (Adam, postdoc, Macrophage Signaling Pathway)</p>	<p>j: "After you have been working with them [modelers] for a while, you start thinking that way. In many of my analyses, I understand their way of thinking about things, and I understand which computational tools will be used, and what's the limitation, and what's the requirement of these tools? Then you can plan your experiment very well so that they will like it, because you were thinking about some of the elements they want." (Jin, postdoc, Gene Expression Model)</p>

^a An "i" before an excerpt indicates that it pertains to the application of foreign evaluation standards, and a "j," planning for requirements in other domains.

illustrates alignment. Jennifer started out as an experimentalist and then became proficient in computational modeling. She addressed changes in her experimental practice that were due to her understanding of modeling:

My work in modeling has really strongly influenced the way we do experiments just because it's helped me realize how important—at least for the kind of questions that I want to ask in science—how important it is to think about single cells as opposed to averaging all the cells or saying all the cells are doing the same thing. That basically shifted the way I plan a project. Projects are going to involve single cell-based measurements, that's a given now. Also my experiments are now pretty much always quantitative because I feel like it gives you an additional power to ask questions that couldn't have been asked before and I think that's in part influenced by just knowing the power of modeling to go along with the experiments.

Jennifer's appreciation of modeling influenced her work in the laboratory to the effect that she developed expertise in a particular type of experiment. These experiments measure the behavior of single cells, yielding more refined and richer data than do common biological approaches that break cells open and measure average behavior. Computational power can be more efficiently leveraged with the type of comprehensive and accurate data that Jennifer was able to collect from single cell experiments. She designed her experiment to make her contribution more compatible with modeling by creating symmetry between expert practices. Alignment linked work back to the preceding coordination practices of joint assessment and consultation by incorporating what had been learned about the other discipline. Counterprojection implies willingness to embrace foreign insights as complementary and to codefine appropriate solu-

tions; alignment implies the ability to execute this understanding.

Table 6 further illustrates how scientists adjusted their expertise to create symmetry across domains, and how they tailored expert practice to prior results from their collaborators (k and l in Figure 1). Modelers developed tools for data management and analysis as expansive data sets required processing before modeling could begin. They built models around what experiments were able to measure. Experimentalists took much more care to control for variation in experiments than customary in bi-

ology to satisfy the computationalists' need for accurate data. Scientists used insights from the other discipline to enhance their contribution. For example, one experimentalist in the project on breast cancer cell lines collected a sample large enough for initial analysis and designed subsequent data collection according to how the data could best be analyzed. Alignment served to adjust expert practice so as to accommodate requirements in the other discipline. Yet developing novel tools and expertise in scientific practices was time intensive.

TABLE 6
Collaborative Practice: Excerpts from Alignment^a

Interviews with Computationalists	Interviews with Experimentalists
<p>k: "It is such a challenge to keep track of the manipulations that you've done in terms of organizing your data and reorganizing it and normalizing it in different ways. So I've developed some tools to make those challenges a little easier to deal with when you have a hundred thousand different measurements. But it is a challenge—if [the experimentalist] just hands you off a spreadsheet, it still may be a significant amount of work to get it [into] some form that's easy for you to build models with." (Adam, postdoc, Datarail)</p>	<p>k: "Our experiments are designed very quantitatively. For example, all the conditions that we probe the Westerns with—concentration of antibodies, etc.—all have to be the same, exactly the same run, exactly the same biologist. So things are done in our lab very carefully to minimize variations, and that type of thing is not necessary in biology." (Ed, Ph.D. student, Mass Spec 3D)</p>
<p>k: "I'm working with a novel methodology to develop models for the cellular systems. So I've been spending, I guess, four months, five months learning the biology, learning the mathematics. I know the chemistry and the physics already. And learning how to use this new tool to apply it to something." (Luca, postdoc, LittleB)</p>	<p>k: "I tend to treat [modeling] like a biological experiment where something's not working. I'll try to insert little tags at different points or try to break it at a different point. I basically just run the same sorts of experiments logically that I would run on a cell." (Jennifer, postdoc, Mother of All Datasets)</p>
<p>l: "I tailor what I do to what the data is. . . . There are techniques we're developing now for analyzing mass spec data. So to some extent the techniques are being developed to analyze the data we have. . . . We're learning what we can do, and what we can't do with it, and they're learning at the same time, and beginning to get a chance to craft the data they come out with and the questions they want to ask to things we're well equipped to answer." (Tom, lead research modeler, Mass Spec Novel Protein)</p>	<p>l: "So I'm trying to make many different measurements within the pathway simultaneously to see if that can help us find the parameter values. Based on whether I'm successful or not with measuring a certain protein activation level, that will determine what we try computationally." (Donna, Ph.D. student, EGF Receptor Model)</p>
<p>l: "You're going to model all of this [hundreds of molecular players] computationally. Experimentally, you probably can't measure all of those things. You can measure a certain subset of those, or often you can measure a combination. So there's maybe four phosphorylated states of a particular protein and you can measure the sum of all those together, but you can't measure any individual one. The sum of all those together doesn't really explicitly exist in your computational model. So, if you didn't know about the experiment, you would just probably use your model, and you would make predictions about what this one phosphorylated state of the protein does. But you grab from the experiment. You say, 'Okay, I know that experimentally. I can't measure that thing; what I can measure is this set of things, so I'm going to phrase my computational questions in a way that I can think about with the experiment.'" (Kenneth, Ph.D. student, Drug Toxicity Inflammatory Cytokines)</p>	<p>l: "The model suggests a hypothesis that a pathway of biological activity is important for governing a certain cell function. . . . It's all a balance of developing inferences and hypotheses, and then going back in and testing those. And you usually only test the ones that are the most likely—the ones that, quantitatively, the model says are probably the most strong correlations." (Michael, Ph.D. student, Drug Toxicity Inflammatory Cytokines)</p>
	<p>l: "I collected a large enough data set that we can use to figure out how to analyze. So I collected a fairly large data set on four cell lines of the eight that I have, and I'm essentially using this as a test data set. Once I know how to analyze the data, then I'm going to recollect the same data on eight cell lines and then just run it through. There are certain things that I'm not certain yet of how to collect the data." (Bob, postdoc, Breast Cancer Cell Lines)</p>

^a A "k" before an excerpt indicates that it pertains to adjusting expertise to create symmetry, and an "l," tailoring experimental practice to foreign results.

Alex described how he learned to work with Bio-plex technology:

When everything was up and running, you knew that your assays are working perfectly and you knew that you have all the beads and the beads are working nice and everything, then to do the high throughput screening takes two weeks or maybe less. It takes like one week. But, yes, it can take one week but actually you need one year in order to take one week. But now if I want to do another screening experiment, it's going to take one week.

Developing expertise involved significant learning, planning, and preparation that preceded making the contribution that collaborators were going to employ. Scientists adjusted expert practices and designed tools that would allow them to better collaborate. Jennifer and two other experimentalists spent two years on assay validation and one year on data collection for modeling. Her colleague spent 18 months making live cell reporters that would allow him to measure a chemical reaction preceding cell death. It took a computationalist two and a half years to sort through the literature, identify cellular reactions, and write a program that assigned mathematical equations before he could start building the actual model. The lab employed three full-time staff members to meet the needs for administration and data management. Alignment was mutually enabling but had considerable coordination costs.

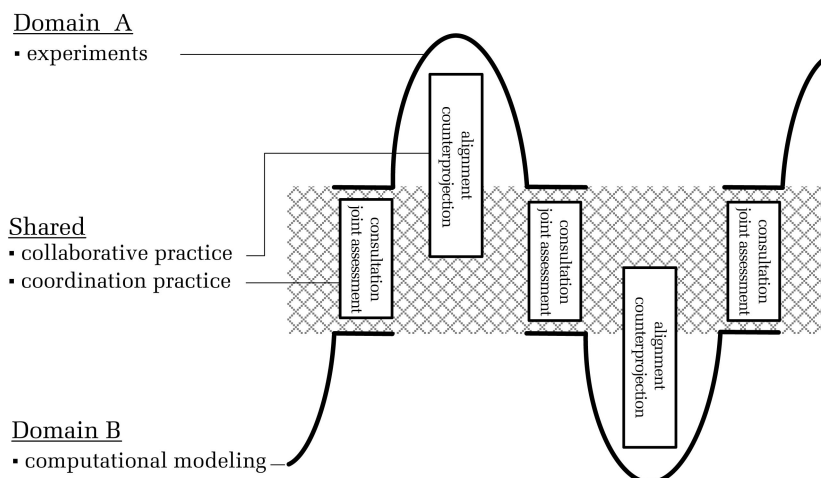
Coordination in Cross-Domain Collaboration

Working across highly diverse domains on novel tasks resulted in collaboration that progressed in intervals. Rather than working on a research project simultaneously, computationalists and experimen-

talists took turns applying expert practice to contribute to the joint project. Computational practice was suspended during experimental practice, and vice versa. Each research project consisted of an iterative process of increasing synthesis of diverse contributions that evolved hand in hand with the project goal. An iterative mode of working implies that scientists had to transcend two critical barriers in collective work: domain differences and temporal differences. Sharing collaborative and coordination practices allowed for transcending these differences. Figure 2 illustrates how the practices of joint assessment, consultation, counterprojection, and alignment support scientific practices of experiments and computational modeling.

Phases of expert practice alternated with coordination practice at meetings where scientists would assess past accomplishments and confirm the next objective. Collaborative practices informed expert practice with cross-domain insights. Coordination created correspondence between contributions that emerged in different domains and at different times. In joint assessment, scientists reviewed results from prior expert practice; in consultation, they developed ideas for the application of expert practice during the next project phase. Collaborative practices, while shared across domains, were applied independently in the respective expert domain in which they guided expert practice. Counterprojection and alignment directed adjustments to models and experiments that installed cross-domain references in contributions. Working asynchronously implied that one party gained additional insights that collaborators had to incorporate when it was their turn to apply expert practice. Coordination needed to ensure that relevant knowl-

FIGURE 2
Process Model of Coordination in Cross-Domain Collaboration



edge specific to domain A affected expert practice in domain B, and vice versa. Coordination can therefore be understood as an ensemble of different types of practices that together enable collective work.

The model idealizes the situation inasmuch as it suggests a clear temporal separation between expert practices and evenly distributed shared and remote work phases. Scientists would spend significantly more time on expert practice than in meetings. Toward the end of projects, application of diverse expert practices tended to overlap as scientists fine-tuned their contributions. The model captures the general dynamic of cross-domain collaboration that I observed in all the research projects. When scientists were not engaged in expert practice on one project, they were free to pursue other projects. Systems biology projects could easily take four years from inception to publication. Time required for developing new expertise and multiple project membership required a funding cycle that endowed the time needed for expert work and cross-domain integration. Research centers have formed around systems biology with multiple projects to better leverage a high degree of expertise in diverse domains to achieve breakthrough innovation.

DISCUSSION

Contributions

This study sheds light on how diversely specialized experts coordinate their work when working apart from each other and on how these efforts complete the overall process of coordination. Prior research on coordination in cross-functional work has not addressed these two important questions. A theoretical framework of expertise and practice allowed me to conceptualize diversely specialized work. To coordinate under conditions of novelty and complexity, scientists in systems biology worked in alternating phases of consecutively applying expert practice. Along with specialized work, a second layer of practice appeared in the form of counterprojection and alignment. These collaborative practices coordinate collective work by directing expert practice toward compatible contributions. This argument provides an in-depth explanation of how coordination works (Okhuysen & Bechky, 2009). The study contributes to the literature a conceptualization of collaborative practices and a process model of coordination.

Evidence of collaboration work in the form of counterprojection and alignment suggests that a considerable portion of coordination in cross-functional work occurs *within* domains. Although coordination practices determine whether and when

expert practice is conducted, collaborative practices influence *how* it is conducted when experts work apart from each other. Collaborative practices differ from efforts at cross-domain coordination in their capacity to effect changes to expert practice. These changes require developing novel expertise, which is different from the transformation of knowledge (Carlile, 2004) or creation of shared understanding (Bechky, 2003) that might ensue from cross-domain coordination. The study also showed how the interplay of practices informs temporal dynamics in the coordination process of collective work across highly specialized domains. Developing novel expertise took time and made project members difficult to replace. In contrast, studies of tasks with shorter time frames report little learning and fluid team memberships (Faraj & Xiao, 2006; Kellogg et al., 2006). This study identifies the incorporation of changes to expert practice as a critical component of within-domain coordination that complements a focus on cross-domain coordination in practice-based studies of collective work.

Collaborative practices are integral to leveraging diverse expertise in collective work that requires tight integration. Counterprojection thrives on prior discussion with collaborators in which requirements from the other domain are made apparent. It limits the risk that experts take when introducing changes to specialized practice by directing these changes toward desirable outcomes. Collaborative practices may therefore serve to overcome resistance to learning what is required for collaboration (Carlile, 2004). Alignment enabled scientists to eliminate conflicts with work in the other domain and leverage desirable features by subjecting their expert practice to foreign standards. Counterprojection and alignment result in learning that guides expert practice beyond a collaborative project. For example, Duane continued to build models around empirical verifiability, which is not necessary in mathematics. Together, counterprojection and alignment constitute a central approach in organizations to capitalizing on differences that result from specialization.

An understanding of how work is coordinated within domains sheds more light on how coordination unfolds overall. This study's second contribution to the literature is a model of coordination in cross-domain collaboration that explains how individual coordination efforts complement the overall process. Counterprojection and alignment mediate between coordination practices and expert practices by enabling a feedback loop that effects changes to expert practice based on insights from another domain. Coordination within domains in cross-functional work consists of linking knowl-

edge that is specific to one domain to practice in another domain. The process model of coordination suggests that collaborative practices become instrumental inasmuch as they relate different types of practices: coordination practices allow exchange of details about domain-specific practice across domain interfaces, and collaborative practices create changes in expert practices to reconcile differences in emerging contributions.

The process model displays coordination as an ensemble of different types of practices whose combination and arrangement drive collaboration across diverse domains. Scientists moved work forward by applying different practices at different times. The combination and temporal arrangement of practices generate teleological and dialectical forces that drive organizational development (Van de Ven & Poole, 1995). Scientists pursued a clear purpose and adapted and monitored their progress (teleological); they sought to synthesize a novel construction that departed from two diverse disciplines (dialectical). These change forces usher in a constructive mode of development associated with high uncertainty and a break with past frameworks. An ensemble of diverse practices orchestrated the collective work of specialists aimed at breakthrough innovation. These findings have important implications for the literature on coordination in cross-functional work, innovation, and practice.

Coordination in cross-functional work. Differentiating coordination in terms of form and function of practices and their interaction during collaboration brings into focus the quality rather than quantity of coordination. A quantitative conceptualization of coordination suggests that some tasks require more coordination than others (e.g., Faraj & Sproull, 2000; Lafond et al., 2011). The current study suggests that experts have to coordinate *better* to conduct complex cross-functional tasks. Scientists were individually responsible for coordinating expert practice within their domains. Yet how efficiently and effectively collaborative practices create correspondence around points of leverage in *both* expert practices determines the quality of coordination. Because collaborative practices operate as an additional layer atop expert practice, they manifest in changes to expert practice. To the extent that within-domain coordination is embedded in domain-specific work, coordination costs become difficult to determine. This idea further explains why working across specializations is costly even within one institution (Cummings & Kiesler, 2007). Increasing specialization shifts a significant share of coordination in cross-functional work into individual domains.

Conditions of domain diversity, novelty, and complexity emphasize the temporal dynamics that characterize coordination in cross-functional collaboration. Developing novel expertise meant considerable time investment for the scientists observed here, as well as their incurring downtime while their collaborators contributed to the project. Under these conditions, multiple project membership maximizes organizational benefit from diverse specialization (Bruns, 2009). As scientists had to successively build on each other's insights and were not continuously engaged in one project, they pursued two or three projects. Both cross-domain learning and novel expertise were important for collaboration, and scientists applied their learning across projects. Multiple project membership enabled scientists to continuously engage not only in expert practice, but also in collaborative and coordination practices. As scientists specialized in tailoring their practice to standards from another discipline, they also improved their skills at collaborating. Collaborative practices that enable collective work across specializations may be costly, yet they lead to learning and enable innovation.

Innovation. Systems biology is exemplary of the learning required to innovate at the cutting edge of science. The study suggests that innovating and developing knowledge across specializations imply the incorporation of learning from one domain into another to the extent that expert practices sufficiently address requirements of the other domain. This achievement differs from mere extrapolation of extant capabilities, for example by translating prior solutions into different contexts (Hargadon & Sutton, 1997), or "scaling up" extant skills (Carlile, 2002). Innovation resulted from directed changes to expert practices made in two domains that required individual scientists to develop novel scientific expertise. This finding differentiates the role of the community of practitioners as an important locus for learning and innovation (Brown & Duguid, 1991). Although learning in systems biology is fundamentally collaborative, individual ability to counterproject and align expert practices critically enables innovation. The two systems biology programs explicitly aimed at cross-disciplinary training, in which expertise was continuously made relevant to and evaluated from the perspectives of diverse domains. Two implications are that innovation is rooted in a change of expert practice and that it hinges upon the ability to coordinate both across and within domains, rather than upon performance inside any one domain of specialization.

Scientists engaged in collaborative practices to bring diverse expertise together. Counterprojection

and alignment illustrate practices that firms should build across specializations (Grant, 1996). They form an additional layer of practices and have the special capacity to align domain-specific work. Directed changes to expert practice implied further specialization. Scientists acquired new techniques or made tools that often involved learning processes of one year or more. Modern expertise comes at the expense of narrowness (Becker & Murphy, 1992), and hence the capability to collaborate adds great value to expertise by making it relevant to other domains. Conceptualizing such a capability as practice implies that it improves with execution. The scientists demonstrated a striking engagement in coordination and in continuous learning about the other domain in multiple ongoing research projects. In systems biology, learning how to collaborate dovetailed with the development of novel expertise. Collaborative practices are essential for firms on a quest for innovation because they serve the application of expertise across domains.

Practice. More broadly, this study answers calls for more empirical research on practice (Sandberg & Dall’Alba, 2009; Sandberg & Tsoukas, 2011). It suggests ways to capture and compare practices in collective work. Expert practice is used as an observable dimension to more fully explore collective work, and a comparison of computational and experimental practice highlights differences between domains. Identifying multiple layers of practices points to an important portion of collective work that is not readily apparent. Expert practice tied to an empirically manifest contribution and more obviously shared among practitioners through apprenticeship, purposefulness, terminology, and artifacts is expected in organizations; however, collaborative and coordination practices are just as critical for reaching a collective objective. This study advances literature on practice by stressing the importance of more assiduously specifying practice to focus not only on expert practice but also on underlying practices that arise as a function of expertise diversity. This study additionally provides examples of how to do that.

A close examination of collective work makes accessible other types of practice embodied in collective work. Practice emerges as a multilayered concept. Notions of practice such as “organized human activity” (Schatzki, 2006: 1864), “structured action manifolds” (Schatzki, 2005: 471), and “anything people do” (Osterlund & Carlile, 2005: 95) have led to its conception as elusive (Turner, 1994) and “not directly accessible, observable, measurable, or definable” (Corradi, Gherardi, & Verzelloni, 2010: 267). A multilayered conceptualization of practice reconciles this view with the contention

that practice is observable (Clancey, 2006; Cook & Brown, 1999; Orlikowski, 2010; Sandberg & Tsoukas, 2011) in suggesting that some layers of practice are observable and some are not. This notion supports the idea of a type of practice that orchestrates other types (Swidler, 2001) and therefore does not stand alone but accompanies expert practices in individual domains. Collaborative and coordination practices constitute second-order practices that pull diverse expert practices together. In cross-functional collaboration, they arise when coordinating work requires customized adjustments rather than routine interaction. Collective work is not simply an aggregate of expert work but includes an integral component of coordination work and collaboration work.

Boundary Conditions, Practical Implications, and Suggestions for Future Research

Boundary conditions. Leveraging data richness in extreme settings also requires identifying boundary conditions of the resulting theory—that is, detailing when the observed patterns are not likely to apply (Weick, 2007). Two boundary conditions merit attention: integration of contribution and refinement of expert practice. In systems biology, a tight integration of highly diverse expertise required considerable changes to specialized work. Where collective work requires loose coupling of contributions rather than a tight integration, collaborative practice to change specialized work would appear to be less relevant. Loosely coupled contributions remain distinct and only nominally respond to changes in other contributions (Orton & Weick, 1990). For example, recent evidence suggests that loosely coupled cross-functional work does not require deep dialogue (Majchrzak, More, & Faraj, 2012) or changes to practice. The tight coupling relevant to collective work in the present study constitutes an important limitation of the generalizability of the developed theory. Tight integration augments the share of collaboration work in collective work.

The scientific practices described in this study were highly refined in that they consisted of many elements that bore upon contributions. In collective work carried out across domains with high degrees of expertise, executing changes to expert practice is precarious, and a thorough application of counterprojection and alignment becomes particularly important because coordination errors are costly. Experiments and models that could not successfully be developed signified months or years of wasted time. If expert practices are highly refined and require tight integration of contributions, coun-

terprojection and alignment are not additional or optional practices; rather, they underlie the execution of expert practice and therefore are vital in bringing diverse expertise together. In less specialized domains of expertise, these practices may work in more subtle ways and imply less significant changes to expert practice.

Practical implications. Managers concerned with improving the effectiveness of work conducted across departmental divisions should keep in mind that exposure to work in other domains is particularly important whenever integration of diverse contributions is desired. Beyond shadowing and job rotation, more formal ways of familiarizing experts with practice in other domains merit attention. Workshops and minicourses could convey basic information, including terminology, priorities, and bottlenecks relevant from a cross-domain perspective. In addition, communication training along the lines of joint assessment and consultation would foster dialogue conducive to collaboration. Experts should discuss their efforts to align domain-specific practice with their peers before negotiating with collaborators. Inversely, a valuable starting point in addressing dysfunctional collaboration is shared practice. Efforts targeted at coordination and collaboration will fail if they are insufficiently shared. Cross-domain collaboration becomes critical to leveraging diverse specializations and avoiding conflict in practices, loss of productivity, and a lack of a shared strategic direction.

There is much debate about the merit of funding large-scale research efforts such as those in systems biology at the expense of multiple traditional, smaller, single investigator grants (Weinberg, 2006; Werner, 2007). The current study accounts for considerable increases in time spent on scientific work within disciplines, as well as for the logic of a comprehensive arrangement of multiple overlapping projects in research centers with substantial funding. Beyond the inadequacy of publications as measure of scientific collaboration (e.g., Katz & Martin, 1997), such an arrangement makes collective performance particularly hard to assess. Effects that are subtle yet significant may not be quantifiable at all, such as shifts in perspectives of pioneering scientists. Funding decisions should be motivated by the novelty of objectives and take into account staggering costs of managing complexities in the coordination of diverse knowledge and expert practice. The time it takes to develop novel expert practice to make contributions compatible and integrate them suggests that half the funding will not get the research halfway there. Novel scientific practice and distribution of resulting in-

sights through publication may serve as proxy for societal learning and therefore public good. Notably, learning in the current setting took place in an institutionally protected environment. The collaborating pharmaceutical lab was dissolved in an economic downturn, along with all systems biology expertise and collaborative capability the company had developed.

Future research. Scholars of organizational theory need to pay attention to the degree and nature of expertise to better understand the consequences for collective work. Previous studies have described very different temporal dynamics in work processes (Bechky, 2003; Carlile, 2002; Faraj & Xiao, 2006; Hutchins, 1990; Kellogg et al., 2006). Insights into the temporal unfolding of coordination and how it relates to the degree of expertise and domain diversity would provide a more nuanced understanding of coordination in collective work. Specifically, the quality of coordination constitutes an important requirement for collaboration on a continuum of tight and loose coupling of contributions. To what extent are expert practices that are closely tied to domain-specific knowledge amenable to change in response to domain diversity? Do coordination costs for collaboration work rise gradually or suddenly with specialization? These considerations are particularly vital in settings where innovation across domains is desired. For this reason, future research should further examine what is required to drive knowledge processes in innovation that involves diverse expertise.

Another concern is the issue of leadership in areas of novel expertise. In the systems biology labs, junior students worked under postdoctorate scientists, and principal investigators oversaw the research and raised funding. Studies often imply hierarchical settings (Faraj & Xiao, 2006; Lafond et al., 2011), but with increasing diversity in teams, hierarchy becomes inefficient as means of coordination (Grant, 1996). This raises the question of how critical decisions are made when relevant expertise is emergent and the role of expertise is unclear. Lastly, nature and functioning of different types of practices form an important opportunity for future research. For example, scholars need to know how shared practices develop in collective work. Since sharing of practice is a prerequisite for knowledge flow across domains (Brown & Duguid, 2001), how are practices sufficiently shared? Instead of singular forms, practices in collective work can perhaps best be seen as fundamental means of work organization that merit further investigation.

Conclusions

This study examined an extreme case of cross-functional collaboration in which contributors were highly and diversely specialized and the task was novel and complex. It advances understanding of how experts coordinate domain-specific work when they conduct specialized work apart from each other. Coordination is an ensemble of practices that drives collaboration by linking emerging contributions across domain differences and over time. The collaborative practices of counterprojection and alignment transcend temporal and domain differences by importing insights from prior cross-domain exchange into individual domains where these insights effect changes to expert practice. The quality of coordination—how well it is executed—emerged as important because alternating phases and highly refined practices made coordination more precarious. Sharing collaborative practice not only enables experts to gain and apply insights across domains, but moreover allows them to progressively synthesize emerging contributions. It also initiates changes in domain-specific work that usher in innovation. These observations matter because an increase in specialized and complex work implies both more work in isolation and more cross-functional collaboration. To dismantle the notion of collective work, this study has embarked on the creation of a language that identifies different aspects of practices and how they relate to one another. In so doing, it contributes some pivotal stepping-stones for an integrative theory of coordination in collective work.

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