FACILITATING INTERDISCIPLINARY COLLABORATION AMONG THE INTELLIGENCE COMMUNITY, ACADEMY, AND INDUSTRY

Edited by Jessica Katz Jameson,
Beverly B. Tyler, Kathleen M. Vogel
and Sharon M. B. Joines

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The editors wish to dedicate this book to Richard Tait. From the day he arrived at LAS, it was evident to all who worked with him that he was a committed public servant and an advocate for collaboration. He inspired us and his presence is deeply missed.

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FOREWORD

GREGORY F. TREVERTON

Many people, including me, have pointed out through the years that the canonical intelligence cycle—from requirements to collection to analysis to dissemination—never really worked that way. It may have been decently appropriate for the Cold War world rife with puzzles about the Soviet Union for which we sought the answers: how many warheads does an SS-19 missile carry, how accurate are they? It cannot be right for a world of ubiquitous information but also intelligence issues that are complexities or "wicked problems," ones in which many actors, some of them new or unknown, are interacting in ways for which we have no precedents. In that world, one of the central tenets of activity-based intelligence (ABI) is right on the mark: we may have the answer before we know the question.

In that world, the Laboratory of Analytic Sciences (LAS), the subject of this rich book, is not just an impressive venture in collaboration, it is a look at the way intelligence analysis should be done in the 21st century. It is just what I and my Swedish colleague, Wilhelm Agrell, had in mind some years ago when we called for hybrid organizations in which "experts, policymakers, and stakeholders are linked not just through a requirement-dissemination loop but interact on a more continuous and integrated basis" (2015, p. 197). It brings intelligence analysts, who have a practical understanding of needs and tradecraft, together with university experts from many disciplines and colleagues from industry, who bring knowledge of the latest technologies, and are also enriched in their understanding of analysts' needs, so that new tools are less likely to bring the later rebuke from those analysts "that's not what I need." The three groups work arm-in-arm from the beginning in what LAS refers to as "immersive collaboration."

The book's chapters One through Four lay out, first, the driving motivations and basic frameworks for LAS, with due attention to the tensions at play in the kind of collaboration the Laboratory seeks. Chapters Five and Six focus on the interventions, processes, and technology necessary to support immersive collaboration, and chapters

Seven through Thirteen share case studies of collaboration at work. The cases are especially interesting as they demonstrate the kinds of work done at LAS, the challenges that were faced and how they were managed, illustrating the possibilities of these partnerships.

For instance, in the run-up to the 2016 Summer Olympic Games in Rio de Janeiro, Brazil, LAS formed a 15-member LAS Team of researchers and analysts from NSA and other U.S. Intelligence Community organizations, North Carolina State University professors and students, and industry collaborators. It illustrated another tenet of the LAS approach, drawing on open sources and so keeping the work unclassified for as long as possible. LAS Team developed a variety of innovative open source tradecraft and analytics to support a range of U.S. Intelligence Community officers during the Rio games. The team shared its unclassified analytic results that were used then to enrich classified analysis. The Rio project issued into an ongoing effort, described in Chapter Ten, to develop tools for selecting and organizing open source data, and methods for using it analytically—a critical area where the Intelligence Community has lagged behind commercial enterprises.

In another case, LAS employed agent-based modelling (ABM) to probe illicit networks—an example of an intelligence complexity. Plainly, running experiments on illicit networks is impossible, so ABM offers rich simulations, with agents, rules for their behavior, and an environment in which they operate. ABM also played well to LAS strengths, for the models, usually with many actors, require broad interdisciplinary teams. Content specialists, such as anthropologists, economists, sociologists, and psychologists provide the richness, but then the challenge remains translating their ideas into high-level machine code. No topic or idea would belong only in one content specialist's domain; and when a topic was hard to communicate across the team, the team relied on the secondary proficiencies of its "bridge" members in order to identify the friction in communicating the concept.

The book's cases drive home the point that the kind of collaboration LAS represents are relevant not just for the Intelligence Community but beyond for those in relevant fields of education, or anyone interested in collaborating with government agencies.

—Gregory F. Treverton, October 22, 2019

Preface

Jessica Katz Jameson,
Beverly B. Tyler, Kathleen M. Vogel
and Sharon M. B. Joines

The need for collaborative partnerships in the U.S. intelligence community (IC) was laid out in *Vision 2015: A Globally Networked and Integrated Intelligence Enterprise*, a report prepared by the U.S. Office of the Director of National Intelligence (ODNI 2008b). *Vision 2015* made the case that the siloed and distributed model of intelligence that served our Nation in the recent past will not continue to be successful in the fast-paced, interconnected world we live in today. As the *Vision 2015* report describes it:

> *In this new environment, geographic borders and jurisdictional boundaries are blurring; traditional distinctions between intelligence and operations, strategic and tactical, and foreign and domestic are fading; the definitions of intelligence and information, analysts and collectors, customers and producers, private and public, and competitors and allies are changing. Simply distinguishing between intelligence and non-intelligence issues may prove a major challenge.* (5)

Vision 2015 concludes with a call for commitment to integrating policy, people, processes, infrastructure, and technology to optimize intelligence and provide "decision advantage" to IC customers, such as the President, military leaders, and policy makers charged with protecting our Nation and our allies. The same year Vision 2015 was released (2008b), the ODNI released "Intelligence Community Directive Number 205 (ICD 205): Analytic Outreach," which charged intelligence analysts to "leverage outside expertise as part of their work." This mandate directs analysts to identify the leading experts within the knowledge domains that made up their portfolios of analytic work, and to seek opportunities to engage with them to "explore ideas and alternative perspectives, gain new insights, generate new knowledge, or obtain new information," in order to challenge their assumptions, address cultural biases, and mitigate groupthink (ODNI 2008a).

Wilhelm Agrell and Gregory Treverton's book, *National Intelligence and Science: Beyond the Great Divide in Analysis and Policy* (2015), further calls for collaborative approaches to intelligence to anticipate future intelligence needs. These authors acknowledge that information deemed irrelevant today has the potential to be relevant in the future, calling for movement from linear to more holistic analysis. The ability to collect information is aided by the proliferation of open-source information available through social media, yet the ease with which anyone can spread information requires increased emphasis on data validation, veracity, and integrity (Agrell and Treverton 2015). Perhaps more than ever, analysts must be part of a dialogue with each other and with the broader community. Agrell and Treverton call for the creation of hybrid organizations in which "experts, policymakers, and stakeholders are linked not just through a requirement-dissemination loop but interact on a more continuous and integrated basis" (197). The subject of this book, the Laboratory for Analytic Sciences (LAS), directly responds to all of these calls.

LAS is a cross-sector academic-industry-intelligence organization that connects researchers from multiple intelligence agencies, industry, and interdisciplinary academic scholars, and serves as a useful model for examining collaborative approaches to intelligence. LAS was founded in 2013 as the largest sponsored research contract in the history of North Carolina State University ($60 million over five years), with funding from the National Security Agency (NSA). LAS has created teams of intelligence analysts, who provide practical understanding of their needs, customers, and tradecraft, and work collaboratively with university scholars and industry partners of varying disciplines, who bring their expert knowledge and understanding of cutting-edge technologies and/or human behavior. These interdisciplinary teams work side-by-side to produce results that enhance how analysts create integrated and innovative analysis.

Importantly, LAS is unique in that it is a translational big-data research laboratory focused on the development of new analytic tradecraft, techniques, and technology. Translational research is a term LAS borrowed from the medical community that denotes "from bench to bedside"—or in this case, from ideation and research to delivery of practical tools, techniques, and tradecraft for intelligence analysts. One of the key features of LAS is that the technologies and tradecraft they are developing now are aimed at helping future intelligence analysts perform complex, integrated analysis to produce information and intelligence that meet our nation's most critical needs.

A practical example of LAS work reveals the promise of this type of innovative collaboration. In response to intelligence challenges presented during the 2016 Summer Olympic Games in Rio de Janeiro, Brazil, a 15-member LAS Team was created that included government researchers and analysts from the NSA and other U.S. IC organizations, North Carolina State University professors and students, and industry collaborators. The LAS Team developed a variety of innovative open-source tradecraft and analytics to support a variety of national IC customers during the Rio Summer Olympics. LAS researchers collaborated with other NSA and IC elements to provide and share unclassified analytic results that were used to enrich classified analysis. Upon receiving the prestigious National Intelligence Meritorious Unit Citation (NIMUC) for this work, the LAS Team was called out for "mission engagement, collaboration, and agile teaming with a mix of skills and expertise in systems engineering, data science, visual analytics, mission collections, and program management that enabled the IC mission to monitor and warn of emerging threats to the Rio Olympics" (Office of the Director, National Intelligence 2017). The Olympics project is just one example of the benefits of multiagency and multisector collaboration being realized at the LAS.

While government, industry, and academic partnership is not new, there are two especially unique aspects of the LAS. First, LAS is characterized by an unprecedented level of occupational diversity, including government staff from a variety of agencies, departments, and job classifications (including the presence of Five Eyes partners), as well as academics and industry partners from disciplines as varied as business management, communication, computer science, design, engineering, English, political science, psychology, and statistics. To date, LAS has attracted and funded over 60 faculty members and their students from 20 departments and eight of NC State's ten colleges, as well as faculty from Duke University; George Mason University; Rensselaer Polytechnic Institute; Smith College; University of Maryland, College Park; University of North Carolina, Chapel Hill; University of North Carolina, Greensboro; University of Notre Dame; University of Texas, Dallas; and University of Utah. The inclusion of scholars from the humanities and social sciences, as well as science, technology, engineering, and math (STEM), adds to the lab's disciplinary diversity. LAS has also hosted representatives from over 150 different companies, ranging from one- or two-person startups to large, multinational corporations. Many of these companies have been able to identify a role for their company in the lab's collaboration model and national security mission.

A second distinguishing feature of LAS is its commitment to "immersive collaboration." The Office of the U.S. Deputy Director of National Intelligence for Analysis, which sets analytic standards and policy across U.S. intelligence, has defined collaboration as "the interaction among members of the Intelligence Community and their partners—exploiting their diverse expertise and organizational resources to create higher value intelligence than an agency or officer can do individually to achieve the mission of the Intelligence Community" (McIntyre, Palmer, and Franks 2009). LAS takes collaboration a step further in defining *immersive collaboration* as a process through which cross-sectoral members share their disciplinary perspectives, cultures, methods, and insights to create a shared, transdisciplinary approach to problem finding and definition, project planning, and solution development.

LAS leaders and participants also engage in continuous and intentional *reflection* on unfolding processes, *observation* of the environment and outcomes, and *imagination* of how collaboration can be advanced and optimized. Indeed, the "reflect-observe-imagine" mantra was an initial core value for how LAS operated, and many of the original LAS participants internalized these ideas in support of a collaborative and innovative atmosphere.

While the LAS can boast several indicators of success in its first five years (recounted in Chapter One), immersive collaboration among diverse participants is hard work. Each sector—government, academia, and industry (and the sub-units within them)—has its unique jargon and acronyms, recognition and reward systems, occupational norms, and work habits. These structures create both physical and social psychological barriers to information sharing, collective sensemaking, and collaborating.

The goal of this book is to document and share what we have learned in the first five years of the lab's existence about the nature, process, and outcomes of interdisciplinary, cross-sectoral, immersive collaboration in order to better inform academic-industry-intelligence partnerships today and into the future. The editors of this book are academic faculty funded by LAS who were initially brought into the lab to facilitate team collaboration, observe and record processes, develop protocols, and participate in mission-based activities. The four of us represent the fields of business management; communication; science and technology studies, and science and technology policy; and design. We joined the lab in 2014, just six months into the first delivery order, and were part of a larger group tasked with facilitating meetings, observing lab activities, and designing interventions to optimize collaboration. In addition, individual chapters of this book have been written by LAS staff and LAS-affiliated industry and academic partners. This book represents individual and collective reflection and analysis of hundreds of hours spent in LAS meetings, seminars, workshops, and symposia; interviews with LAS members, visionaries, and customers; surveys of LAS member perceptions and processes; and reviews of relevant scholarly work on action research and engaged scholarship, organizational innovation, interdisciplinary communication and collaboration, and security studies.

Audiences

We believe this book will be of interest to several audiences in the IC, the academy, and industry. There are leaders in the IC, for example, who want to replicate similar cross-sector labs on other academic campuses. Many IC members want insights into how to enhance collaboration and facilitate change in a culture that has privileged individual success and the maintenance of information silos. Examples of change in IC culture include the creation of research centers (see, for example, McIntyre, Palmer, and Franks 2009; Ehrhart 2009), and a group of NSA employees who study and improve collaboration by identifying barriers to cooperation and information sharing among analysts and agencies. Several LAS participants are members of this group, thus providing an important feedback loop as we share our LAS discoveries with them.

Interest in collaboration throughout the IC is also evidenced by the Collaboration Summit held in March of 2016 (see https://www.govevents.com/details/19303/ic-collaboration-summit/). While there was no government mandate to hold this conference, it was organized by U.S. intelligence officers and affiliates from all over the world. There were 500 registrants for this conference and approximately 350 attendees. In addition, previous books, such as Hackman's (2011) *Collaborative Intelligence, Using Teams to Solve Hard Problems* and Agrell and Treverton's 2015 book, described above, also demonstrate the desire to better understand, promote, and improve collaboration and information-sharing processes throughout the IC. These books draw from the fields of psychology and intelligence analysis, respectively, to prescribe best practices for team collaboration and describe the science of intelligence. The current book builds on and extends these predecessors, and others, by integrating academic fields such as management, communication, computer science, and design with our experiences and action research to document what we have learned about the structure, leadership, and interpersonal dynamics over several years with one model of multiagency collaboration with academic and industry partners. This book also differs from others by exploring all three levels of analysis—program, team, and individual—to promulgate a model for collaboration that can be replicated and adapted to build and sustain immersive collaboration with internal and external partners at the academia-industry-intelligence interface.

The desire for relationships between the IC and academic scholars from a variety of fields suggests there is also an academic audience for a book on IC collaboration. The historical relationship between the IC and the academy was featured in a book called *Cloak and Gown: Scholars in the Secret War 1939-1961* (Winks 1987). This book provides useful historical background for understanding collaborations between the academy and the IC, yet does not provide guidance for creating new collaborations today, when there is a demand to understand how to better connect intelligence and academia. Professor Bowman Miller, at the National Intelligence University, one of the IC's training grounds for analysts, has argued that the IC must increase its engagement with outside experts to facilitate "cross-pollination" of ideas—to bring into the IC the unique depth and time horizon of knowledge that academics possess, and to help intelligence analysts "think outside of the box" (Miller 2010). This sentiment was reiterated at the 10th Anniversary Homeland Defense and Security Education Summit in March 2017 at George Mason University. This conference included 275 federal and state participants representing 14 government agencies, such as the Federal Emergency Management Agency (FEMA) and the Department of Homeland Security (DHS), 43 academic institutions, and eight industry partners. Keynote Speaker Susan Coller Monarez, U.S. Deputy Assistant Secretary for Strategy and Analysis in DHS' Office of Policy, spoke about the importance of IC collaboration with the academic community, saying specifically that she appreciates academic engagement in conversations about homeland security and believes "we should never stop thinking about ways we can improve ourselves" (Keynote presentation, 10th Anniversary Homeland Defense & Security Education Summit, March 24, 2017). This book will also be of interest to academic scholars interested broadly in team science and interdisciplinary collaborations (see, for example, Aboelela, Merrill, Carley, and Larson 2007; Barbour and James 2015; Fiore 2008; Walker and Stohl 2012). Finally, members of the industrial sector who are interested in forming collaborative and engaged partnerships with government or academia should be interested in better understanding how to work collaboratively, and they would thus benefit from exposure to the comparison of various models of collaboration, as well as the description of innovative team processes and outcomes featured in this book.

Organization of the Book

The book includes three parts. In Part I (Driving Motivations and Basic Frameworks), authors who were part of the original research team write about their experiences conducting research on and creating interventions to support immersive collaboration. Part I begins with a recounting of the motivation for the creation of LAS in Chapter One, "Innovating National Security through Immersive Collaboration: The Vision and Construction of the Laboratory for Analytic Sciences." Drawing from interviews with NSA and NC State leaders and visionaries, Chapter One describes the IC environment that surrounded creation of the lab, logistical details, the partnership model, and the evolution of structures and protocols in the first years of the lab. Chapter Two, "Supporting Immersive Collaboration," describes the administrative decision to create teams of facilitators, designers, and observers to support and study interdisciplinary communication and collaboration at LAS. The chapter is an overview of our team's initial observations and conclusions regarding how structures support or impede collaboration. Chapter Three, "Member Perceptions of Collaboration," presents a theoretical model of collaboration and the results of a longitudinal survey and focus-group interview with LAS members to examine member perceptions of the immersive collaboration at LAS. Chapter Four, "A Social Network Analysis of Collaboration at LAS," describes a social network analysis of LAS relationships that reinforces the notions that networks expand over time, and that each team's success is related to the role of the leader and their connection to others in the network.

Part II, Social and Technological Interventions for Collaboration, includes two chapters. Chapter Five, "Promoting Collaboration," describes a variety of interventions designed to bring LAS participants together and enhance collaboration. Activities included expert-led seminars, a series of short- and longer-term workshops, development of an LAS lexicon, networking events, team health checks, and an annual symposium. The interventions are described to showcase their potential as well as demonstrate the benefits and limitations of each. In Chapter Six, "Supporting Collaboration and Discovery with Novel Computing Technologies," we discuss a set of key LAS prototypes that are being developed to promote collaboration in future intelligence work.

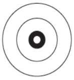
Part III of the book (Chapters Seven-Thirteen) includes a series of case studies that describe the experiences of LAS personnel and partners as they collaborated in specific research teams. Rather than merely arguing for the need for collaboration, these cases demonstrate real processes and pitfalls that collaborators experienced on their way to developing innovative research, products, solutions, and/or prototypes. Each case includes a description of how the team formed, the problem they intended to solve, team processes and pitfalls, what they learned about collaborative work, and how their output directly supported mission. The team projects described include "Anticipatory Thinking" (Amos-Binks, Browning, and Argenta—Chapter Seven), "Agent-based Modeling" (Artman, Li, Laber, and Johnston—Chapter Eight), "Learning from One Another" (Keyton, Jones, and Argenta—Chapter Nine), "Open Source Knowledge Enrichment" (Slankas—Chapter Ten), "Internet of Things" (Crawford, Kotlar, and Sherman—Chapter Eleven), "Analytic Rigor" (Tait, Vazquez, Tyler, Keyton, and Kampe—Chapter Twelve), and the "Technical Maturity Framework" (Kampe and Schmidt—Chapter Thirteen). Chapter Fourteen concludes the book with a synthesis of lessons learned from LAS and the implications for interdisciplinary and cross-sector collaboration within the U.S. intelligence community.

To mark important ideas for the reader, each chapter begins with a list of key terms and key points that carry practical implications for supporting or enacting immersive collaboration at program, group, and individual levels of analysis. In this way, we hope to make clear how readers can foster and implement collaboration, whether they are directing a cross-sector research lab, leading an interdisciplinary team, or participating as an individual in a collaboration. Figure 1.1 provides an example of how the key points at each level are highlighted throughout the chapters of this book. We hope that the LAS serves as an inspiration for other collaborative partnerships and helps participants navigate the challenges they entail in order to engage in continuous learning and realize the potential and promise of immersive collaboration.

KEY POINTS

Program: This refers to a method worked out in advance for achieving some objective. In the key points at the beginning of each chapter, we use the term *program* to refer to policies or procedures that apply to the entire Lab; we often refer to implications at the "the programmatic level," such as communication, cultural alignment, and leadership.

Team: Throughout this book we use the term *team* to discuss any group of LAS members who work together to achieve a goal; we often refer to implications at "the team level," such as meeting logistics and membership and team goals.



Individual: Throughout this book we use the term *individual* to refer to individual LAS members; we often refer to implications at "the individual level," such as recruiting, onboarding, motivating, rewarding, and giving feedback.

Figure P.1: Description of "Key Points" visual for each chapter.

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Part One:

Driving Motivations and Basic Frameworks

1

INNOVATING NATIONAL SECURITY THROUGH IMMERSIVE COLLABORATION: THE VISION AND CONSTRUCTION OF THE LABORATORY FOR ANALYTIC SCIENCES

BEVERLY B. TYLER

LAS Brings together forward-looking academics and established industry, small business and start-up partners to collaborate hand-in-hand with the Intelligence Community and the Department of Defense mission partners, analysts, and researchers. Together, these teams envision, research, and create common analytic tools, tradecraft, and methodologies that further the art and science of analysis.

–Quoted from Invitation to 2016 LAS Symposium

CHAPTER 1

KEY TERMS

- **Collaboration**: communication and activities among interdependent parties that includes the sharing of information, resources, and ideas.
- **Delivery Order:** Also referred to as DO, is literally an order by LAS funders to deliver products within a set time frame. DOs are mostly annual, but several can run at the same time. Only academic and industry performers complete deliverables under DOs; however, LAS-G staff align their efforts with DOs to support immersive collaboration efforts. Throughout this book when we refer to a DO#, we are referencing the goals of or deliverables completed for that delivery order.
- **Immersive collaboration:** Immersive collaboration is a process through which cross-sectoral members share their disciplinary perspectives, cultures, methods and insights to create a shared, transdisciplinary approach to problem finding and definition, project planning, and solution development.
- **Interdisciplinary:** A mode of research that integrates concepts or theories, tools or techniques, information or data from different bodies of knowledge (Yegros-Yegros, Rafols, and D'Este 2015)
- **Operational Processes: (noun)** a series of actions or operations conducing to an end; (verb) to subject to or handle through an established usually routine set of procedures. In this book, we use the term processes to refer to patterns that develop to achieve a goal that may become routinized, either at the individual, team, or program level.
- **Physical Structure:** Something arranged in a definite pattern of organization. Here we use the term physical structures to refer to organizational features that apply to LAS as a whole.
- **Translational:** The efforts of LAS are to translate basic science and research into practice through the development of methods and prototypes that address mission needs.

KEY POINTS

Program: The primary goal of LAS is to *reinvent the intelligence analysis process* in a way that leverages the expertise of academic and industry partners. LAS is expected to bring greater scientific rigor to analysis through academic and industry engagement, and generate innovative ideas for data analysis. It is believed that engagement with external partners can address several barriers to effective decision making, motivate consideration of alternative hypotheses, encourage proper sourcing and tradecraft, and potentially alleviate confirmation bias.

Careful partner selection is important to the success of any IC program collaborating with an academic institution. Universities may all be institutions of higher learning, but their histories, competencies, cultural values, visions, and leadership vary widely. When partnering for innovative solutions to security challenges, the IC must diligently assess the different institutions they could partner with and make a very complex multi-dimensional decision. Such financial commitments tend to be large and path dependent, so caution and care in deciding are imperative.

Decisions about the *contractual relationship* between the IC and an academic institution, as well as the *physical structure* and *operational processes* of the lab, are important, but they must also be malleable, so they can be revised over time. One reason for LAS success has been the willingness of leaders to learn what worked well and what needed to change from year to year; this has served to increase commitment to the lab and the concept of immersive collaboration.

Over the past 20 years, in response to changing technologies, data infrastructures, and emerging threats, the US National Security Agency (NSA) has experienced significant transformations in the methods needed to accomplish their mission for intelligence gathering and analyses. To address the challenges of the 21st century, the NSA has sought solutions through a number of investments designed to support their needs in the evolving intelligence landscape. Accordingly, the NSA theorized and proposed an innovative research and development (R&D) program that would connect, focus, and help coordinate government experts' participation with academic and industry experts: the Laboratory for Analytic Sciences (LAS).

LAS, also referred to here as "the Lab," is a partnership among the NSA and North Carolina State University (NC State) that brings together some of the brightest minds from government, academia, and industry to address the most challenging "big data" problems related to national security, and to promote new advances in the science of analysis. The purpose of this introductory chapter is to tell the story of the initial motivation to create the LAS, describe how the partnership between the NSA and NC State was formed, and recount the physical structures and operational processes that were created to realize the LAS vision. The goal is to provide practical information for those who might be involved in constructing a similar cross-sector, interdisciplinary lab, as well as supply important information about the LAS context.

For a comprehensive understanding of the partnership's formation, we have reconstructed the origins of LAS from a variety of sources: interviews with eight NSA and five NC State leaders involved in the initial planning and start-up of the Lab; the authors' experiences, observations, and analysis of LAS documents; and the insights of LAS members who have read and contributed to this chapter. Many of the interviewees also read our history and provided additional commentary or verification.[1] In sum, our method for constructing this history mirrors the LAS vision of cross-sector collaboration and offers rich, qualitative insight into the creation of the Lab.

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[1] From November 2015 through March 2016, Dr. Beverly B. Tyler, with the assistance of colleagues, interviewed eight NSA personnel and five NC State administrators actively involved in the establishment of the LAS at NC State. The transcribed interviews form the foundation for this historical overview of the motivations, set-up, and early years at LAS. Although inconsistent understandings were at times reflected in the interview responses, Dr. Tyler acknowledges any potential mistakes in the overview as her own.

Creating the LAS: Motivations

Early motivations for the creation of LAS derive from the growing technological and personnel challenges that developed from the rise of the age of information and previous intelligence community (IC) programs that sought to leverage the knowledge of academics and industry. Because the job of the NSA is to collect timely information, embed it in the appropriate context, and transmit it to decision makers in a way that can be easily consumed and acted upon, many urgent questions had arisen: How can NSA better manage data? How do we sort through it? What should be labeled as "important data" coming out of this information? How do we understand it? How do we get the information that we need quickly and effectively? How, then, do our analysts communicate it effectively to the customers who most need it? How do we double the productivity of an individual analyst? As exemplified by these questions, the exponential rise in the amount of data increased the strain on analysts to perform an already very difficult job, and required researchers and designers to re-think the tools they were using and developing. NSA leaders recognized that re-engineering the analysis process would require not only a new, improved process and methodology, but a new venue for innovative research. The IC had experience with several previous programs designed to encourage cross-sector collaboration, and these models provided a blueprint for the vision of the LAS.

One model that has been in place for 50 years involves bringing NSA employees, government researchers, and academics together for 10 weeks each summer to focus on a few very important national security problems that tend to be mathematical in nature. The dynamic of cross-sector researchers working in a co-located space for an intensive period has been universally hailed as a stunning success that highly influenced the thinking of those involved in setting up the LAS.

Another initiative was designed as an outreach program to invite experts to examine analytical problems within the IC; introduce analysts to new tradecraft, technologies, and diverse thinking; and strengthen networks inside and outside intelligence. This model of collaboration was even more interdisciplinary than the program described above. It consisted of different kinds of government analysts, such as technologists, collectors, policy experts, and academics; and a broad set of industry partners, such as entrepreneurs, angel investors, medical doctors, film producers, and game developers. Inspired by the above model, participants in this new program were sequestered at a remote, off-site location for four weeks each summer to study, analyze, and assess a particularly thorny national security problem, with as much of the work as possible being done at the unclassified level. The immersive nature of this program resulted in the development of strong, long-term, sustainable bonds among participants. Although this program has since been discontinued, former participants retain a cohesive community in which they collaborate and solve problems using the social network they developed during the program. Those setting up the LAS wanted to adopt lessons learned from this program as well.

LAS was envisioned to incorporate the best of these previous IC programs while making a sustainable commitment to immersive collaboration. The concept of *immersive collaboration* denotes a culture that goes beyond collaboration as coordination or cooperation to the idea of analysts and government researchers tackling problems “arm-in-arm” with academic and industry partners. At LAS, it is a process through which cross-sectoral members share their disciplinary perspectives, cultures, methods, and insights to create a shared, transdisciplinary approach to problem finding and definition, project planning, and solution development. This approach creates new knowledge and innovations informed by the interdisciplinary, multisector perspectives of the participants. In particular, interviews with the visionaries and first leaders of LAS revealed that the primary goal of LAS is to reinvent the intelligence analysis process in a way that leverages the expertise of academic and industry partners. LAS would bring greater scientific rigor to analysis through academic and industry engagement and generate innovative ideas for data analysis. Engagement with partners external to the IC could address several barriers to effective decision making, motivate consideration of alternative hypotheses, encourage proper sourcing and tradecraft, and potentially alleviate overall confirmation bias.

Finding the Venue: LAS and NC State

The initial conversation that sparked what would become LAS at NC State likely dates back to 2009, when Mike Wertheimer, Director of Research at NSA, paid a visit to SAS CEO Jim Goodnight in Cary, North Carolina. Wertheimer shared his vision of the formation of a NSA Laboratory: a hybrid of the best practices of the mathematics community at NSA and other IC programs. Goodnight then took Wertheimer to meet NC State Interim Chancellor James H. Woodward. Following that eventful meeting, NSA leadership began the two-year process of securing financial support, developing a budget, getting buy-in from faculty and industry partners, and exploring precisely what the Lab was going to do, where it would be housed, and how it would be built.

In December 2011, members of the NSA Research Directorate extended the initial vision for LAS in a whitepaper. Mike Wertheimer made a convincing case for LAS, and by the following December, the project was officially approved. NC State was awarded a five-year contract in June 2013. Following this award, the new LAS leadership, including the director, technical director, and mission director of the LAS program, headed to Raleigh to begin this new endeavor and initiate conversations with faculty at NC State and other local universities, as well as with industry partners, to encourage collaboration with LAS. Research at LAS commenced in September 2013, marking the Lab's official opening, in tandem with that of the fall semester on the Raleigh campus.

NC State's academic resources were important to their selection as research venue by NSA leaders. On the academic side, the NSA was interested in a university with both a strong science, technology, engineering, and math (STEM) reputation, and respected social and behavioral sciences programs. The fact that NC State had the Institute of Advanced Analytics, the only master's program of its kind at the time, suggested that LAS would find traction with faculty in this space (Amstat News 2014). One of NSA's requirements was a campus that would support a flexible collaborative environment in which students, faculty, industry, and government participants could work jointly to advance national security analysis and tradecraft. At the time, NC State was building its reputation as a highly interdisciplinary, inter-institutional, cooperative academic institution. In addition, many of its students were US citizens, resulting in fewer obstacles to student participation. Finally, NSA needed a campus that permitted classified work on campus. Although this disqualified a large number of universities in the United States, NC State has permitted classified work. When they narrowed down the schools that met all the other requirements and allowed restricted research on campus, NC State was at the top of the list. These qualifications also allowed NSA to employ a sole source contract—uncommon in government contracting—in which multiple bids are typically required.

In addition to its academic resources, NC State is also attractive due to its proximity to the academic, industrial, and cultural diversity of nearby Research Triangle Park (RTP) and its location in Raleigh, North Carolina's state capital. Fort Meade, the home of NSA, is also a relatively convenient drive for visitors and NSA staff to travel between facilities when needed. The local community was also interested in participating with the LAS, especially industry partners such as IBM and SAS. Locating in Raleigh and RTP would allow LAS to leverage the skills of both larger, well-established information technology firms and smaller, more entrepreneurial firms involved in the development of analytic science (Kulikowski 2013). Furthermore, central North Carolina is known for its moderate climate, reasonable cost of living, and high quality of life, compared to other high-tech regions such as Silicon Valley.

NC State leadership was eager to house LAS in partnership with the NSA. The main motivations were to (1) increase engagement in the defense sector, (2) strengthen their reputation in analytics, and (3) improve translational, interdisciplinary, and collaborative research methods. First, NC State had the least defense funding of the three universities in the "Triangle" (University of North Carolina at Chapel Hill, Duke University, and NC State). At the time, the monetary award to create LAS would be the largest sponsored research project in the history of NC State, and would solidify NC State's position in defense research. Second, NC State also wanted to formalize their affiliation with NSA and strengthen their advantage in analytics. For the university, LAS was a great opportunity to further enhance their established reputation in "big data analytics" and cement their leadership role in "intelligence analytics" (Dewitt 2014). Finally, the LAS partnership also leveraged additional funding sources for doing advanced research in video gaming and cyber security, as well as funding for faculty in the behavioral and social sciences (e.g., business, communication, design, political science, and psychology)—all disciplines vital to NSA's efforts to reinvent the intelligence analysis process. Ultimately, NC State saw LAS as an opportunity to enhance their reputation as a research university dedicated to interdisciplinary, collaborative, and translational research—research that can be put into practice.

Contracting: Physical Structures and Operational Processes

Setting up the Lab was a complicated endeavor requiring new and innovative efforts on the part of NSA and NC State to establish a mutually agreeable contract. In total, it took three years and seven months of negotiations, starting from the initial meeting with interim Chancellor Woodward to finalize and sign the sponsored research contract. A number of issues needed to be addressed before work could begin on the physical facilities to house LAS. For example, NC State's accounting procedures needed to be adapted to manage the contract, the parties had to agree on the public face of LAS, the pre-publication review processes had to be acceptable to both parties, adjustments were needed regarding the timing of awards, a high-speed network had to be made available for the lab, and the extent of foreign national involvement had to be negotiated. Once these issues had been resolved, many different people were called in to consult on construction of the physical facility, or Sensitive Compartmented Information Facility (SCIF), as nothing like this had ever been established before at NC State. Ultimately, a location was found on NC State's Centennial Campus, an innovative space that houses the College of Engineering and is home to a variety of entrepreneurial institutes, centers, and partnerships with government, industry, and nonprofit organizations. Once the contract was in place, construction began on the SCIF close to existing space that could house LAS members who were not cleared. This facilitated collaboration between researchers, regardless of their level of clearance.

The work and contracting structure was equally new for NSA and NC State. After some consideration, NSA determined that the most appropriate arrangement for LAS was a $60 million, five-year Indefinite Delivery/Indefinite Quantity (IDIQ) contract (WRAL 2013). IDIQ contracts provide for an indefinite quantity of services for a fixed time, in this case, five years. The contract serves as the umbrella agreement under which the government issues delivery orders to NC State over the life of the contract.[2] Each delivery order (DO) lays out the specific research and development requirements defined by NSA for a given period (typically, six to twelve months), to which NC State responds by soliciting and contracting with academics and industry partners to conduct projects to fulfill these requirements. The initial goals for LAS included a focus on the science of analysis, improving the processes analysts use to accomplish their work, and taking advantage of publicly available (open source) data.

Initially, NSA staff at Fort Meade were asked to select key areas that would benefit from cooperative data analysis and intelligence work with academics and industry partners. The plan was for NSA to submit one or two important analytical problems to LAS regularly; LAS personnel would then experiment with new techniques for solving these problems. However, over time, the project selection process for LAS became more localized to LAS government leadership with input solicited from LAS

[2] The initial contract ran from September 2013 through 2017, but was later extended to December 31, 2018. A new five-year contract will run January 1, 2019–December 31, 2023.

stakeholders throughout the IC. They begin with a *requirements document* and pass it to the acquisition/contracting group at headquarters. Upon arrival, the document goes through a thorough review to ensure there are adequate funds to execute the proposed scope of work and that it is within the bounds of the umbrella contract. Once all the approvals are gathered, the Fort Meade contracting officer (CO) for the project (not the LAS director) issues a Request for Proposal (RFP) to NC State.

At the University, the program management team for LAS (primarily the principal investigator [PI] and the program manager [PM]) review the RFP, and then identify and recruit academic faculty and industry subcontractors who they believe can meet all the requirements described in the RFP. They request brief proposals or whitepapers from these potential partners that describe the research questions they are seeking to answer, their technical approach to the problem, and what deliverables will result from the work. For example, the RFP might request research into recommender systems for analytic workflows. Several relevant proposals might respond: one describing how to instrument and collect data on analyst workflows, another developing analytics for the instrumented data, and a third developing prototype recommender technology. The deliverables include the data set, the analytics and supporting analysis tools, and the recommender prototype.

From these whitepaper responses, the PI and PM submit an integrated response/proposal to the RFP. The response is then shared with the technical contract officer representative, who reviews the NC State response to determine whether it is acceptable from a technical standpoint. Once this review is complete, the CO begins a comprehensive review of the proposed costs to ensure they are fair and reasonable. Should the CO find anything incomplete or objectionable, the CO begins a negotiation with NC State. Upon the conclusion of the review process, the CO issues an award to NC State, which allows the University to negotiate with contractors and begin work. This process of ongoing communication between the NSA and NC State is critical to conducting translational research that directly supports activities connected to the NSA mission.

Recruiting LAS Participants

The ongoing partner recruitment goal is to communicate across a broad range of academic fields and try to find the common domains in which faculty, industry, and NSA personnel can work together to tackle big challenges in intelligence analysis.

Academic Partners

Prior to August 2013, LAS goals were to build the facility to host the lab and recruit the right partners to accomplish its fledgling mission. As such, significant effort was invested in engaging with faculty and industry. The LAS leadership team was busy learning what the academics at NC State were interested in researching without making a direct connection to NSA mission at that point. LAS leaders wanted to learn what topics would engage faculty members across all disciplines, including STEM, and less traditional IC partners, such as business, communication, design, and psychology. The reason for this was straightforward: NSA leaders we interviewed believed there were important insights to be gleaned from research areas such as cognitive psychology, human interaction, social media, and strategic management, and they recognized that humanities and social science faculty could assist them in translating these disciplines to the practice of analysis. In these early days of recruitment, faculty were encouraged to reflect on how their current research agendas might contribute to solutions to data management and analysis challenges. The LAS management team emphasized that faculty could continue their ongoing research programs while collaborating with LAS. It was critical for academics to understand the innovative LAS model that would leverage greater participation by funding "a little bit of time from a lot of people." LAS leaders listened to research presentations by faculty from dozens of departments from every college on campus, including the College of Veterinary Medicine. Listening events were also hosted at nearby campuses of the University of North Carolina at Chapel Hill and Duke University.

Industry Partners

A similar process was used to recruit industry partners. LAS leaders and NSA's Acquisition Research Center (ARC) initially contacted suppliers with whom they had pre-existing relationships. Likewise, they announced and held an "industry day," in which approximately 50 companies participated. During this full-day event, LAS team members from government and NC State met with companies for 20 minutes to hear their "elevator" speeches and try to identify potential partnering opportunities. Several future partners, such as Signalscape and ARA (Applied Research Associates), were involved in this event.

LAS also developed a tool for ongoing communication with potential industry partners known as "First Tuesdays." Following a whitepaper submission, potential partners were selected to come discuss their ideas on the first Tuesday of each month. First Tuesday events were announced through the ARC and attended by LAS leadership and representative government personnel, who engaged in conversations with these potential industry partners to determine the most promising partnerships.

Government Partners

LAS Government personnel are recruited through direct recommendations from their mentors, by word of mouth, and by internal position–opening announcements posted at Fort Meade. Government personnel are typically NSA employees, although there are also efforts to include members from other domestic and international partner IC agencies. The original work expectation for government personnel was described as approximately 40% of their time on LAS research and activities, 40% on operational activities, and 20% on professional development activities. A primary objective of the 40% operation requirement was to ensure that government personnel remained connected to operational work and, importantly, their IC network. Over time, that requirement has become less compartmentalized, as by the very nature of the collaborative work performed at LAS, government personnel maintain ongoing communication with the IC and its customers. This is crucial to the LAS goal of producing translational research that directly responds to and addresses challenges of data management and analysis.

While interdisciplinary and cross-sector collaboration are both vital aspects of LAS, the immersive collocation of government researchers and mission personnel is another important innovation. NSA leaders believe the best solutions are discovered when capabilities developers (researchers) work consistently with operations personnel (mission) to better understand each other's roles and contributions to the mission. At LAS, mission personnel sit side by side with researchers, so that they appreciate what science brings to the table. Likewise, collocation means that researchers better understand the operational problems to be solved and the most relevant short- and long-term problems. Thus, the goal for LAS isn't merely to have a group of researchers from the agency work with researchers from NC State and industry, but also to have operations personnel work arm in arm with government researchers from diverse backgrounds. This joint effort by government researchers and mission personnel is critical to how teams emerge to tackle important security and data analysis challenges.

Delivery Orders and LAS Project Teams

As described above, the contracted work at LAS is organized by DOs negotiated by the NSA and LAS leaders. Between its official opening and January 2019, LAS has completed eight delivery orders. The iterative process of each delivery order is a useful way to think about the adaptation and growth within the organization, although until DO6, begun in January 2016, DOs overlapped. Over this time, there have been three primary phases in the development of delivery orders: building the SCIF, early experimentation, and fine tuning of the LAS model. Delivery Order 1 (DO1) constituted the first phase of building the SCIF from May 14, 2013, to August 15, 2014. The second phase of research lasted from August 13, 2013, to December 31, 2015, and included Delivery Order 2 (DO2) through Delivery Order 5 (DO5). Thus, in only 17 months, four DOs were completed. The final phase, which could be described as the fine tuning of the LAS model, extended from January 1, 2016, through December 31, 2018. Only three DOs were executed over this three-year period, each beginning on January 1 and ending on December 31. The changes in the process used by LAS leadership to determine the DO requirement, solicit whitepapers from academic and industry partners, and develop a Statement of Work to link the projects funded with the requirement they met were minor during this period.

The IDIQ contract between NSA and NC State served as an umbrella contract that allowed the relationship to evolve over the life of the contract, rather than dictate development of specific, short-term “widgets” or prototypes. The NSA structured the LAS-sponsored research agreement in a flexible manner to allow them to tap into the diverse set of research avenues they wanted to pursue over time. Part of their intent in putting an IDIQ contract in place was to continually explore emerging areas for engagement over the course of the contract. With this in mind, DO1 was contracted to hire the core personnel required to administer the LAS and build the physical facility. Funds were used to hire a program manager, an administrative assistant, and a contract special security officer, as well as a subcontract manager, who was responsible for building the SCIF.

DO2 established the first eight LAS projects in late 2013. These project teams were largely comprised of computer science faculty, with minimal representation from other disciplines, such as civil engineering, statistics, communication, psychology, and business. These early teams met on a weekly basis, along with the LAS leadership team (as they were the only NSA personnel on campus at the time) and a few doctoral students. In DO2, LAS leadership asked participants to come up with *grand challenges* similar to those issued by the Defense Advanced Research Projects Agency (DARPA). This involved coming up with an interesting set of questions that could be addressed by an interdisciplinary group of faculty around a particular theme. Once the questions were established, the groups were then asked to create a roadmap of how they might go about investigating those research questions. The roadmap was to be a long-term, three- to five-year plan, rather than a tactical approach to the problem. Sample DO2 projects included a group looking at how we might use criteria such as validity, veracity, and volume to develop a tool to gauge the readiness of a body of data to be acted upon. Another team examined issues of cognitive processing, including an experiment in how group members influence each other's decision making when predicting the results of a Presidential election.

Despite the initial directive to think about the grand challenge, there was a clear push toward the final quarter of DO2 to develop prototypes for new technologies and tradecraft in areas that the NSA wanted to capitalize on. As described by one interviewee, the LAS was to help NSA "not be behind the 8-ball, so to speak, behind the curve from what was actually going on out in the real world." Another tension became apparent, as it was clear the LAS needed to provide tangible evidence of progress while also providing space and time for big-picture, innovative ideas in support of the mission.

DO3 established four new team projects in May, 2014, and was concurrent with DO2. The DO3 projects were more diverse and interdisciplinary in nature than those in DO2, and one focus of DO3 was to begin to transition some of the research done at LAS into mission effects. For example, the *Mission Enabling* team was charged with taking research from the other teams and integrating it to create a mission effect. One project from this team was a recommender system intended to assist analysts in selecting and practicing with new analytic tools based on the successes of senior analysts. DO3 therefore included a shift from grand challenges to prototype deliverables.

Having observed some challenges and growing pains of establishing an interdisciplinary, cross-sector Lab in DO2, LAS leaders created the *Collaboration Group* in DO3, to both study and facilitate collaboration at LAS. The editors of this book were all members of the original collaboration group. Chapter Two details the introduction of the Collaboration Group and its role in the ongoing evolution of LAS collaboration.

In response to NSA leaders' request for software tools that would help them with their intelligence mission, DO4 was launched to focus on work with industry partners to more quickly develop prototypes and technical solutions. For example, a DO4 project called *Collaborative Critical Thinking Skills Prototype Development* is described as a rigorous, structured analytic process to determine the quality of intelligence products. Resilient Cognitive Solutions (RCS), an industry partner, proposed an approach that would place structured analytic techniques used in practice into the larger context established by a Cognitive Work Analysis framework. This would allow better understanding, insight, and design of decision support for those who engage in structured analytic tradecraft. By integrating structured analytic techniques into a broader analysis workflow, the Collaborative Critical Thinking Skills (CCTS) prototype was posited to "help analysts improve judgment when faced with questions and issues requiring careful weighing of alternative explanations and conclusions."

DOs 5 (May–December 2015), 6 (January 1–December 31, 2016), and 7 (January 1–December 31, 2017) led to a shuffling (and some attrition) of participants. This time period included recruiting participants with different expertise and interests and a build-up of NSA staff at LAS. A new team structure was experimented with in DO5, in that every LAS participant—from government, academia, or industry—was required to participate in at least one *Cross-Cutting Team* (CCT). The CCTs were created by LAS members at a DO5 kick-off event, which also included a workshop on engaged scholarship and team leadership. The CCT members had complete autonomy to determine the deliverable of their CCT, which was expected to support their individual work while providing a space for interdisciplinary and cross-sector information sharing. CCT examples included one on developing principles of effective cross-sector collaboration and one that involved optimization of a journaling prototype designed to study and document workflow.

In DO6 LAS leaders introduced the exemplar structure, in which teams of government, academia, and industry participants were organized according to 12 specific phenomena or projects. *OpenKE*, for example, is a collection and analysis system for open-source information available on the Internet, while *Cyber* investigated five facets of cybersecurity: recovery from cyberattack, plan-based models of anticipatory intelligence, cyber risk analysis, open-source tradecraft for cybersecurity, and cyber defense. As of the writing of this book, LAS is completing DO7, which has seen a further refinement in the exemplar structure by creating 11 thematic areas, many of which are extensions of previous work. Examples of DO7 projects include *Cyber*, *Small Conflict Economies*, *Smart Cities*, and *Trafficking*.

Thus, the early history of the LAS was characterized by constant addition of government participants, shifts in project directions, interventions to encourage collaboration, and structural adaptations. The conditions created by dynamic short-term goals and constant evolution exposed challenges for LAS and generated many learning opportunities for the participants involved.

Overview and Key Learning Objectives

The excitement of LAS continues to attract experts from government, academia, and industry. New leadership and participants continually bring innovative insights to actualize the dream of the early LAS founders. Government personnel returning to NSA take with them an expanded network of colleagues and experience with immersive collaboration, in the hope that this will assist them in their future work and make them change agents in the transformation to a more collaborative IC culture. Meanwhile, LAS participants continue to explore how cross-sector, interdisciplinary research can help to address the most challenging analytic, mission-oriented problems related to national security and promote new advances in the science of analysis.

Moving forward from the history of the Lab's formation, this introduction presents four overarching themes interwoven throughout the chapters of the book:

1. The primary goal of LAS is to *reinvent the intelligence analysis process* in a way that leverages the expertise of academic and industry partners. LAS is expected to bring greater scientific rigor to analysis through academic and industry engagement and generate innovative ideas for data analysis. It is believed that engagement with external partners can address several barriers to effective decision making, motivate consideration of alternative hypotheses, encourage proper sourcing and tradecraft, and potentially alleviate confirmation bias.
2. *Careful partner selection* is important to the success of any IC program collaborating with an academic institution. Universities may all be institutions of higher learning, but their histories, competencies, cultural values, visions, and leadership vary widely. When partnering for innovative solutions to security challenges, the IC must diligently assess the different institutions they could partner with. Such financial commitments tend to be large and path dependent, so caution and care in deciding are imperative.

3. Decisions about the *contractual relationship* between the IC and an academic institution, as well as the *physical structure* and *operational processes* of the lab, are important, but they must also be malleable, so they can be revised over time. One reason for LAS success has been the willingness of leaders to learn what worked well and what needed to change from year to year; this has served to increase commitment to the lab and the concept of immersive collaboration.
4. The concept of *immersive collaboration* introduced here goes beyond "collaboration" as mere coordination or cooperation, to the idea of analysts and government researchers tackling problems "arm-in-arm" with academic and industry partners. Immersive collaboration is about inclusiveness and everyone working from the same page because they have the opportunity to define, plan, implement, and evaluate goals from a common starting point. Immersive collaboration is required to achieve LAS goals for discovery of innovative solutions that can be translated into the practice of analysis and tradecraft. Interventions intended to assist in the creation of a culture of immersive collaboration are discussed in Chapters Two and Five.

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2

SUPPORTING IMMERSIVE COLLABORATION

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Within the teams, it's taken a good long time for people to get comfortable with each other … most people don't trust themselves to ask a possibly silly question … nobody wants to sound stupid in front of a bunch of PhDs. … It's gotten better, but it took us a solid six months to feel comfortable with each other.

–Government employee, 2014

CHAPTER 2

KEY TERMS

- **Affinity Diagramming**: is a tool that gathers large amounts of language data (ideas, opinions, issues) and organizes them into groupings based on their natural relationships (Viewgraph 1). The affinity process is often used to group ideas generated by brainstorming.
- **Backstage:** Side or private conversations among a subset of team members not intended for the entire group.
- **Collaboration champion:** the individual within business who has both the passion for, and the authority to implement collaboration solutions for their workforce.
- **Collaboration group:** A project team created by LAS to facilitate, study, and improve its collaboration process.
- **Facilitation teams:** These were sub-teams within the CG that included a facilitator, an observer, and a designer. Each collaboration facilitation team worked with two groups for a one-year period.
- **Mapping Exercises:** Concept mapping is a general method that can be used to help any individual or group to describe their ideas about some topic in a pictorial form.
- **On-/Off-boarding:** the action or process of integrating a new member into an organization or team; conversely, the process of debriefing an organizational or team member as they exit the organization or team for the purpose of receiving feedback, information sharing, and promoting institutional memory.
- **Third place:** A place separate from one's home and work spaces where community building occurs.

KEY POINTS

Program: Program leaders are responsible for articulating a vision and mission and communicate the expectation of inter- or transdisciplinary work in which ideas are integrated to develop something new. They must create an environment that incentivizes members to spend time together in both formal and informal spaces; this requires attention to alignment of the professional cultures represented by program participants.

Team: Teams are responsible for negotiating a clear goal and ensuring that individual members understand how their knowledge, skills, and expertise will help produce the team deliverable while also helping individual members achieve their personal goals. Team members, especially those in leadership roles, must be trained in effective communication of meeting agendas, documentation of action items, and holding team members accountable for being engaged and making a contribution to the team.

Individual: Individual members are responsible for effective communication, including asking questions and making a commitment to the time it will take to listen to other Lab members. This includes a willingness to spend time with people within and external to their specific project teams. Participants in cross-sector, interdisciplinary research labs must learn to become comfortable with some level of ambiguity, what often felt like a waste of time at the moment ended up being an important part of the process of discovery.

As described in Chapter One, LAS was formally established in the fall of 2013, and six project teams were assembled to begin the process of identifying the major challenges and long-term research agenda across several domains of interest to the NSA. These initial teams were largely populated by faculty, as there were few government personnel on site at the time. During the first few months, it became apparent to LAS leadership and some team leaders that there was a difference between multidisciplinary teams, in which different disciplines are brought to bear on a topic, but work in parallel, and interdisciplinary or transdisciplinary teams in which two or more disciplines learn from—and with—each other to develop innovative insights. LAS leaders determined that if they were to achieve the goal of immersive, cross-sector, interdisciplinary collaboration, they would need assistance. It is important to note that this degree of self-awareness among LAS leaders did not occur by accident. The slogan LAS used in its early internal branding was "Reflect, Observe, Imagine," which was colloquially referred to as "ROI." All LAS members were expected to engage in continuous *reflection*, which required *observation* of both the content of their work and the processes they used for the achievement of goals and the *imagination* of the future. The management philosophy driving LAS encouraged recognition and acknowledgement of what was and *was not* working and a willingness to be flexible and responsive to feedback. This agility is critical for any new venture, especially one in which *collaboration*, *innovation*, and *transformation* are core values.[1]

LAS leaders recruited faculty and industry partners with the technical skills and research interests to support immersive collaboration, and the Collaboration Group (CG) was created in the second year of LAS, along with three new project teams. The initial objectives of the CG were twofold: (1) to facilitate collaboration among LAS research project teams, and (2) to study LAS collaboration and generate recommendations for optimizing collaboration. To achieve the first objective, the CG divided into three collaboration facilitation teams, each of which was assigned to work with two project teams. This created a natural experiment in which three existing LAS project teams had no facilitation team, three existing project teams had a facilitation team join them midway through their work cycle, and the three new project teams had a facilitation team join them from the very beginning of their work together. This structure gave each CG member the ability to observe and compare two LAS teams on an ongoing basis, and the CG met

[1] After a branding retreat held at the beginning of 2016 by LAS management, the branding changed from "Reflect, Observe, Imagine" to "Collaborate, Innovate, Transform." There is some evidence, however, that LAS members who were present in the early days have internalized the ROI framework.

biweekly to share perceptions of project team communication as well as successful (and unsuccessful) facilitation strategies. This allowed us to achieve our second objective of studying project teams and generating recommendations for optimizing immersive collaboration through a natural experiment (see Figure 2.1).

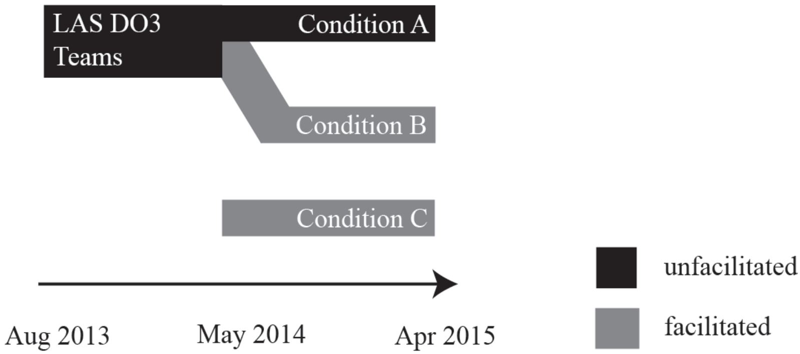

Figure 2.1: Original Collaboration Group natural experiment research design.

In addition to our ongoing participation in and observations of the project teams, CG members took notes, recorded audio, shared observations at team meetings, distributed a survey, and interviewed LAS members. The remainder of this chapter describes our role as facilitators and designers, and the processes we used to help optimize collaboration within LAS teams. We also describe our main observations in that first year and offer practical recommendations for supporting cross-sector, interdisciplinary collaboration.

Facilitating Interdisciplinary and Cross-Sector Teams

As we reflect on the processes we used to facilitate immersive collaboration in the early days of LAS, it is important to note that we did not have a unitary approach, which presented some challenges to our experimental design. Each facilitator came with a unique set of skills, experiences, and expectations of the performance of their role. Furthermore, project teams differed in how they responded to the presence of the collaboration facilitation team assigned to them. Not surprisingly, the integration was somewhat easier in project teams that included members of the facilitation team from the beginning of the group's formation, but this did not necessarily lead to greater success in helping individuals communicate, learn from each other, and collaborate.

To illustrate the way the collaboration facilitation teams engaged with the LAS project teams, two narratives are provided below. These narratives are not based on specific LAS teams, but are an amalgamation of group dynamics we observed across teams. They allow us to compare and contrast levels of collaboration as reflected in the experiences of the "Bronze Team" and the "Gold Team."[2] These cases help illustrate the philosophy and approach we took in trying to facilitate immersive collaboration.

In order to compare and contrast these hypothetical project teams in terms of group development, we use Tuckman's (1965) group formation framework for our team descriptions. The stages of group formation include: *Forming*—the initial phase of selecting team members, setting goals, and coordinating behaviors; *Storming*—the conflict that emerges once team members feel safe enough to disagree and contest each other's ideas and views; and *Norming* and *Performing*—overlapping phases that involve the creation of shared mental models and expectations, as well as task and goal achievement and ongoing feedback. While the stages are proposed as linear, it has been observed that groups often return to earlier stages, such as when there is a change in membership or as new conflicts arise. Identifying where teams are in the group development process has implications for facilitation, intervention strategies, and collaboration, as described in the narratives below.

Bronze Team: Sub-optimal Team Collaboration

A collaboration facilitation team joined the Bronze Team early in the summer of 2014, more than a year after the team's initial formation. As one of the largest groups, the Bronze Team consisted of over 25 members, composed primarily of STEM researchers. Over the past year, Bronze Team had experienced leadership and membership changes, and because of its size, the collaboration facilitation team spent a great deal of time trying to understand the context of the project team and the roles of its members before initiating any interventions. Their technical lead and members did not seem to understand the role or value of the collaboration facilitation team members. Bronze Team appeared to have completed its forming process, and members did not want to return to that stage to integrate the new collaboration facilitation team members.

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[2] To keep the identity of the participants in the teams confidential, we have created these two fictitious team names.

Within the first month of the collaboration facilitation team's infusion into the team, it became clear that Bronze Team had not developed collective norms ("norming"), and collaborative information sharing and discussion appeared to be limited. One team member questioned the university's capacity to accomplish LAS goals, providing evidence of storming. The collaboration group observed individual members having backstage discussions about their research and team problems, and there were obvious "in" and "out" cliques within the team. It also appeared that group members tended toward criticizing instead of encouraging their fellow team members when they took initiative. The critical delivery of feedback impeded team members from constructively engaging with new ideas and information. The team lead's struggle to lead the team exacerbated the lack of collaborative information sharing, and its members appeared to pursue their own research agendas independently rather than working toward larger team goals. We also observed that when outside visitors or participants in other LAS projects attended meetings to share their research with the team, no follow-up discussion occurred regarding how this research could be integrated to help achieve Bronze Team's goals.

At the three-month mark, collaboration facilitation team participants worked with the project team lead to stage an intervention at a monthly meeting, in the form of a facilitated group discussion and mind mapping exercise. Although initially resistant to the process, some Bronze Team members became more positively engaged when the mind mapping exercise revealed gaps that inhibited the team's work. This exercise marked the first time faculty team members directly engaged with government members and asked them to express their purpose and goals for attending team meetings. By the end of the meeting, it appeared that some group tensions had been reduced, members actively thought about how to resolve team problems, and certain members recognized the narrow disciplinary approaches they were taking to their team's work. It was clear that Bronze Team had reached an "aha moment" of recognizing the challenges before them and their shortcomings thus far, but were not sure how to proceed. Building on the positive feedback from the exercise, collaboration facilitation team participants planned to continue this facilitation process at the next meeting in order to continue to move the group forward, toward norming and performing, with the development of a more integrated, interdisciplinary research agenda.

However, this follow up intervention never occurred because the Bronze Team's lead was removed and replaced. From that point on, team members communicated primarily via email, and monthly team meetings were cancelled. When a new team member became Bronze Team's leader, older team members became even less engaged. This loss of group cohesion was compounded by the continued appearance of new government personnel who came to meetings as part of their orientation to LAS. While the goal was for new members to visit team meetings, meet people, and learn about the various LAS projects, existing members were not aware of this process and were thus confused by the new faces at meetings. The appearance of new members also required that time be spent on introductions and catching people up, rather than completing the tasks on that meeting's agenda.

Already struggling to frame their research question and develop an agenda to address it as a collaborative unit, Bronze Team became further fragmented when participants learned that some members would not be participating in the next LAS delivery order. Some members openly questioned why they should continue to work on finishing the project, and those whose contracts were not being renewed became less engaged in the group's tasks. As a result, Bronze Team's deliverables at the end of the contract period were minimal and primarily reflected the work of only a few individuals.

Gold Team: Optimal Team Collaboration

In contrast to Bronze Team, collaboration facilitation team participants joined Gold Team shortly after its establishment, when the team was still in the forming stage. Although initially unsure of how collaboration facilitation team members could be of assistance, the team treated them as equals and were open to learning more about the expertise they could offer the team. Instead of focusing on team member differences, team members encouraged each other to think of their collaboration as a joint effort. Gold Team included approximately 10 team members, and thus was about one-third the size of Bronze Team. As in Bronze Team, there were few government and industry participants, and most project team members were academics. Gold Team was composed of STEM faculty as well as social scientists.

Initial Gold Team meetings focused on brainstorming, discussions of the team's purpose and identity, and individual team member goals. The collaboration facilitation team encouraged members to think about how their individual goals and priorities could be aligned with the project team and LAS goals. These discussions also involved defining individual roles and responsibilities, which continued to be revisited as the group progressed. Team members shared relevant literature using the team's Google Drive to facilitate interdisciplinary conversations. The collaboration facilitation team participants helped Gold Team by facilitating mapping exercises around the team's brainstorming, and assisted in creating action items and deliverables for each meeting.

Originally, the team met biweekly in different locations across campus, although this changed over time. After several weeks, Gold Team found a convenient location for all team participants and agreed to meet there every two weeks to enhance team stability, an important indicator of successful norming. Several weeks into the team's formation, they realized that their progress was being disrupted by unplanned visits from new government staff when the team was still trying to make important innovations in thinking. Gold Team began to schedule more closed, unannounced meetings and subsequently began to make more progress toward its goals and deliverables. The introduction of coffee and snacks during team meetings and the presence of team banter and jokes also furthered team cohesion and productivity. In addition, one team member (neither a collaboration facilitation team participant nor the team lead) emerged as a *collaboration champion.* This person pulled people into the team meeting conversations and encouraged the team to think of the work as a joint effort.

At the three-month mark, the collaboration facilitation team members further guided Gold Team toward integrating its expertise and achieving its goals. This involved more mapping exercises drawn from literature that the team had identified in its early deliberations. This proved to be especially helpful, as it worked to unify the various disciplinary perspectives across the team. The "aha moment" for this team was when the group realized that it could utilize one key paper as the platform through which to explore a variety of interdisciplinary research questions and design a set of research experiments. Group members also realized that such research would add value to each of the team participants' existing individual research interests and agendas. An engineering team member, for example, realized through these discussions and mapping exercises that collaborating with social scientists could provide a whole new perspective that would move his own academic field forward and generate exciting top-tier scientific publications.

This intervention lead to further use of mapping exercises and encouraged participants to take the initiative and leverage this technique to move the team toward their specified goals. Several Gold Team members would stand up during meetings to contribute to mapping exercises on the board. Activities from previous meetings (as well as photos of the mapping exercises) were revisited at following meetings to build on past work, serve as a reminder of team progress, and illustrate how individual and team goals were interconnected. Individual team participants who had previously been less open to interdisciplinary collaboration became more engaged in team discussions, which revealed previously unseen gaps in the team's proposed activities. This collaborative environment was further enhanced by the Gold Team lead's strong administrative skills; the lead constantly reinforced the need to keep on track toward year-end deliverables. Team members also encouraged reticent teammates to actively contribute to group discussions. By the end of the summer, Gold Team had coalesced its research vision around one key paper and integrated the disciplinary expertise of many participants into a research agenda for the team. The team had constructed a unified vision for itself and developed team pride; several team participants would often tout without prompting, "we are the best team."

Norming and performing were evident in Gold Team, as the collaboration facilitation team observed open communication, frequent exchange of ideas, team member participation and commitment, and collegial support. Gold Team's small size may have enabled the smooth negotiation of clear roles, which contributed to transparency and accountability. Deliverables were divided amongst team participants with clear expectations and deadlines attached, and most participants followed through with their responsibilities to the team. If a participant was unable to accomplish a task because of time or work limitations, they were supported through workarounds created by the team. Instead of chastising participants, Gold Team created an environment that allowed members to be honest with one another about their work and time constraints, and fostered the feeling that teammates "had their back." Furthermore, Gold Team did not develop cliques or subgroups, potentially because of its smaller size. Its members were very good about keeping everyone informed when they could not attend regular team meetings. For example, when one team member was out on leave, other team members took it upon themselves to regularly brief that member on what the team was working on.

Gold Team also practiced effective on- and off-boarding of members. When a team member who experienced an extended absence returned, this person was reintroduced and seamlessly integrated back into the group. Also, when the next funding cycle was announced and certain participants did not receive further funding, Gold Team worked to soften the exit and transitions of team members. For example, the team lead organized a meeting to discuss the outcomes of the subsequent funding proposal process, who would exit the team, and how the remaining work would be completed for the 2014 deliverable. There was even talk of continuing the team's efforts with an external grant. Although Gold Team was disbanded at the end of 2014, it met its deliverables, and members continued to have conversations about how to continue their co-constructed research agenda.

Case Study Summary and Preview of Lessons Learned

The Bronze and Gold Team experiences reflect well-documented struggles of team formation in any context, heightened by the unique cross-sector and interdisciplinary composition of LAS. Key strengths of Gold Team's process that led to optimal collaboration included: member openness to the idea of being interdisciplinary; a strong lead who kept members on task, held members accountable, and was open to facilitation from the collaboration facilitation team; early sharing of information in the form of articles from various disciplines; integration of mapping exercises into the work process to emphasize interdisciplinary connections; frequent communication with members who missed meetings; inviting participation during meetings; and a collaboration champion, who reminded the group of their task and goal interdependence. It is worth noting that this team also created social routines by bringing coffee and snacks to meetings, which may have helped develop the sense of team identity and camaraderie that enabled collaboration and cohesiveness. Another important point is that Gold Team avoided the obstacles associated with outside visitors by holding meetings "off book." While this is somewhat counter to the LAS interest in having visitors attend project team meetings, in this case it served to enhance group cohesiveness, goal clarity, and productivity in the early stages, when the team was still seeking to identify and establish a shared research agenda.

While Gold Team contrasts with Bronze Team in almost every way, it is notable that when the collaboration facilitation team was able to facilitate an intervention with Bronze Team, there was a clear turning point and a potential opportunity to leverage the intervention for a more fruitful collaboration moving forward. However, the challenges underlying Bronze Team's collaboration processes required more time and attention than one intervention could resolve. This indicates that an extended period of intervention is necessary to effectively change problematic group dynamics. In addition to illustrating the relevance of Tuckman's model of group development, these two cases are intended to highlight and preview the six major themes we uncovered in our initial study of LAS collaboration: (1) individual motivation, (2) setting group goals, (3) meeting logistics and team membership, (4) power and leadership, (5) cultural alignment and integration, and (6) effective communication. Table 2.1 provides a comparison of how these six themes are illustrated in the Bronze and Gold teams.

	BRONZE	GOLD
INDIVIDUAL MOTIVATION	Motivated by individual projects	Motivated by idea of interdisciplinarity
SETTING GROUP GOALS	Unclear goals for each meeting	Defined individual and group goals and developed a group paper idea
MEETING LOGISTICS AND TEAM MEMBERSHIP	Very large group; sub-groups emerged; did not use CG FT optimally	Closed meetings to avoid unexpected visitors to stay focused; accepted CG FT right away and allowed them to suggest processes
POWERAND LEADERSHIP	Critique of individual ideas; Changing leadership	Encouraged team members to participate and created a sense of esprit de corps
CULTURAL ALIGNMENT AND INTEGRATION	Lack of collective norms	Mapping exercises and a collaboration champion facilitated emergence of collective norms and creation of an interdisciplinary research project
EFFECTIVE COMMUNICATION	Lack of collaborative information sharing or understanding of how members could help each other	Clear negotiation of member roles and deliverables; sharing of information during meetings and documented in Google docs

Table 2.1: Comparison of six collaboration themes across the Bronze and Gold teams.

Studying Early Collaboration at the LAS

In conjunction with the technical, facilitative work, CG members were also engaged in the scholarly study of cross-sector, interdisciplinary collaboration at LAS. Our initial study was designed to address the overarching research question: How can academic, government, and industry participants better organize (reporting structure, controls, and rewards) in large, interdisciplinary collaborations to transcend institutional and disciplinary boundaries, enhance innovative output, and optimize learning? This section of the chapter describes the observation and interview methods we used during our first nine months with LAS, and overviews the recommendations we made for optimizing immersive collaboration at program, group, and individual levels.

Observing the LAS

As described above, three collaboration facilitation team participants attended all meetings of their two assigned project teams (see Figure 2.1). At least one member took notes during these meetings and some meetings were audio recorded as well. One member of the CG also attended biweekly meetings with all LAS project team leads and LAS leadership. One or more CG participants attended quarterly reviews and other LAS events. The entire CG met biweekly for eight months to share, reflect on, and document our individual and collective observations.

At two points during our initial observation period, the CG engaged in affinity diagramming (Martin and Hanington 2012). This involves identifying key attributes or characteristics of a phenomenon and capturing their relationship to one another. The affinity diagram process involved identifying key words and phrases that reflected project team observations and writing them down on post-it notes. In stage two, the post-it notes were posted on a whiteboard, and CG members worked collaboratively to identify duplicate items, clarify words and phrases that needed elaboration, and place the terms into clusters to create a diagram that captured the array of attributes and characteristics. Photos were taken and the diagram was transcribed into a spreadsheet for further review and agreement on the final themes (see Figure 2.2). When the affinity diagram process was repeated for a second time, three months later, the results were compared with the first affinity diagram, and the group identified categories that remained the same, those that had changed, and new categories that emerged.

Figure 2.2: Affinity diagram of LAS project team observations.

Interviews with LAS Members

In order to avoid bias based solely on our team members' interpretations, we conducted in-person interviews with LAS leadership, government personnel, faculty members, and industry partners participating during that time period. We interviewed 31 LAS members to directly ask about their perceptions of collaboration and to solicit ideas for how collaboration might be improved. The CG members read interview transcripts individually and then discussed our interpretations, comparing the resulting themes to our observations.[3] This process resulted in the six themes previewed above. In the next section we describe these themes, provide examples from our observations and member interviews, and provide recommendations for optimizing collaboration based on this early research at LAS.

Early Immersive Collaboration at LAS

For each of the six themes we provide examples from our observations and interviews, relate to the Bronze Team and Gold Team vignettes, and present the practical implications for program, team, and individual levels of analysis, as applicable.

Motivation

When recruiting members to join a cross-sector, interdisciplinary lab based on immersive collaboration, it is critical to make sure that new members are motivated to do collaborative work. Interviews provided several examples of government personnel who applied to work at LAS because they wanted to get away from standard work routines and be stimulated by new people and ideas. These personnel (including the government staff) were motivated by the desire to think about Intelligence Community challenges and problems in a new environment, as one government leader stated about the government staff at LAS:

> *It gets them out of the daily grind of being in DC, which is produce, produce, produce. You're here to write reports. So, they kind of get away from that. It allows them to kinda sit back and think, which we don't always have the luxury of doing when you're in that [office] environment.*
>
> –Government staff, September 2014

[3] For more detail on the data collection and analysis process, see Vogel et al. (2017).

Another government personnel member pointed to the benefits of breaking away from traditional routines:

> *I mean the cool thing is that this exists on North Carolina State University, right? So from a government standpoint, you're working on a university doing hopefully cool things, or certainly different. That you're working with people who you would not normally work with on a particular problem because they're from a different background or different specialties than you are, which is intentional ...*
>
> –Government employee, November 2014

Similarly, many faculty were motivated to join LAS by the opportunity to find a practical application for their work or learn from IC members. One faculty member described his experience with two LAS teams:

> *For each of them there is a problem that I've thought about in the past, and it's a prominent element of what LAS needs and this is an opportunity to work on it. ... Figuring how to formulate these ideas as mathematical theories is a wonderful idea for me and I'm all excited about it; and it's a bigger area than I can do on my own, so I'm happy to have all these other people from different perspectives. ... So they are real problems and they would be useful to LAS.*
>
> –Faculty member, September 2014

Faculty with this mindset were open to collaboration with and learning from fellow LAS project team members, as also illustrated in the Gold Team description above, in which members actively shared and engaged with articles from each other's disciplines.

In contrast, our early team participation also revealed that some members came to LAS primarily focused on their individual research programs. As one faculty member described it:

> *I think a lot of professors are repurposing their own research and naturally they cling to it ... which is entirely understandable, because if you're a PhD student and you've got a program of research that's going to lead to a dissertation [in] three or four years, it's not really subject to the vagaries of the US government. That just doesn't work.*
>
> –Faculty member, January 2015

A new government employee described that the expectation was not made clear before they first came to LAS:

> *I've been researching for a long time so my natural inclination is to make my own thing, as opposed to [joining] an existing thing, but it wasn't necessarily made clear to me .... I mean, as a professional researcher, this*

is what I do, so if you want me to join somebody else's team, then that's less attractive to me than saying you can come down here, and you can get a pool of resources, and you can start your own team.

–Government employee, March 2015

Another LAS member described the problem this way:

If you delegate right away, then this can cause people to not be forced to move out of their comfort zone … instead, they just continue to work on what they are good at, and they interpret the LAS requirements as to do what they are already working on, and so each of the PIs [Primary Investigators] has proposed stuff based on their existing narrow area of expertise."

–Government employee, September 2014

When LAS members came in primarily motivated by the desire to complete a research program in progress, it was more difficult to appreciate the value of obtaining input from government personnel or faculty from outside disciplines. For these LAS members, they either left LAS (usually not an option for government personnel), were not funded for future delivery orders (if faculty or industry contractors), or discovered synergies between their work and IC needs that changed their attitude toward collaborative work and motivated them to continue their work with LAS. In some cases, it just took time for members to figure out how they could contribute, as one faculty member described:

The group seemed to function well. But it took me a long time to figure out where my research might fit in or my other, the other things, the things that I talked about in my original presentation [to LAS].

–Faculty member, October 2014

A member of government personnel similarly shared the challenge of figuring out how their skill set could contribute to LAS:

And, um, my analyst skills … that's a harder one, because they're really skills that are just sort of really relevant to the third floor [SCIF], which is something—I mean that's where we all—everything sort of breaks down into—it's really just peculiar to the high side [classified side], so—customized side, so. It's—I think we're all still struggling with how to better incorporate those aspects of our work into what we're doing here at LAS.

–Government employee, November 2014

These excerpts from interviews demonstrate that the very thing that motivated some individuals to join LAS, the opportunity to break from traditional routines and work with new people, also created ongoing challenges to communication and collaboration.

Practical Implications

There are examples of creative ways that LAS members enhanced motivation by aligning their personal goals with LAS goals, as highlighted in the Gold Team vignette in which participants developed a research program everyone was excited about. Another creative solution for some government and industry personnel was the decision to pursue a PhD while at NC State. Completing doctoral work enables LAS members to devote significant time to research topics that are of direct interest to the IC and LAS project teams, and serve as additional motivation for collaborative work. Some faculty members have recognized direct applications of work they are doing for the IC, such as a computer scientist developing a computer system that can be used to help junior analysts choose a faster or more appropriate tool for a specific task. One important key to sustainable collaboration is to motivate participants by encouraging them to discuss their individual goals and how they might contribute to the bigger team and program goals. Aligning goals at the individual, team, and programmatic levels strengthens common values, group cohesiveness and sense of community, and social fit, which are as important as technical knowledge in encouraging creativity and radical innovation (Judge, Fryxell, and Dooley 1997).

The most important practical takeaway regarding motivation is for program leaders to have initial conversations with recruits about the expectation of immersive collaboration, and the need to align individual goals with team and program goals. For teams, there is a clear need to negotiate member roles and contributions, and develop routines to ensure continuous collaboration and integration of member ideas into the team deliverables. At the individual level, whether coming from the government, academic, or industry sector, all LAS members must be open to investing the time in developing relationships with and learning from fellow team members. This relates directly to the second major theme: the need to set and clarify team goals.

Team Goals

It is well known that effective teams must negotiate clearly articulated goals (LaFasto and Larson 2001), and this is especially critical for interdisciplinary, cross-sector teams, in which members operate from different assumptions, norms, and routines (Keyton, Ford, and Smith 2008). We discovered that the initial LAS groups experienced challenges related to aligning individual goals and team goals and balancing short- and long-term goals. One project team member, a government employee, described the team's frustration with the amount of time it was taking to figure out the team goal:

> *We spent a lot of our time over the summer, instead of working, more on, uh, I guess, sort of rehashing where we are and who we are and what we are. … And so I think some of that, at least initially, was challenging. And I kind of go back and forth in my brain about whether that was useful at a conceptual level, because it really solidified what our foundations were and helped us clarify it. … At the same time, I know that the team was sort of frustrated in general about sort of slowing down the productivity.*
>
> –Government employee, November 2014

Another government employee similarly described the time spent trying to figure out how their knowledge and expertise could help the team achieve a collective goal:

> *We focused in on a specific, more specific, question, and sort of used that as a way to have those conversations and at least develop the framework. Um, I think a lot of our initial conversations were all of us just trying to figure out what we thought we were supposed to be doing.*
>
> –Government employee, October, 2014

An industry partner described the challenge of figuring out how various contributions could be integrated to solve a problem:

> *Developing problem scope, this is critical to being effective—how long it will be to solve it [the problem], can it be done in pieces? Currently, we have problems with identifying how those pieces fit together; we need someone who has the vision across groups and agencies.*
>
> –Industry partner, October 2014

Some of the challenges experienced by the initial project teams were related to programmatic decisions that were a necessary part of the LAS structure. For example, the contracting process used by LAS (described in Chapter One) requires individual negotiations between LAS leaders and government personnel or contractors. Some project teams managed this by focusing on their individual deliverables as a discrete component of the overall team goal. This practice describes multidisciplinary, rather than interdisciplinary, collaboration. Yet LAS project teams learned that this research model requires an up-front time investment, and time spent communicating about individual and team goals pays off, as one faculty team leader explained:

> *What I wasn't very interested in doing, and I think that the rest of the team agreed, was splintering off too early into sub-groups and starting to work on specific studies and tasks, and basically fractioning the group. And I think we have produced something that, even if we start doing [dividing into sub-groups] now, because not everyone can be working on each piece all at the same time; we all understand rather clearly, "How does this contribute to the big picture for the group?" At least it's my hope.*

As the previous quotes illustrate, the program design of LAS as a long-term, sustainable partnership, as opposed to an immersive, short-term collaboration (such as intensive summer programs described in Chapter One) has the practical implication of requiring teams to spend more time developing initial goals. As another government team member reflected, "there's still a question in my mind about whether or not we would have been much further than we are now, had we had more concentrated time." Yet LAS project teams learned how to manage this challenge, as described by this anecdote from one faculty team leader:

> *And so finally I laid a study in front of everyone with a methodology and with a focal problem, and framed that as being one thing that we could do and one methodology. I was not wedded to that, but wanted to see if we might use that as a basis to start adding each person's research interests and strengths to it, so that we could morph it into something that was more complex than what we were starting with, and that overlapped with everybody's interests and strengths. And I was willing to throw that out and replace it if someone had a better idea, but it gave us something tangible, and I think that that's when we really started getting traction and more excitement.*
>
> –Faculty member, October 2014

In addition to the challenge of developing team goals, the CG observed a tension regarding team members' focus on short- versus long-term goals. While the initial project teams were instructed to develop a five-year research plan to study the grand challenge (see Chapter One) presented by their research area, team progress was monitored and evaluated during a quarterly review process in place for the first year of LAS. This involved each team making a presentation to the entire LAS community to report on the team's progress. The biggest advantage of the quarterly review was that LAS team members shared information and could ask questions or provide feedback. However, emphasis on the quarterly review focused project team members' attention to short-term deadlines and may have inadvertently reinforced an individual work process, as described by one faculty team lead:

> *And, uh, the approach was where she's gonna wanna sorta take a stab at it, and then everybody else is gonna take a look at what she did. And [a team member] then made some suggestions. So we had two or three different sets of suggestions, and it came down to the deadline, and I sort of just tried to cobble [something] together based on all their input, um, the best I could.*
>
> –Faculty member, October 2014

While the quarterly review had the advantage of requiring team members to focus on their common goal, the short-term focus may have prevented teams from engaging in important information sharing and planning discussions that had greater potential to generate team learning and innovative long-term results.

Practical Implications

As a response to the limitations of the quarterly review process, an early programmatic change was made to move from the quarterly review to other forms of monitoring progress, obtaining feedback, and sharing information. In subsequent years (and delivery orders) LAS leaders also changed the team structure, so that project teams were centered around specific mission-relevant exemplars (such as Smart Cities or Cyber), rather than more global, abstract concepts such as Knowledge Management. These innovations are described in Chapter Five.

At the team level, the CG made two concrete recommendations for project team leaders regarding the challenges of team goals. The first was that all project teams needed to begin with negotiation of a team charter, a document in which each member explicitly defines the goals they plan to achieve, the specific tasks that support them, and how these goals are integrated into the overarching project team goal. Project management tools such as charters and Gantt charts would make team goals more visible and raise the level of accountability for direction setting and task completion (Gantt.com 2016).

A second recommendation was that project team leads engage team members in ongoing assessment of their short- and long-term goals. This would enable project team participants to take stock of how things are going; renegotiate tasks, goals, and timelines as needed; and consider how the project team and team lead might adapt to enhance their level of collaboration and effectiveness. This would facilitate ongoing reflection and accountability for individual LAS team members. We recommended this "team health check" be conducted routinely every three months, or at least at midyear. We discuss this intervention in more detail in Chapter Five.

Meeting Logistics and Team Membership

A variety of issues regarding meeting logistics impeded or facilitated LAS teamwork and effectiveness in the early days. Challenges included technological barriers, meeting attendance, agendas, meeting frequency and length, and participant skill sets. LAS teams relied on technology to connect geographically dispersed team members, and to present and share ideas during meetings. Currently, LAS uses a WebEX conferencing system that allows all LAS members to participate in LAS-wide programs, but individual team members do not always have access to WebEX for their meetings. Although each team has the autonomy to use the virtual teleconferencing system they prefer, this decision is not easy for cross-sector teams because of their different levels of access or familiarity with various platforms. While some groups use publicly available tools such as Skype, Google chat, and GoToMeeting, others use proprietary platforms associated with an industry partner on the team. During our work, we observed that teams did not spend time training members on the platform they chose, which led to delayed meeting starts and ongoing distractions as team members overcame connection and usability issues.

Other technological barriers to collaboration included inconsistent access to whiteboards, smart boards, and adequate seating/table configurations. While most of the meeting rooms at the main LAS facility had those features, the LAS facility location on NC State's Centennial Campus is approximately two and-a-half miles from the main campus (an eight-minute car or twenty-five-minute bus ride), where many NC State faculty have their offices. Challenges of finding meeting locations that were easily accessible to all team members resulted in some sacrifices that impeded effective discussion and the ability to use mapping or other visual reflection tools to support collaboration.

Meeting attendance and uncertainty around team membership also impeded immersive collaboration in the early days. Again, there were programmatic issues that augmented this challenge. For example, LAS leaders were interested in the project team discussions and wanted to be available to provide feedback and direction to teams as needed. As a result, a member of the leadership team would occasionally appear at a project team meeting without advance notice. Furthermore, a continuous stream of new government personnel flowed into LAS during the first year, and they were directed to visit different project teams to learn about the diverse projects and determine where they wanted to work. While these processes were practical and met important program (and individual) objectives, they created an atmosphere in which project team leaders and members did not know who would or would not be present during a given meeting. Having visitors meant that project teams spent meeting time introducing themselves, describing their work, and answering visitors' questions, which impacted the tone of the meeting and the team's ability to address agenda items:

> *And so it wasn't that we were getting new team members, but it was a lot of the LAS members that were coming down from the Fort who were trying to find a place. And so we wasted a—I don't know if we wasted a lot of time. We spent a lot of our time over the summer, instead of working, more on [task], uh, I guess, sort of rehashing where we are and who we are and what we are.*
>
> –Government employee, October 2014

A related limitation of these early LAS project team meetings was a lack of consistency in pre- and post-meeting rituals. Project team members often did not receive an agenda in advance and thus were uncertain of a meeting's purpose. As one team member describes:

> *We immediately started having these every-two-weeks meetings, or something, of this large amorphous group of people, and those meetings were absolutely not conducive to doing anything. I wanted to talk with the other researchers but there wasn't time—and who are all these people? Why are they involved in the conversation? The other thing is that these meetings had no purpose as far as I could tell.*
>
> –Faculty member, November 2014

In some cases, members chose not to attend meetings because of the perception that no real work would get done. Team members expressed frustration when meetings did not end with a clear set of outcomes or action items. Project teams developed diverse routines for meeting times, ranging from one hour per week to one to two hours per month. This lack of consistency was challenging for LAS members participating on multiple teams, which was a common feature in the early days, as LAS members invested the time to determine where they could ultimately make the best contribution.

Practical Implications

To address the issue of meeting logistics, LAS leadership was able to secure space with whiteboards and technology adjacent to the Lab. This provided a third place (Oldenberg 2000) in which government personnel could work away from the SCIF (classified space) and hold collaborative meetings with faculty and industry partners. While this did not completely solve the problem of distance between the two campuses, government personnel were also encouraged to meet faculty on the main campus, as needed. The other main implication at the program level was to improve communication between LAS leaders and project team leads, so that teams could get advance notice of visitors to group meetings and/or negotiate the best time for visitors in order to avoid disrupting team progress. While the description of the Gold Team vignette indicated that the team held meetings “off book” (not listed on the LAS calendar), a more transparent solution is to communicate in advance and indicate on the calendar when a meeting must be closed to visitors due to the nature of the work.

At the team level, several implications were made to overcome the obstacles associated with meeting logistics. Team leads were encouraged to carefully consider meeting locations, alternate locations between campuses when practical, talk with team members about virtual meeting participation, select a platform that team members were comfortable with, and provide training when needed. Rather than using meeting time to simply report on project updates, team leads were encouraged to distribute meeting agendas and relevant information in advance, so that team members were prepared to attend meetings and engage in collaborative work.

Power and Leadership

Teams need an effective group leader to share a vision for the team, motivate members, and coordinate team activities to make sure members have the resources they need to achieve clearly defined goals. One of the major challenges of LAS team leadership is determining the most effective leader. Even the idea of a team leader is complicated by an organizational structure in which government personnel cannot task faculty or industry contractors, and conversely, contractors cannot task government personnel. Government personnel are tasked by the LAS director, while academic and industry contractors pursue the activities outlined in their annual delivery order. As described above, the earliest delivery orders were dominated by academic faculty, as only a few government personnel had arrived. Understanding the academic culture as one in which faculty are used to having autonomy, LAS leaders initially chose not to assign leaders, but to allow them to emerge naturally. One LAS staff member described the early thinking and how it evolved over time:

In DO2 [Delivery Order 2], we went in with the mindset that that we wouldn't have a leader because obviously, you know, as tenured faculty members, you're not used to taking orders from anybody, right? No one can tell you what to do. That's part of the reason you get into this business. So we understand that. And so, what we thought is that, sort of, the cream would rise to the top. That eventually a leader would emerge ... And then everyone would respect that and be on board with that. That was the theory. Uh, it didn't work out so well. And well, I'll say this, in some groups that happened. A lot of groups, that didn't happen. And so, the process for DO3 [Delivery Order 3] was that very early on we selected a, um, someone to lead the group, someone to coordinate the group.

–LAS staff member, September 2014

Not surprisingly, the teams that were most successful in the early days of LAS were those in which strong, yet democratic, leaders emerged. One faculty team member described an effective leader as a facilitator rather than a dictator:

He's not one of the most senior people there, to be sure, but he has shown a lot of wisdom in how to execute his role. So he's really more of a structurer and a facilitator rather than seeking to persuade people and developing vision on his own and trying to persuade people on it and such.

–Faculty member, October 2014

Other leadership activities that were described as motivating included asking for team member input and comments, emphasizing the value of individual member contributions to the team, summarizing topics discussed at the end of the meeting, and reminding members of tasks and deliverables before the meeting.

Even when leaders were assigned at the outset, however, they were often selected because of technical knowledge and experience rather than leadership skills per se. One faculty team member described an example of an ineffective leader:

So, uh, so—so for example, uh, one of the teams the guy who was leading the team would show up to the meeting, no notes, just sorta wing it—what they've been up to, here's vaguely what this—here's what this person's done. This person told me they did this. That's all I know.

–Faculty member, October 2014

Such leaders were less effective at motivating and engaging team members. Other behaviors we observed that discouraged team member participation and engagement included: dismissing certain lines of inquiry, unwillingness to hold individual members accountable for task completion, and allowing team members to work in isolation. As with any organization, leadership requires adaptability and flexibility, as teams have different needs. A government employee who was working toward a PhD described a leader whose style was more effective in some settings than in others:

> *[She] is a natural leader and is a person who achieves real results. ... She has a controlling parent style, which works well and is effective when leading a team of graduate students and she needs to direct them more closely. However, this kind of directing style can be threatening to some academics—these faculty members can react to it like a bullied child, or they clam up, get on the defensive. ... So, this could be a deal breaker for that person to remain on the team.*
>
> –Government employee, October 2014

This example illustrates the leadership challenges related to different power structures across settings. There are subtle and non-so-subtle hierarchies in government, academic, and industry realms. As the funding organization, the government has ultimate authority regarding LAS activities. This can create an awkward relationship among team participants. Within academia, there are hierarchies based on faculty rank, research contributions, and academic disciplines. These status distinctions have been observed in terms of who dominates meeting participation, which team members appear to have more influence, and whether team members are willing to ask questions or raise counter arguments. As organizational psychologists Morrison and Rothman (2009) have described, those who have greater power in their organizational structure are more likely to consider potential rewards over risks when communicating. This means that those with higher power are less likely to self-censor and often less open to others' input. Higher status members may come off as overly aggressive or dominating. Conversely, those who have less power or status may be more concerned about potential risks than rewards. These team members are less likely to contribute for fear of embarrassment, as illustrated by the quote about "looking dumb in front of PhDs" that opened this chapter. One government member summarizes the challenge around government leadership at LAS:

> *LAS needs this to work with academia, to be able to get results from academic researchers. LAS staff are typically chosen for their technical and analytic skills, but what they need to have in [their] LAS role is, they need to know how to get information from others. ... So, LAS needs to understand that it needs leadership and people skills—listening, motivating—to be able to elicit what it needs from the team members. LAS staff need to have more than just a technical vision, but they need these people skills. They need to*

be able to motivate and inspire faculty instead [of] just stating the right technical vision. All of LAS staff need training in these areas.

–Government employee, September 2014

Practical Implications

LAS has evolved such that government personnel typically serve as the technical leads of project teams in each delivery order. Advantages of this model include: (a) government personnel have the biggest time commitment to LAS, as that is their primary responsibility, as opposed to contracted academic and industry partners; (b) government personnel have weekly staff meetings, during which they can update LAS leadership about team activities; and (c) government personnel are direct liaisons to the IC, from which they can recruit external partners to ensure LAS projects are translatable and mission-focused. To appoint technical leads with strong leadership skills, government personnel who are interested in serving in leadership positions apply for that role and share their vision and leadership style. LAS is also developing a series of workshops, ranging from half-day to week-long classes that provide government personnel training and practice in topics such as design thinking, the scientific method, and building collaborative environments.

In addition to the technical leads, each project is also assigned an LAS staff member called an "I2I," which stands for "integration to implementation." The I2I team members serve a coordinating and networking function, in that their purpose is to "ensure projects move from basic research to applied methods and prototypes, advise and engage in development of prototypes, and provide technical input to projects and development activities."[4] The I2I staff have a variety of backgrounds and expertise in research, engineering, analysis, and software development. They also work with more than one project team, which allows them to facilitate inter-team communication, and help teams connect with internal and external experts who can help them achieve their goals.

At the team level, it is important to communicate that leadership can emerge in a variety of ways, and that one person does not bear all responsibility for nurturing an effective group. In some cases, the technical lead may have strengths related to the content of the team's work (knowledge or expertise), while another group member may have strengths in relational aspects, such as serving as a collaboration champion (as illustrated by the Gold Team) or being an effective conflict mediator. Individual team members should therefore also take responsibility for

[4] See https://ncsu-las.org/mylas/members/sectors-and-roles/.

leadership in terms of holding each other accountable and remaining active and engaged team members.

Cultural Alignment and Integration

An underlying challenge to any cross-sector program is the diversity of institutional cultures that members bring to the working relationship. In the LAS teams, we observed several challenges related to the varying interests, priorities, norms, and expectations of government, academic, and industry professional cultures. To further complicate matters, each of these sectors includes diverse perspectives, as noted by one government member, who stated:

> *I make assumptions that all the academic—like, all the academic performers—that they know each other and they're on the same team, they work together; and I realized that, that's not always true. Just like in the intelligence community we have our own organizations and silos.*
>
> –Government employee, September 2014

Faculty made similar assumptions about government personnel and had to learn about the differences among roles such as analysts, researchers, and information technology specialists. Industry partners also have different professional cultures, and have more or less experience working in collaboration with government or faculty. In this section, we highlight three examples of cultural differences LAS has to contend with: expectations of autonomy, annual work cycles, and reward systems. While some cultural differences can be aligned through program level changes, others require constant attention and management.

As described above in the section on leadership, one of the barriers to collaboration at LAS has been differing expectations of autonomy. Government organizations operate in a culture of asset allocation, in which personnel are assigned to projects for a given time period as the organization needs their efforts. In contrast, academic faculty members have autonomy to choose the projects and lines of investigation they work on; and even when they receive external funding, academic faculty typically operate on stable, predictable, multiyear projects. Many faculty were anxious about the short funding cycle (6–12 months), and whether they could fund graduate students without more advance knowledge of funding decisions. As one faculty member explained:

> *It's like the timing of funding for the graduate students. I have never been able to think about a graduate student for this project, because the funding*

availability has never matched up with semester boundaries. I know I am not at all alone on that. I would have loved to have had somebody working on this and thought I would, but in fact, no, the funding—at the times when they needed to know was I going to give somebody an RA, I didn't have the money or would only have it for part of the semester, or something like that.

–Faculty member, January 2015

A third cultural challenge is how individuals are rewarded for their LAS participation by their home organizations. While government personnel were being asked to engage in a very different type of work and work process than they were used to, they knew they were on a three-year billet at LAS and they would be evaluated according to their contributions and participation. Industry partners may perceive they are rewarded through enhancing their relationship with government customers, as described by one industry partner explaining the mutual benefit of LAS collaboration:

Through LAS experience, we have more access to government members' interest in products, we benefit from the customer's perspective on how to use the technology—then we interact with the customers, and they give us another angle on how we can do it better. Also, government has another set of expertise in tradecraft, they have different methodologies from similar people in industry (how they look at the problem, practical cases—they get deeper understanding of the problem). We get educated through the process of interacting with customers.

–Government employee, October 2014

The question of rewards is more complicated for faculty, however, due to an academic system that has historically emphasized independent contributions to one's field, as evidenced by single-authored publications in disciplinary journals. While universities are becoming more open to, and even boast about, faculty involvement in community engaged, interdisciplinary work, the reality of change in the reward structure is very slow, as articulated by one full professor:

And explicitly they're looking for cross-functional, cross-disciplinary. And we keep pushing for that, but we really aren't putting mechanisms in place to try to promote that or shelter people who are doing it. So it's not such a big issue for me. I'm a full professor. However, we have assistant professors on our team. If we were to publish something in, I don't know, group and organization management, maybe psychology would understand that and accept it as being the contribution that it is. What if we publish something in [a prominent engineering journal]? They might give one less note of credit to it, when in fact people in engineering would look at it and say, "This is fabulous." And so, we want to do cross-disciplinary, but we are, as a

> *university, we are dealing with some of the fundamental aspects of how to promote that, that we need to. That's not LAS's fault, but LAS could be a key driver in helping push the university to do something proactive about this.*
> –Faculty member, October 2014

As this professor explains, academic culture is one in which you are evaluated by your peers, and if they do not value or understand interdisciplinary work, it can create an obstacle for faculty seeking tenure or promotion. These are entrenched cultural issues that LAS and other interdisciplinary labs around the world are continually up against.

Practical Implications

One commonly discussed way to ameliorate the barriers created by cultural differences is to foster opportunities for members with diverse backgrounds to interact and get to know each other. While it can be difficult to find ways to bring academic and industry partners together with government personnel outside of project team meetings, LAS has worked to build an LAS culture by providing opportunities for social interaction and networking among all LAS members. These activities are discussed in detail in Chapter Five. As evidenced in the Gold Team vignette, creating a climate that promotes personal interaction at the team level—through the introduction of snacks, for example—can also facilitate team interaction and enhance members' ability to ask for clarification when language or cultural differences arise. LAS was also able to align work schedules by funding projects on a consistent calendar year (January–December). This is a compromise solution that does not precisely align with the government's fiscal year or the traditional nine-month academic year, yet the change enables government personnel, faculty members, and industry partners to plan and coordinate schedules on a consistent calendar.

Communication

The communication challenges of interdisciplinary science research projects have attracted a great deal of academic research across disciplines. This is seen in the emergence of a new interdisciplinary field called the Science of Team Science (SciTS) (Stokols et al. 2008). Two specific issues we focus on here include differences in vocabulary and the need for feedback from LAS leaders as well as other LAS teams.

As noted above in the cultural alignment and integration theme, teams consisting of individuals who come from different institutions, as well as from STEM, social science, and humanities fields, have different vocabularies, mental models, and routines. A few noteworthy examples that occurred at LAS were words such as "mission," "framework," and "knowledge management," which hold different meanings across the IC, academic disciplines, and industry, and in some cases even within each sector. On top of this, each group has an intricate set of acronyms and jargon, as well as terms unique to LAS, such as "immersive collaboration." When team members hear terms they do not recognize or that seem out of context, we have observed myriad responses, including: tuning out the conversation, becoming confused but not asking for clarification (perhaps for fear of appearing stupid, as described above), or asking others to explain what they meant, sometimes leading to conflict over the "right" use of the term. The most ideal scenario was the open discussion of a term, how it was defined by different team members, and negotiation of how the word would be used by the specific project team to facilitate team identity and productivity.

Another significant communication challenge is the need for both individual and project team feedback from LAS management and other project teams. Information about team progress, deadlines, deliverables, and funding was absent, inconsistent, or included mixed messages. Several interviewees commented on their desire for feedback, and the ambiguity created by its absence, as one faculty member explained:

> *I certainly haven't gotten much feedback, and the directions I have, have been given or seem to be at odds with what I thought we were going to do, and we really haven't had a lot of time to do the research.*
>
> –Faculty member, October 2014

Especially in the early delivery orders, individual team members struggled to understand what they were supposed to be doing, whether they were helping their team or LAS achieve its goals, and how this would relate to future funding. One interviewee described the lack of clear and consistent communication channels that impeded clear communication:

> *Even though there are so many different paths for communication to go, there is still a problem with communication getting out there, because you don't know where to go for the information. Is it going to be on emails, is it going to be on Yammer, is it going to be Google drive, or one of the ten places on Google drive that we need to go to be able to get the information. There is not a one-stop shop, even though there is the MyLAS page [internal webpage] which just started to bring it together. It's still not providing the information that I think is really needing to go out. That's one thing, and especially with the government analysts, we are working in two domains [classified and unclassified] now. I have missed multiple meetings, because*

my calendar is on this computer, which I don't have, giving me alarms and stuff like that, going, "Hey, you need to be at this meeting."

–Government employee, October 2014

Practical Implications

One important activity that helped overcome barriers surrounding language use was the use of diagrammatic representations—drawings, graphs, sketches, and other pictorial representations—to help clarify disputed or unclear descriptions. As described in the Bronze and Gold team vignettes above, moments in which such visualization processes occurred within the teams were ones of intense activity, involvement, debate, and emergence of collective team understanding. We also encouraged development of an LAS glossary or official lexicon, similar to the one in this book, that defines commonly used words and documents the various definitions used by LAS members from different institutions, professions, and disciplines. It was difficult to motivate individual teams to develop such a document, as it took valuable time away from other work. While a few teams have created their own lexicon, the Collaboration Group took responsibility for identifying commonly used terms, and developed an LAS Lexicon in a Wiki space, which can be accessed and edited by all LAS participants. The hope has been that this Lexicon will serve as a living document and entries will continue to be added.

Also important is the development of more formal mechanisms to provide clear, consistent, and timely feedback to project teams and individual participants. For example, integrating LAS leadership feedback into team meeting agendas, so that information can be disseminated and discussed among the whole project team, is part of the ongoing review of short- and long-term goals. This recommendation meets the goals of improved feedback as well as enhanced intrateam communication. Other important aspects of team communication relate to motivation, goal-setting, and leadership, each of which we have described above. A final recommendation to improve inter-team communication was a series of regular seminars, during which project team participants would share their ongoing research and results. This weekly meeting would provide a space for discussion of various terminology, provide feedback from peers and LAS leadership, and promote a collective sense of the work happening throughout LAS. Many of these recommendations have since been implemented and institutionalized. We discuss these in more detail in Chapter Five.

The purpose of this chapter was to provide a description of the reflective work LAS leaders encouraged and engaged in at the beginning of the LAS experiment to be intentional about optimizing collaboration. The Collaboration Group, a team of interdisciplinary scholars and industry specialists, immersed themselves in LAS project teams to facilitate and study collaboration. Over a year of participation, observations, interviews, and surveys, we identified six major thematic areas that called for attention: (1) motivation, (2) setting group goals, (3) meeting logistics and team membership, (4) power and leadership, (5) cultural alignment and integration, and (6) effective communication. Looking at these as a whole, we summarize the key takeaways for supporting immersive collaboration at the program, team, and individual levels below.

Key Points

- *Program level*: Program leaders are responsible for articulating a vision and mission and communicate the expectation of inter- or transdisciplinary work in which ideas are integrated to develop something new. They must create an environment that incentivizes members to spend time together in both formal and informal spaces; this requires attention to alignment of the professional cultures represented by program participants.
- *Team level*: Teams are responsible for negotiating a clear goal and ensuring that individual members understand how their knowledge, skills, and expertise will help produce the team deliverable while also helping individual members achieve their personal goals. Team members, especially those in leadership roles, must be trained in effective communication of meeting agendas, documentation of action items, and holding team members accountable for being engaged and contributing to the team.
- *Individual level*: Individual members are responsible for effective communication, including asking questions and making a commitment to the time it will take to listen to other Lab members. This includes a willingness to spend time with people within and external to their specific project teams. Participants in cross-sector, interdisciplinary research labs must learn to become comfortable with some level of ambiguity; what often felt like a waste of time at the moment ended up being an important part of the process of discovery.

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3

MEMBER PERCEPTIONS OF COLLABORATION

BEVERLY B. TYLER and JESSICA KATZ JAMESON

Trust is the beginning; without trust nothing else matters

If we all think the same thing it is not interdisciplinary; greater diversity equals greater potential to innovate

–LAS Focus Group Participants, June 2017

CHAPTER 3

KEY TERMS

- **Collective Identity:** "The emotional significance that group members in a given group attach to their membership in that group" (Van Der Vegt and Bunderson, 2005, p. 533).
- **Discovery:** New ideas or insights for problem solving that emerge from interdisciplinary team interaction.
- **Diversity:** The distribution of differences among the members of a unit with respect to a common attribute, X, such as tenure, ethnicity, conscientiousness, task attitude, or pay (Harrison & Klein, 2007).
- **Emergent states:** Processes that are dynamic and emerge as team members work together over time (Majchrzak, More, and Faraj 2012; van Dijk et al. 2017).
- **Translation:** The practical application of newly discovered solutions to a real world problem.
- **Team Knowledge Diversity:** The dissimilar experience and education of team members required for the team to meet its goals (Horwitz & Horwitz 2007).
- **Team Knowledge Meshing:** Tyler et al define knowledge meshing as an interdisciplinary team's ability to pool and interlace their knowledge to blaze new scientific pathways to discovery and subsequent translation into practice (e.g., Zucker, Darby, and Armstrong 2002; Kotha, George, and Srikanth 2013)

KEY POINTS

Program: Intelligence community program leaders should create structured opportunities to bring team members together, either before or early in the project teams' funding period, to allow members get to know each other better, share domain knowledge, and negotiate individual tasks and goals. This early engagement will enable members to participate actively in team decision making, make them more aware of connections across their fields and interests, and support task and goal interdependence.

Team: Information elaboration goes beyond mere sharing of task-related information to include an interactive process, during which team members ask clarifying questions or relate the information to their own experience to confirm their understanding; it helps ensure that team members are looking at an issue from multiple perspectives; and facilitates knowledge meshing. Team learning behavior includes handling differences of opinion privately or offline, getting all the information you can from others, frequently seeking new information, and speaking up to test assumptions about issues under discussion. Communication, broadly speaking, is fundamental to each of these actions and activities.

Individual: Individual members should actively participate in collaborative conversations with team members, even when they believe their task for the project can be completed independently. Individuals should be open to learning new knowledge and vocabulary, and engaging in information elaboration that contributes to knowledge meshing. They should be willing to talk through misunderstandings and use humor, when appropriate, to help build trust—and an environment that is supportive of that "wacky idea" that just might work.

As described in Chapter Two, the Collaboration Group was tasked to: (1) facilitate teamwork in six of the nine existing LAS research teams, and (2) conduct a study of LAS team dynamics to generate recommendations for more effective interdisciplinary collaboration and innovation. While the previous chapter emphasized what we learned from our observations and interviews with LAS personnel, this chapter details the Collaboration Group's continued efforts to study the LAS program as it evolved, as well as the changes in research team dynamics over time (2014–2018).[1] We used a longitudinal survey methodology to help us answer an overarching question: *What factors are most important in the design of large-scale, long-term, cross-sector collaborative programs in order to transcend institutional and interdisciplinary boundaries to enhance the generation of innovative output?* We define "factors" broadly as elements, features, or characteristics of the program (the Lab) itself, of project teams, and of individual members.

To answer this question, we located a theoretical framework to guide the Collaboration Group's research efforts. We investigated this framework through two surveys and a focus group workshop and feedback session with LAS members. In 2014, the Collaboration Group modified an existing theoretical model (Tyler, Appleyard, and Carruthers 2014) for the LAS context (see Figure 3.1). A survey based on this model was developed and used to assess 2014 project participants' perceptions of the LAS program and their project teams' collaborative efforts. A follow-up survey was conducted in early 2018 with both repeated and new measures, in which participants were asked about their project team experiences in 2016 and 2017. Both of these surveys were distributed and completed online. In June 2017, the first author used a focus group approach to present a somewhat modified theoretical framework to LAS personnel at a weekly research meeting to gain more in-depth feedback from participants on their perceptions of the model.

[1] The authors would like to recognize several graduate students who assisted in collecting and analyzing the data we report in this chapter. Hector Rendon (PhD) created and managed the Qualtrics survey conducted in 2014, while Christopher Kampe (PhD candidate) created and conducted the survey in 2018. Abigail Schneider (MS) and Haddon Mackie (MS) assisted with the analysis of the focus-group feedback session. Christopher Hoina (MBA) assisted in structuring and simplifying the analysis we report. The authors acknowledge any shortcomings in the chapter as their own.

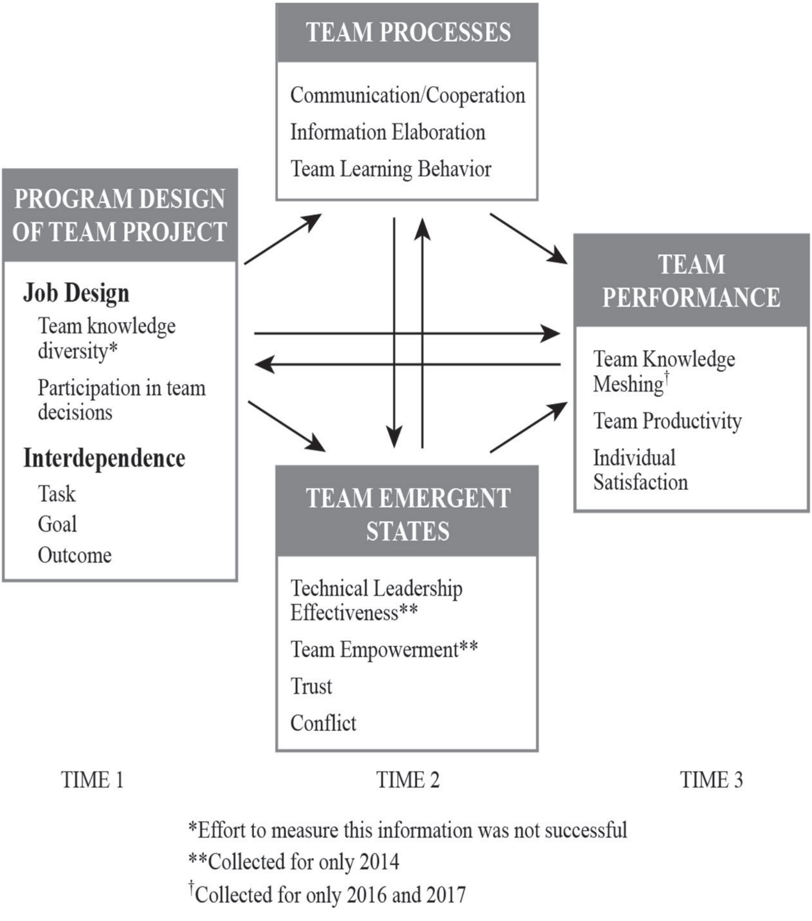

Figure 3.1: Theoretical Model.

Below, we describe the theoretical model illustrated in Figure 3.1 and discuss the results of the two surveys and focus-group feedback session. Finally, we provide implications from this research to provide suggestions for organizing future large-scale, long-term interdisciplinary collaborative programs so they might transcend institutional and interdisciplinary boundaries to enhance the generation of innovative output.

Theoretical Framework

In developing their model of factors that contribute to collaborative innovative output, Tyler, Appleyard, and Carruthers (2014) adapted a dynamic capabilities perspective focused on the firm (or program) level of analysis (Barney 1986, 1991; Teece 2007; Teece et al. 1997). However, they also included research on team management and team science to propose how team processes and psychological and social foundations influence interdisciplinary team performance (e.g., Campion, Medsker, and Higgs 1993; Cronin, Weingart, and Todorova 2011; Gardner, Gino, and Straats 2012; Grant 1996; Hodgkinson and Healey 2011; Kessel and Rosenfield 2008; Metzger and Zare 1999; Srikanth, Harvey, and Peterson 2016). Tyler and her colleagues (2014) moved beyond the firm to propose that a revolutionary cross-sector, interdisciplinary research and development program could develop resources and capabilities to transverse sectoral and disciplinary boundaries, and improve the probability of radical innovation. Thus, based on dynamic capabilities theory, team science, and team management literatures, Tyler et al. (2014) proposed a conceptual model to link the initial design of cross-sector, interdisciplinary research and development projects by program leadership, the evolving team processes, and the team's emergent cultural state, to team-knowledge-meshing capabilities, which in turn influenced team performance.[2]

In order to operationalize the modified model we used to study LAS team dynamics, we located simple, published, perceptual measures for all but two of the constructs in the model (see Appendix A for the sources of these scales). We introduced a new construct and measure in the 2018 survey—"team knowledge meshing"—and a new measure for individual satisfaction included in both surveys. Our description of the model moves from the far left to the far right of Figure 3.1. Block one considers key components of the team project designed by the program leadership, examining how diverse the scientific disciplines are within a team; members' freedom to participate in decision making by the team (Campion et al. 1993); and the task, goal, and outcome interdependencies required for

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[2] They assumed that at the heart of interdisciplinary innovation success is the researchers' ability to "mesh" their knowledge bases; "knowledge meshing" recombines existing knowledge into new patterns or leads to the co-creation of new knowledge (Cummings and Kiesler 2005, 2007; Kodama 1992). Tyler et al. (2014) proposed that knowledge meshing breaks down interdisciplinary barriers and allows for the integration of fundamental technology principles, frames of reference, approaches to hypothesis development, and experimentation (Caudill and Roberts 1951; Dougherty 1992).

team members to accomplish their work (Campion et al. 1993). Decisions about team composition, members' ability to participate in decision making, and team members' interdependencies can all impact the barriers LAS members must overcome to exchange and recombine knowledge and co-create new knowledge (Bercovitz and Feldman 2011; Campion et al. 1993; Harrison and Klein 2007; Phene, Fladmoe-Lindquist and March 2006). Although we asked two leaders of the LAS program to assist us in assessing how diverse the participants' scientific disciplines were within teams—in the hopes of having a measure to describe the differences in disciplinary or knowledge diversity across the teams—our two informants found this to be a daunting task. Thus, we were not able to incorporate this important theoretical factor into the study.

In the center of the model, blocks two and three illustrate team processes and team emergent states. Team processes incorporated in this model include *communication and cooperation* (Campion et al. 1993), *elaboration of task-relevant information* (Homan et al. 2008), and *team learning behavior,* a process that leads to adaptation and greater understanding among team members (Edmonson 1999). The team emergent states—processes that are dynamic and emerge as team members work together over time—we included were *technical leadership effectiveness* (Van de Ven and Chu 2000), *team empowerment* (Kirkman et al. 2004), *trust* (Kirkman et al. 2006), and the presence and management of *conflict* (Jehn and Mannix 2001). The third section of the model, on the far right (block four), reflects the outcomes of collaboration: *team knowledge meshing* (proposed by Tyler et al. 2014), *team productivity* (Kirkman and Rosen 1999), and *individual satisfaction*. As the arrows illustrate, all the variables within the components of team processes and emergent states influence each other and the team's knowledge meshing capabilities, team productivity, and individual satisfaction with the teams' efforts over time.

Thus, as is consistent with Tyler et al. (2014), we proposed that the team project design developed (or selected) by program leaders, efforts to enhance evolving work processes within team projects, and efforts to contribute to positive emergent states in project teams would assist in the management of the complexities associated with cross-sector, interdisciplinary research and enhance the likelihood of scientific breakthroughs. It is important to remember that LAS administrators negotiate the specific projects and team membership, sometimes alone and other times in collaboration with LAS members. In other words, some teams have been able to choose their own members, and in other cases, LAS leadership determine the skills and expertise they want in a particular team. Therefore, our survey examined the relationships among the following factors: (1) *program-specified team project design,* in terms of members' ability to participate in the design of the project team, and project interdependence (task, goal, outcome); (2) three *team processes* (communication and cooperation, elaboration of task-relevant information, and team learning behavior); (3) four *emergent states* (technical leadership effectiveness, team empowerment, trust, and conflict); and (4) three *outcomes* (team knowledge meshing, team productivity, and individual satisfaction with the teams' work). We did not include a perceptual measure for team heterogeneity because of challenges associated with perceptions of team member differences.

Survey Measures and Data Collection

All the variables included in the model shown in Figure 3.1 had existing measures associated with them, except team heterogeneity, team knowledge meshing, and individual satisfaction (see Appendices A and B). We used the variables (excluding team knowledge meshing) to design a 65-item survey intended for all LAS team members participating in Delivery Order 3, which included six teams who had been together since August 2013 and three teams that started in the May 2014 time period (see Chapter Two). The questions for the 2014 survey appear in Appendix B (the five items added in 2018 for team knowledge meshing are also included for our readers' convenience). Most of the measures used a Likert scale (1, "strongly disagree," to 7, "strongly agree," with 4 denoting "neither agree nor disagree"). The exception to this is the group conflict scale, which measures perceptions of the frequency of different types of conflict, using a Likert scale of 1 to 5 (1 = "None at all"/"Never," and 5 = "A lot"/"Always") (Jehn and Mannix 2001).

The first survey was emailed to the entire LAS team population of 114 LAS members in November 2014. Survey respondents were asked to report their observations and opinions regarding one current team. Given that several of the faculty were involved with multiple teams, we decided to restrict those members to a single team to avoid oversampling. Of the 114 invited to participate in the survey, 67 individuals responded (59% response rate). Of these responses, 61 surveys included complete data, although 8 respondents did not provide enough information to be assigned to one of the nine teams. We therefore analyzed the data at both the individual level (aggregate results of all respondents, n = 61) and the team level (n = 53). See Table 3.1 for descriptive statistics of 2014 survey and Table 3.2 for the correlation matrix.

Independent Variable	*n*	Mean	SD	Min.	Max.
Participation	61	5.30	1.41	2.00	7.00
Task Interdependence	61	4.69	1.28	1.67	7.00
Goal Interdependence	61	5.22	1.28	2.00	7.00
Output Interdependence	61	4.98	1.39	1.33	7.00
Communication	61	5.54	1.15	2.50	7.00
Information Elaboration	61	5.51	1.04	2.67	7.00
Learning Behavior	61	4.68	0.97	2.43	6.86
Technical Leadership	61	5.02	1.28	1.83	7.00
Empowerment	61	5.60	1.06	1.92	7.00
Trust	61	5.40	1.29	2.00	7.00
Conflict	61	2.19	0.68	1.00	3.78
Team Productivity	61	5.37	1.28	2.00	7.00
Team Satisfaction	61	5.36	1.42	1.00	7.00

Table 3.1: Descriptive Statistics for 2014 Data.

Analyzing results across teams allowed us to compare results across the three conditions described in Chapter Two: Condition A, teams that began in August 2013, no facilitation; Condition B, teams that began in August 2013 and received facilitation starting May 2014; and Condition C, teams that started in May 2014 with facilitation (see Figure 3.2, repeated from Chapter Two). The teams had therefore been in place either 15 months (Conditions A and B) or 6 months (Condition C) at the time of survey distribution in November 2014.

			1	2	3	4	5	6	7	8	9	10	11
1	Participation		1	2	3	4	5	6	7	8	9	10	11
2	Task		0.4248	1									
		p	0.0006										
3	Goal		0.6236	0.5024	1								
		p	<.0001	<.0001	1.0000								
4	Output		0.6408	0.5788	0.5643	1							
		p	<.0001	<.0001	<.0001								
5	Communication		0.6301	0.3839	0.5529	0.5010	1						
		p	<.0001	0.0023	<.0001	<.0001							
6	Elaboration		0.6049	0.4297	0.5209	0.5117	0.7406	1					
		p	<.0001	0.0005	<.0001	<.0001	<.0001						
7	Learning Behavior		0.6565	0.4353	0.6711	0.5867	0.6143	0.6402	1				
		p	<.0001	0.0005	<.0001	<.0001	<.0001	<.0001					
8	Trust		0.6291	0.4426	0.5855	0.5338	0.7605	0.7119	0.7101	1			
		p	<.0001	0.0004	<.0001	<.0001	<.0001	<.0001	<.0001				
9	Conflict		-0.3953	**-0.0828**	-0.3994	-0.2734	-0.5688	-0.5152	-0.5352	-0.6250	1		
		p	0.0016	**0.5257**	0.0014	0.0330	<.0001	<.0001	<.0001	<.0001			
10	Productivity		0.6451	0.4644	0.5900	0.5346	0.7182	0.7645	0.6836	0.7755	-0.5653	1	
		p	<.0001	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
11	Satisfaction		0.5436	**0.1519**	0.5783	0.3064	0.5879	0.6482	0.4841	0.5242	-0.4719	0.6338	1
		p	<.0001	**0.2426**	<.0001	0.0163	<.0001	<.0001	<.0001	<.0001	<..0001	<.0001	
		n	*61*	*61*	*61*	*61*	*61*	*61*	*61*	*61*	*61*	*61*	*61*

Values in bold are not significant at α = .05

Table 3.2: Correlations for 2014 Data.

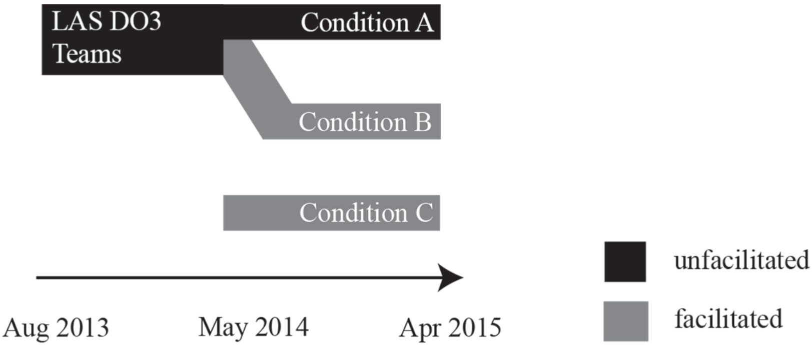

Figure 3.2: Timeline of Team Conditions Showing Facilitation or No Facilitation

In 2018, we created a second survey to assess LAS member perceptions of collaboration and determine how they may have changed over time. The Lab was slightly more complex by this point, given that more government personnel had arrived and team membership was determined primarily by the LAS leadership. Another complicating factor was that we wanted to capture LAS members' experiences over a two-year period: 2016 and 2017. For these reasons, the 2018 Collaboration Survey was unable to exactly parallel Survey One, described above. Appendix A notes which measures were used in the two surveys. The main differences in the surveys are that

Technical Leadership Effectiveness and Team Empowerment data were collected only in 2014, and a new concept, team knowledge meshing, was added to Survey Two.

Survey Two was distributed in April of 2018, a slightly further distance from 2016 and 2017 team experiences than would have been ideal. We sent the survey to all active LAS team members with the instructions that we wanted them to reflect on their team experiences over the past two years. The survey first asked respondents to indicate whether they had participated in LAS teams during 2016. If they answered "Yes," they were asked to report the number of teams they participated in during 2016. Next, respondents were given the following instructions: "Consider your LAS project team for 2016. If you participated in more than one team, consider your overall experience with LAS teams that year." This was followed by the survey items, modified from Survey One (as described in Appendix A). If a respondent had not participated in 2016, they were asked the same questions for 2017. If they had participated in both 2016 and 2017, they answered the entire set of questions twice. In this way, we were able to capture differences in respondent perceptions of their collaboration experiences in 2016 and 2017. Because the teams in 2016 and 2017 were not necessarily the same, the follow-up collaboration survey distributed in 2018 only examined perceptions of collaboration at the individual level, not the team level. Both waves of the survey data were collected using the Qualtrics survey program. Table 3.2 provides the descriptive statistics for the 2016 and 2017 data. It is notable that these measures varied little overtime.

Data for 2016 and 2017 were combined when *t*-tests revealed no significant differences in the variable means across the two years.[3] Table 3.3 provides the descriptive statistics for this data and Table 3.4 provides a correlation table for the scales of the combined data for 2016 and 2017. An important finding of the study is that many of the scales are highly correlated in both waves of data collection. Common method bias is a primary weakness of survey studies, particularly when there are no measures from secondary sources. Given this, it may be most interesting to look at the variables not correlated. In 2014, the only scales not significantly related at

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[3] Paired comparisons were calculated for 2016 versus 2017. Because the same respondents answered questions about 2016 and 2017, we compared their answers between the two years and tested for changes using paired *t*-tests. None of the differences were statistically significant at the 0.05 level, even before adjusting for multiple testing. All differences were calculated as the value in 2017 minus the value in 2016.

Year	Independent Variable	*n*	Mean	SD	Min.	Max.
2016	Participation	30	5.57	1.42	1.00	7.00
	Task Interdependence	30	5.34	1.13	1.67	7.00
	Goal Interdependence	30	5.43	0.98	2.67	7.00
	Output Interdependence	30	4.44	1.52	1.00	7.00
	Communication	29	5.75	1.00	3.33	7.00
	Information Elaboration	29	5.68	1.08	2.67	7.00
	Learning Behavior	29	4.69	0.99	3.14	6.57
	Trust	29	5.34	1.39	1.50	7.00
	Conflict	29	1.68	0.74	1.00	4.00
	Knowledge Meshing	28	5.20	0.99	3.40	7.00
	Team Productivity	28	5.45	1.11	3.17	7.00
	Team Satisfaction	28	5.63	1.45	1.33	7.00
2017	Participation	32	5.74	1.23	2.00	7.00
	Task Interdependence	32	5.53	1.25	2.67	7.00
	Goal Interdependence	32	5.39	1.44	1.00	7.00
	Output Interdependence	32	4.92	1.42	1.00	7.00
	Communication	31	5.68	1.41	2.33	7.00
	Information Elaboration	31	5.62	1.21	2.33	7.00
	Learning Behavior	31	4.74	1.05	2.71	6.71
	Trust	31	5.19	1.63	1.25	7.00
	Conflict	31	1.69	0.85	1.00	4.00
	Knowledge Meshing	31	5.26	1.20	2.00	7.00
	Team Productivity	31	5.31	1.48	2.00	7.00
	Team Satisfaction	31	5.39	1.61	1.00	7.00

Table 3.3: Descriptive Statistics for 2016 and 2017 Data.

the .05 level were task interdependence with conflict and satisfaction. In the combined 2016 and 2017 data, the only scales not significantly related at the .05 level were task interdependence and conflict.

1 Participation	1	2	3	4	5	6	7	8	9	10	11	12
2 Task	0.4990	1										
	<.0001											
3 Goal	0.4159	0.6034	1									
	0.0008	<.0001										
4 Output	0.4177	0.4751	0.5409									
	0.0007	<.0001	<.0001	1								
n	*62*	*62*	*62*									
5 Communication	0.4955	0.2709	0.4495	0.4737	1							
	<.0001	0.0363	0.0003	0.0001								
6 Elaboration	0.5062	0.3112	0.4805	0.5002	0.8579	1						
	<.0001	0.0155	0.0001	<.0001	<.0001							
7 Learning	0.3780	0.2984	0.4284	0.4302	0.6466	0.7650	1					
	0.0029	0.0206	0.0006	0.0006	<.0001	<.0001						
8 Trust	0.5269	0.3105	0.5856	0.5284	0.8949	0.8109	0.6553	1				
	<.0001	0.0158	<.0001	<.0001	<.0001	<.0001	<.0001					
9 Conflict	-0.2829	**0.0009**	-0.2644	-0.2981	-0.5950	-0.5930	-0.3305	-0.6009				
	0.0285	**0.9946**	0.0412	0.0207	<.0001	<.0001	0.0099	<.0001	1			
n	*60*	*60*	*60*	*60*	*60*	*60*	*60*	*60*				
10 Meshing	0.4710	0.2606	0.4509	0.4918	0.7549	0.8172	0.6586	0.7334	-0.4521	1		
	0.0002	0.0462	0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	0.0003			
11 Productivity	0.5826	0.3727	0.5898	0.5509	0.8115	0.7622	0.6683	0.8003	-0.5289	0.6817	1	
	<.0001	0.0037	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
12 Satisfisfaction	0.4514	0.3782	0.5003	0.4589	0.7396	0.7112	0.5589	0.7519	-0.3597	0.7179	0.7030	1
	0.0003	0.0031	<.0001	0.0003	<.0001	<.0001	<.0001	<.0001	0.0051	<.0001	<.0001	
n	*59*	*59*	*59*	*59*	*59*	*59*	*59*	*59*	*59*	*59*	*59*	*59*
Values in bold are not significant at α = .05												

Table 3.4: Correlations for 2016 and 2017 Data Combined.

Table 3.5 reports the Cronbach's Alpha for each scale included in the two waves of data collection. In the discussion below, we report the results from the 2014 survey, illustrate some of the results with figures, and describe differences and variances across the team conditions where these differences are noteworthy. We also incorporate the results of the 2018 survey, which covers perceptions from 2016 and 2017, to illustrate differences over time.

		Survey 1 (2014)		Survey 2 (2016 & 2017)	
Contributing Factor	**Scale (# Questions)**	***n***	**α**	***n***	**α**
Project Team Design	Participation	62	0.8967	61	0.9549
	Task Interdependence	62	0.7196	62	0.6802
	Goal Interdependence	62	0.8492	62	0.8429
	Output Interdependence	62	0.8686	62	0.8062
Team Processes	Communication	61	0.7908	60	0.8253
	Information Elaboration	61	0.8418	60	0.8701
	Learning Behavior	61	0.8040	60	0.8016
Team Emergent States	Leadership Effectiveness	61	0.9185	x	x
	Team Empowerment	61	0.9545	x	x
	Trust	61	0.9257	59	0.9337
	Conflict	61	0.9216	46	0.9307
Team Performance	Knowledge Meshing	x	x	58	0.8241
	Team Productivity	61	0.9722	59	0.9524
	Team Satisfaction	61	0.8864	59	0.9137

Table 3.5: Cronbach's Alpha for full sample 2014 and 2016–2017 Combined (shows missing values).

Results: Scales, Items, and Team Differences

We present results in the order of the theoretical model (see Figure 3.1), starting with block one, the team project designed by program leadership; moving to block two, team processes; to block three, team emergent states; and finally to block four, team performance.

Block One: Program Design

As indicated above, we did not assess the variable of team knowledge diversity in this survey. We did measure perceptions of participation as well as perceptions of task, goal, and outcome interdependence.

Level of Participation in Decision Making. For all three questions regarding members' perceptions of the level of their participation in group decision making, most respondents felt they, as individuals, were able to participate actively in the problem solving of the research team (level of participation: 2014 mean = 5.3, SD = 1.41; 2016 mean = 5.57, SD = 1.42; 2017 mean = 5.74, SD = 1.23). At the team level, however, two of the groups had individuals who did not agree that they were able to participate actively, and one of these groups had a majority of members who disagreed with the statement: “Most members of my team get a chance to participate in decision making.” A closer look across the three team conditions revealed that members of Condition C—which started with a facilitation team in their group—were much less likely to report that they or other members were able to participate in decision making. Two possible explanations for this are that the teams had not been together long enough to build trust and/or that the existence of a facilitator somehow impeded or discouraged participation. While this was not what the Collaboration Group observed, it is possible that this was the perception of some team members.

Task Interdependence. This refers to perceptions that one member must work with others in the team to complete their task. As an aggregate, 64% of respondents agreed that they *could not* accomplish their tasks without information or materials from other team members, while nearly 24% disagreed with that statement (the remaining responses were neutral; see Figure 3.3). The means and standard deviations for the task interdependence scale for the two surveys are reported in Tables 3.1 and 3.3 (2014 mean = 4.69, SD = 1.28; 2016 mean = 5.34, SD = 1.13; 2017 mean = 5.53, SD = 1.25). Thus, participants reported in aggregate (average) that projects in 2014 were less task interdependent than in 2016 and 2017. However, a closer look at these overall lower averages for participants in 2014 appears to indicate that they could be due to the responses of members in a few projects, rather than a common characteristic across all the projects that year. The teams in Condition B (facilitation after nine months of teamwork) had a majority of their members report that they *did not* need information or materials from each other, or they disagreed with the statement that subgroups of the team were related to each other. Teams in Conditions A and C reported higher task interdependence; this suggests that the teams in Condition B had more decentralized team processes in which they worked more independently than the other teams in 2014. Thus, average task interdependence across all participants was lower in 2014, but some of the teams reported being more interdependent than others.

Goal Interdependence. Overall, respondents in 2014 reported a high level of agreement that their work activities, subgroup activities, and individual goals were determined by the team’s goal (around 75% of respondents agreed with all three items). When comparing the means and standard deviations for the goal interdependence scale for the three survey years (2014 mean = 5.22, SD = 1.28); 2016 mean = 5.43, SD = .98; 2017 mean = 5.39, SD = 1.44) the data indicate that participants agreed the goals were relatively interdependent. However, in 2014, the Condition C research

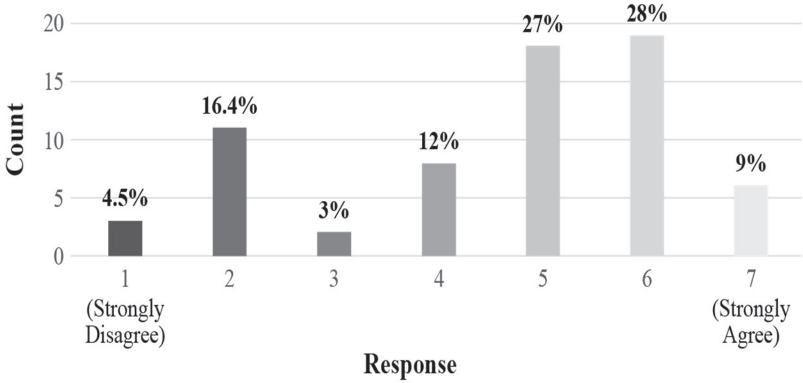


Figure 3.3: Perceptions of Task Interdependence in 2014 survey.

teams were significantly less likely than those in Conditions A and B to agree with the items: "My work goals for this LAS project come directly from the goals of the team" and "Most of the activities I am involved in for this LAS project are related to the goals of the team." As these were the newest LAS teams, we propose that team members had not yet negotiated an understanding of how their individual goals related to team goals as a whole at the time of the survey.

Output Interdependence. The means and standard deviations for the output interdependence scale (2014 mean = 4.98, SD = 1.39; 2016 mean = 4.44, SD = 1.52; 2017 mean = 4.92, SD = 1.42) suggest that participants believed there was less output interdependence than task or goal interdependence. But there also seemed to be more agreement on some items than on others, as well as more agreement in some teams than in others. For example, in 2014, there was a comparatively low level of agreement that feedback on individual performance was impacted by team performance (40%), while most respondents agreed that "LAS will evaluate my performance based on how well my team performs" (70%), and that "individual contributions to the team would affect future opportunities with LAS" (65%). At the team level, teams in Condition B in 2014 stand out, in that they were more likely to agree that feedback on individual performance was impacted by team performance (83%), and that individual contributions to the team would affect future opportunities with LAS (80%). These perceptions are substantially different from the aggregate individual responses as well as from the other team conditions. Because these teams were in place for nine months and then received facilitation, we believe the offer of facilitation may have been perceived by them as feedback that the team needed to work more collaboratively and interdependently to achieve their desired output.

Block Two: Team Processes

In 2014 and 2018, three factors were measured to investigate perceptions of team processes: communication/cooperation, information elaboration, and team learning behavior.

Communication/Cooperation. The means and standard deviations for the communication and cooperation scale (2014 mean = 5.54, SD = 1.15; 2016 mean = 5.75, SD = 1.00; 2017 mean = 5.68, SD = 1.41) indicated participants agreed that their teams communicated and cooperated. For example, overall respondents in 2014 agreed with the statements regarding communication and cooperation, with almost 84% agreeing that team members share information, meetings enhance communication, and team members are cooperative. An interesting difference at the team level in 2014 is that 100% of Condition A teams, with no facilitator, agreed team meetings were helpful, while agreement on this item was at the level of 75% for Conditions B and C, which had facilitation. Importantly, one of the largest teams in Condition A consisted of nearly all academic members of the same discipline. In this team, communication was probably the least problematic; thus, team meetings may have been smoother overall. Some team members in Conditions B and C may have felt that they were required to meet even when they did not need to do so.

Information Elaboration. This series of questions asked respondents whether team members provided useful and unique information, and whether the team integrated all information appropriately. The means and standard deviations for the information elaboration scale (2014 mean = 5.51, SD = 1.04; 2016 mean = 5.68, SD = 1.08; 2017 mean = 5.62, SD = 1.21) indicated participants agreed that teams were elaborating on important information. For example, respondents in 2014 indicated a high level of agreement (80–90%) with all items. While there were a few outliers for each question, there were no meaningful differences among the research teams. This suggests that respondents understood the importance of information elaboration to successful collaboration in a cross-sectoral, interdisciplinary context.

Team Learning Behavior. This measurement category specifically focused on respondents' perceptions of how much the group reflected on their process, questioned assumptions, invited others to present information to their team, and addressed conflict outside of team meetings. The means and standard deviations for the team behavioral learning scale (2014 mean

= 4.68, SD = .97; 2016 mean = 4.69, SD = .99; 2017 mean = 4.74, SD = 1.05) indicated participants agreed their teams were somewhat less likely to accomplish all the behaviors that result in team learning than they were those behaviors associated with communication and elaboration. A sample item measuring team learning is “The team tends to handle differences of opinion privately or offline, rather than addressing them directly as a group” (see Figure 3.4).

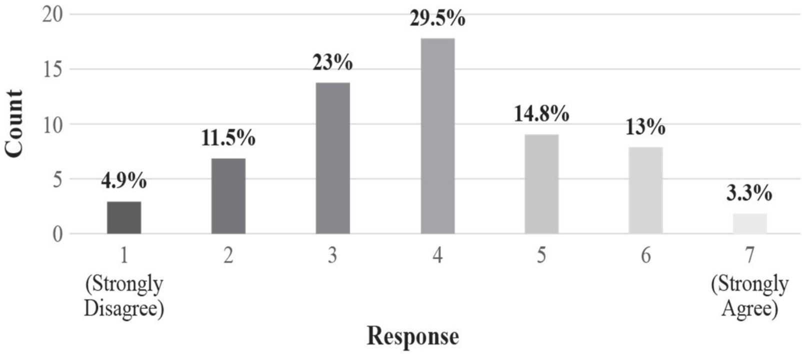


Figure 3.4: Perceptions that the team discusses differences online vs. offline in 2014 survey.

Furthermore, there was quite a bit of variance across team Conditions in 2014 on this factor. Teams in Condition A (no facilitation) were more likely to agree that they address conflict privately or offline, and that they seek new information that leads to important changes. Teams in Condition C (newest groups, with facilitation) were less likely to agree that they regularly took time to improve team processes, and that someone takes responsibility for reflecting on group processes. Teams in Condition B, who received facilitation at the midpoint, were more likely to agree that people speak up to test assumptions, and that they invite people from outside the team to share information. There also appeared to be differences in group processes, in that teams in Condition B tended to invite more outsiders to present to the group, and were more willing to test and question assumptions.

Low overall agreement with the item about addressing conflict offline has several possible interpretations. This could suggest that respondents addressed differences of opinion or other types of conflict during meetings, although this is not consistent with the Collaboration Group’s observations as facilitators and observers. Another possibility is that team members did not address differences or disagreement at all, which would be consistent with the low perceptions of conflict reported. Interestingly, members of teams in Condition A, with no facilitation, were more likely than the other groups to agree that conflict was handled directly offline, perhaps because they did not have a facilitator to help with this during meetings. This could also have been a result of the composition of one of the Teams in Condition A, which, as indicated above, included primarily academic members of the same discipline. The lack of interdisciplinarity on this team likely increased their overall ability to understand each other, reduced the perceived level of conflict, and created more opportunity for handling conflict offline.

Block Three: Team Emergent States

This third block in the center of the model measures respondents' perceptions of emergent states, including team leadership, team empowerment, trust building, and the presence of different types of conflict. As noted above, all four measures were included in the 2014 survey, but only the last two measures were in the 2018 survey.

Technical Leadership Effectiveness. The mean and standard deviation for the technical leadership effectiveness scale in 2014 were 5.02 and 1.28, respectively. Overall, in this series of questions, a majority of respondents reported agreement that their team leader performed the expected responsibilities, with the exception of the item about feedback: "The team leader provided sufficient individual feedback to team members" (see Figure 3.5). Lack of feedback was a common complaint in the early days of LAS, and at least one member of each team made it clear that their team leader did not provide individual feedback to members. However, there is also quite a bit of variance across conditions. For example, Condition B teams were more likely to agree that their technical leader was performing as expected, while Condition C teams were less likely to agree that their technical leader was performing as expected.

These differences across Conditions B and C may suggest important implications of the decision to introduce three facilitation members into a team, either at the time it is formed or after the team has worked together for some time. The lower perceptions of leader effectiveness in Condition C may suggest that there was confusion between the roles of the facilitator and the technical leader. In at least one Condition C team, for example, the facilitator took on the role of creating and distributing agendas in advance and running team meetings. This potential confusion was not

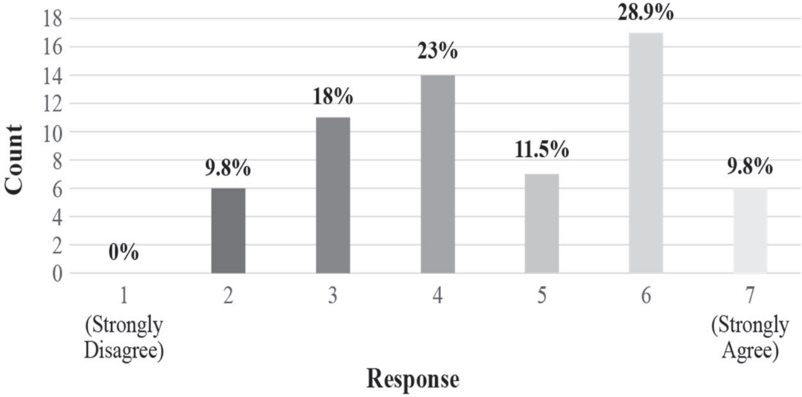


Figure 3.5: Response to item "team leader provided sufficient individual feedback to team members" in 2014 survey.

apparent in the responses of Condition B, which had a technical lead who had been running—or at least participating in—the meetings for approximately nine months before the three facilitation members joined the project team. This difference suggests that if teams use facilitation, time should be devoted to clarifying the role of the technical lead and the facilitation team members so that everyone knows their responsibilities and team members are clear about what to expect. Interestingly, however, perceptions of technical leadership effectiveness were not completely associated with the existence of facilitation team members. Teams in Condition A, which had no facilitation team members, had mixed results on these items, in more cases mirroring the responses of Condition C. This suggests that perceptions of team leader effectiveness may be more influenced by participants' individual differences than by team characteristics.

Team Empowerment. The mean and standard deviation for the team empowerment scale in 2014 were 5.60 and 1.06, respectively. This measurement category has the largest number of questions. Responses indicate a relatively high level of agreement across the board, with only one item below 70% agreement ("My team determines as a team how things are done on the team"). The highest overall agreement on team empowerment items was "My team believes our project is significant" (93% agreement). Lower agreement about how the team determines "how things are done" may be related to differences in team leader behavior, as discussed above, or differences in how much direction the teams perceived they were getting from LAS leadership. For example, Condition B teams were significantly less likely to agree that “My team makes its own choices without being told by LAS.” Condition A teams were significantly higher on most empowerment items, as the only condition with 100% agreement on several of them. An interesting departure here is that Condition A was least likely to agree that “My team can select different ways to do the team’s work.” It is possible the teams in this condition felt their work was more straightforward and they did not need to seek new ways to work.

Trust. This series of questions maintained very similar responses across all questions, with the majority of respondents reporting trust and confidence among members of their team. The means and standard deviations for the trust scale (2014 mean = 5.40, SD = 1.29; 2016 mean = 5.34, SD = 1.39; 2017 mean = 5.19, SD = 1.63) indicated participants appeared to believe members had trusting relationships. The story is somewhat different across teams, at least in the 2014 survey, with those in Condition A reporting a significantly higher level of trust (92%) and those in Condition C reporting significantly lower trust (57.1%). Given that Condition C teams had only been together for six months at the time of the survey, this suggests the importance of time for relationship building and the development of trust among LAS members. (Time as an important factor in collaboration is discussed in more detail in Chapter Four.) Since teams in Conditions A and B both started at the same time, the increased levels of trust reported among teams in Condition A may be related to their lack of facilitation. Perhaps their perception that they did everything on their own, with no assistance, created a stronger bond and sense of trust among team members.

Conflict. This measurement scale required a different set of response options, as these were questions of frequency rather than agreement (1 = “none at all” or “never,” 2 = “almost none,” 3 = “a little” or “sometimes,” 4 = “frequently,” 5 = “a lot” or “always”). The scale we used compares three types of group conflict: conflict over the task and ideas, conflict about relationships among team members, and conflict over process (Jehn and Mannix 2001). The means and standard deviations for the conflict scale (2014 mean = 2.19, SD = .68; 2016 mean = 1.68, SD = .74; 2017 mean = 1.69, SD = .85) indicated that participants in 2014 and 2018 perceived their teams experienced limited conflict. More specifically, there were interesting differences across team Conditions in 2014. Condition B teams reported the highest perceptions of relational and emotional conflict, as well as disagreement about the task and frequency of conflicting opinions. This suggests relatively high levels of both task and relational conflict in Condition B. Teams in Condition C reported the highest level of conflict over ideas, but low levels of relational conflict. Condition A reported relatively low levels of conflict with the exception of conflict over ideas. There was little perception of process conflict across groups. This may reflect that team processes went smoothly, or were consistent with the findings in the above section on team learning behavior, that the teams did not spend enough time reflecting on or discussing their group process for such conflicts to arise. Furthermore, respondents in 2014 perceived relatively low levels of conflict, with the highest frequency reported for conflicts over ideas (see Figure 3.6), followed by conflicting opinions on the project and relational conflict. The fact that the highest frequency of conflict was over ideas is positive, as group conflict literature indicates task conflict (as opposed to relational conflict) predicts team performance and innovation (Amason and Schweiger 1997; Jehn 1995). We would also argue that collaboration requires some conflict as team members discuss and debate approaches to their task or overall goal. The fact that there were greater perceptions of task than other types of conflict supports the presence of collaboration.

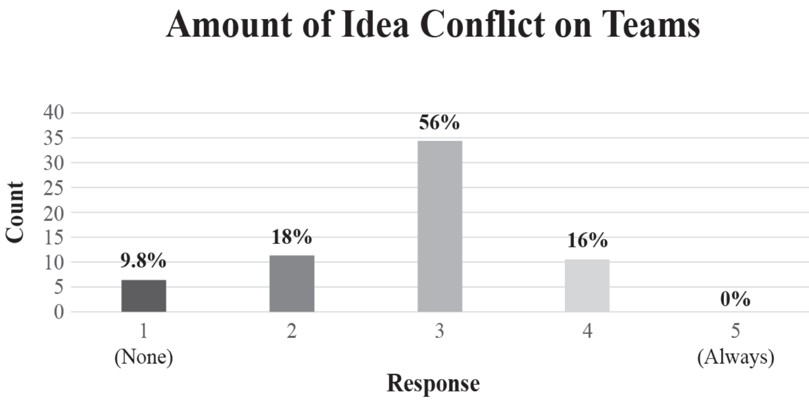


Figure 3.6: Perception of Degree of Team Conflict over Ideas in 2014.

Block Four: Team Performance

The outcome measures we examine in this model include perceptions of team knowledge meshing, team productivity, and individual satisfaction.

Team Knowledge Meshing. This new five-item Likert scale was included in the 2018 survey in an effort to gauge the perceptions of participants vis-à-vis how well the team was able to "mesh" or recombine existing knowledge into new patterns and co-create innovative outputs. In the 2018 survey, we asked participants to tell us about their team experiences in 2016 (mean = 5.20, SD = .99) and 2017 (mean = 5.26, SD = 1.20) using this scale. Overall, these means suggest respondents perceived their teams did a good job of integrating information from one another to jointly produce innovative deliverables.

Team Productivity. For each of the questions in this measurement category, respondents overall were highly likely to agree that their team was productive. The means and standard deviations for the team productivity scale (2014 mean = 5.37, SD = 1.28; 2016 mean = 5.45, SD = 1.11; 2017 mean = 5.31, SD = 1.48) indicated that participants in 2014 and 2018 tended to agree that their team was productive. For example, in 2014, the amount of agreement on items ranged from a low of 74% in response to the item "My team successfully solves problems that slow down our work," to a high of 82% on the two items "My team is productive" and "My team responds quickly to problems that arise." These results suggest that while teams respond quickly to problems, they may not always successfully solve them in an efficient manner. Across team conditions, Condition A had a significantly higher perception of their teams' productivity, at 100% agreement that their teams successfully met or exceeded their goals. As with other survey items, we suspect these differences are due to the lower amount of time Condition C teams had spent together, as they had little evidence of having met their goals at the time of the survey. Condition A teams' higher perceptions of their productivity may also have been a result of their relative autonomy in not having facilitation team members, as well as the fact that one large team in Condition A was not interdisciplinary, making it easier for them to understand each other and work rapidly toward solutions.

Individual Satisfaction. The means and standard deviations on the individual satisfaction scale (2014 mean = 5.36, SD = 1.42; 2016 mean = 5.63, SD = 1.45; 2017 mean = 5.39, SD = 1.61) indicate that participants generally agreed they were personally satisfied with the efforts of their teams. Specifically, for 2014, aggregate responses to this measurement category indicate that LAS members felt their work was intellectually stimulating (85% agreed), and that this work motivated them to do more interdisciplinary research (80% agreed). There was slightly less agreement that working on the research team assisted them in achieving their personal goals (70% agreed). Across conditions in 2014, Condition A was most likely to agree they were intellectually stimulated (100%), and Condition C was much less likely to agree the work motivated them to do more interdisciplinary research (69%). Once again, we believe these results point to differences in the amount of time the teams had been together and the number of different disciplines involved in the teams. The one team in

Condition A composed of computer scientists were highly satisfied and did not need facilitation because of the lack of interdisciplinarity.

Summary of Comparison over Time

Before combining the data for 2016 and 2017, we compared them across all three years, after deleting the information on the subjects. Treating each year as an independent sample, we ran a one-factor Analysis of Variance (ANOVA), with *year* as the factor. This allowed us to test for differences in responses by year (see Table 3.6).[4]

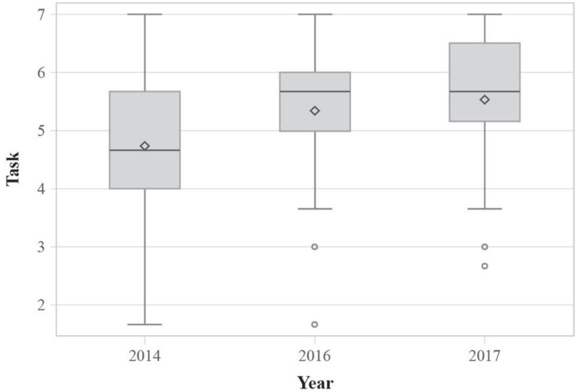
Scale	ANOVA F-statistic	ANOVA P-value	Kruskal-Wallace P-value
Participation	1.16	0.3163	0.28562
Task Interdependence	5.8	0.0039	0.0034
Goal Interdependence	0.34	0.7127	0.76675
Output Interdependence	1.5	0.2264	0.24845
Communication/Coordination	0.33	0.7163	0.50019
Information Elaboration	0.25	0.7772	0.59983
Team Learning Behavior	0.04	0.9562	0.946
Trust	0.22	0.8055	0.97966
Conflict	7.05	0.0013	1.2E-05
Satisfaction	0.34	0.7129	0.59192

Table 3.6: ANOVA and Kruskal-Wallace tests with the Bonferroni Correction Applied (2016, 2017).

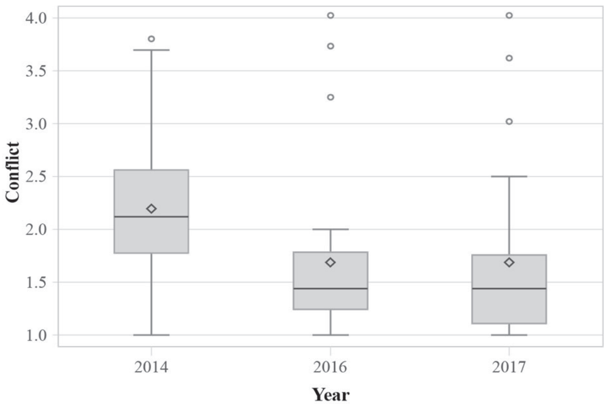
The two statistically significant changes were in Task Interdependence ($p = 0.0034$) and Conflict ($p < 0.0001$). As you can see from the boxplot in Figure 3.7, the scores for task interdependence increased between 2014 and 2016/2017. Post hoc comparisons of means were run for these two metrics.

[4] Diagnostic plots were run to verify the assumptions of the model were met. Because the residuals were not always normally distributed, we also ran nonparametric Kruskal-Wallace tests, a rank-based alternative to an ANOVA. The results did not change substantially. Because there are 10 hypothesis tests, the Bonferroni correction was applied; the adjusted cutoff for statistical significance is 0.005.

For task interdependence, the mean in 2014 is significantly lower than the mean in 2017 (p = 0.0071), but the mean in 2016 is only marginally significantly different from that of 2014 (p = 0.0594) and is not significantly different from 2017 (p = 1.000). The scores for conflict decreased over the same period. The mean in 2014 is significantly higher than in 2016 (p = 0.0085) and 2017 (p = 0.0079).



a. Distributions and Means for Task Interdependence



b. Distributions and Means for Conflict

Figure 3.7: Boxplots for Perceptions of Task Interdependence and Conflict over time.

Although we might have expected more significant differences in perceptions of LAS team experiences and collaboration over time, it is possible that changes in the Lab structure and the methods of collecting the survey data prevented us from obtaining more empirically robust results. The two significant findings are of interest, however, and reflect changes we might have expected. For example, because the Lab is based on the concept of immersive collaboration, we would hope that team members would perceive a high level of task interdependence. The fact that there was movement in this direction is a positive discovery. Furthermore, while effective and innovative teams should have some amount of task conflict, as described above, we would hope that as Lab members form relationships, this is accompanied by increased trust and reduced conflict overall. The fact that conflict has decreased over the years is therefore another significant and positive finding.

Regression Analysis and Results

The research question motivating this research is: *What factors are most important in the design of large-scale, long-term, cross-sector collaborative programs in order to transcend institutional and interdisciplinary boundaries to enhance the generation of innovative output?*

In order to determine the relative importance of the predictive factors or independent variables in our model to predict knowledge meshing, productivity, and satisfaction, we conducted linear regression analysis. First, using the data aggregated for 2016 and 2017, we regressed all the independent variables on team knowledge meshing. The overall model was significant, although information elaboration was the only variable that was statistically significant. We then ran a stepwise regression to allow the computer to select the significant variables; information elaboration was the only independent variable found to significantly ($p < .0001$) predict team knowledge meshing (see Table 3.7).

Next, using our 2014 data and our aggregated 2016 and 2017 data, we regressed team productivity and then team satisfaction on all the independent variables, including team knowledge meshing. For these four models, none of the independent variables were significant. We believe that this is because of correlation among the independent variables. Thus, we used stepwise model selection to pick the best-fitting model for each data set for these two dependent variables. In the stepwise model, using the 2014 data, the best-fitting model for team productivity involved team empowerment, team leader effectiveness, and communication. As those three scales increase, so do perceptions of team productivity (see Table 3.8.1).

	Full Model			Final Model		
Variables	**Estimate**	**Std. Err.**	**p-value**	**Estimate**	**Std. Err.**	**p-value**
Intercept	0.293	0.768	n.s.	0.818	0.431	n.s.
Participation	0.060	0.088	n.s.			
Task Interdependence	-0.125	0.125	n.s.			
Goal Interdependence	0.070	0.113	n.s.			
Output Interdependence	0.067	0.080	n.s.			
Communication	0.116	0.191	n.s.			
Information Elaboration	0.564	0.190	0.0046	0.790	0.074	<.0001
Learning Behavior	0.047	0.141	n.s.			
Trust	0.063	0.155	n.s.			
Conflict	0.142	0.158	n.s.			
Year 2016	-0.125	0.179	n.s.	-0.131	0.167	0.436
Year 2017						
N	59			59		
R-Squared	0.703			0.671		
Adjusted R-Squared	0.642			0.660		
Average VIF	3.565			1.002		
F-Value	11.38			57.20^{**}		
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$						

Table 3.7: 2016/2017 Team Knowledge Meshing Regression Models.

	Full Model			Final Model		
Variables	Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value
Intercept	0.052	1.000	n.s.	-0.523	0.500	n.s.
Satisfaction	0.115	0.104	n.s.			
Conflict	-0.162	0.185	n.s.			
Trust	0.157	0.165	n.s.			
Team Empowerment	0.209	0.202	n.s.	0.485	0.135	0.0007
Technical Leadership	0.221	0.141	n.s.	0.253	0.108	0.023
Team Learning Behavior	-0.017	0.178	n.s.			
Information Elaboration	0.200	0.157	n.s.			
Communication	0.112	0.145	n.s.	0.344	0.101	0.001
Output Interdependence	-0.008	0.098	n.s.			
Goal Interdependence	-0.024	0.115	n.s.			
Task Interdependence	0.107	0.098	n.s.			
Participation	-0.010	0.106	n.s.			
N	61			61		
R-Squared	0.769			0.734		
Adjusted R-Squared	0.711			0.719		
Average VIF	3.440			2.330		
F-Value	13.31^{**}			52.29^{**}		
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$						

Table 3.8.1: 2014 Team Productivity Regression Models.

The best-fitting model for Team Productivity for the combined 2016 and 2017 data includes level of participation, goal interdependence, communication/cooperation, and team learning behavior (see Table 3.8.2). We forced the model to include an effect for *year*. As in the other models, the scales increase together. These findings suggest the importance of members feeling they were able to contribute to the teams' activities, for goals to be aligned, for there to be good communication/cooperation, and for them to use good team learning behaviors in order for the teams to be productive. We should note that the communication/cooperation scale remains an important predictor of team productivity in both the 2014 data and the aggregated 2016 and 2017 data.

	Full Model			Final Model		
Variables	**Estimate**	**Std. Err.**	**p-value**	**Estimate**	**Std. Err.**	**p-value**
Intercept	-0.101	0.806	n.s.	-1.136	0.518	0.0328
Satisfaction	0.126	0.101	n.s.			
Participation	0.198	0.091	0.035	0.169	0.078	0.035
Task Interdependence	-0.088	0.131	n.s.			
Goal Interdependence	0.227	0.116	n.s.	0.216	0.082	0.011
Output Interdependence	0.081	0.082	n.s.			
Communication	0.525	0.198	n.s.	0.553	0.101	<0.0001
Information Elaboration	-0.166	0.212	n.s.			
Team Learning Behavior	0.330	0.145	0.0276	0.248	0.114	0.035
Trust	-0.086	0.164	n.s.			
Conflict	-0.233	0.165	n.s.			
Knowledge Meshing	-0.057	0.154	n.s.			
Year 2016	0.087	0.185	n.s.	0.077	0.174	n.s.
Year 2017						
N	59			59		
R-Squared	0.789			0.767		
Adjusted R-Squared	0.734			0.745		
Average VIF	3.712			1.530		
F-Value	14.34^{**}			34.82^{**}		
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$						

Table 3.8.2: 2016/2017 Team Productivity Regression Models.

For individual satisfaction, the best-fitting model for 2014 includes team empowerment, information elaboration, goal interdependence, and task interdependence. As those four variables increase, so does individual satisfaction with the activities of the team (Table 3.9.1). Given the significance of team empowerment and team leader effectiveness on both team productivity and individual satisfaction, it is unfortunate that these two variables could not be included in the second survey. It is interesting to note that once these two variables were no longer included, some other variables emerged as significant.

	Full Model			Final Model		
Variables	**Estimate**	**Std. Err.**	**p-value**	**Estimate**	**Std. Err.**	**p-value**
Intercept	0.069	1.372	n.s.	-0.120	0.712	n.s.
Team Empowerment	0.555	0.266	0.042	0.365	0.178	0.045
Participation	0.081	0.145	n.s.			
Task Interdependence	-0.266	0.129	0.045	-0.346	0.112	0.003
Goal Interdependence	0.418	0.146	0.006	0.395	0.127	0.003
Output Interdependence	-0.120	0.134	n.s.			
Communication	0.253	0.195	n.s.			
Information Elaboration	0.500	0.203	0.018	0.544	0.169	0.002
Team Learning Behavior	-0.180	0.243	n.s.			
Trust	-0.329	0.221	n.s.			
Conflict	-0.106	0.253	n.s.			
Technical Leadership	0.022	0.193	n.s.			
N	61			61		
R-Squared	0.639			0.597		
Adjusted R-Squared	0.588			0.569		
Average VIF	3.050			1.970		
F-Value	7.89^{**}			20.77^{**}		
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$						

Table 3.9.1: 2014 Individual Satisfaction Regression Models.

The best-fitting model for individual satisfaction for the combined 2016 and 2017 data includes only trust and team knowledge meshing (see Table 3.9.2). Again, we forced the inclusion of a year term, and the scales increase together. It is interesting that this is the first time that trust has been a significant predictor in any of the models. The fact that information elaboration is a strong predictor of team knowledge meshing (Table 3.7), and team knowledge meshing appears in this model (Table 3.9.2), while information elaboration does not, suggests that team knowledge meshing mediates the effect of information elaboration on team satisfaction, as proposed by Tyler and her associates (2014). Future research should further investigate how team knowledge meshing mediates the effects of program-determined team project design, team processes, and team emergent states on team productivity and team satisfaction.

	Full Model			**Final Model**		
Variables	**Estimate**	**Std. Err.**	**p-value**	**Estimate**	**Std. Err.**	**p-value**
Intercept	-1.658	1.141	n.s.	0.154	0.625	n.s.
Participation	-0.067	0.132	n.s.			
Task Interdependence	0.254	0.186	n.s.			
Goal Interdependence	-0.029	0.168	n.s.			
Output Interdependence	-0.032	0.119	n.s.			
Communication	0.233	0.284	n.s.			
Information Elaboration	0.115	0.306	n.s.			
Team Learning Behavior	-0.089	0.209	n.s.			
Trust	0.399	0.230	n.s.	0.487	0.125	0.0003
Conflict	0.223	0.236	n.s.			
Knowledge Meshing	0.441	0.214	0.045	0.515	0.169	0.004
Year 2016	0.187	0.266	n.s.	0.169	0.252	n.s.
Year 2017						
N	59			59		
R-Squared	0.670			0.628		
Adjusted R-Squared	0.593			0.608		
Average VIF	3.680			1.810		
F-Value	8.68^{**}			34.82^{**}		
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$						

Table 3.9.2: 2016 and 2017 Individual Satisfaction Regression Models.

LAS Focus Group: Participant Reflections on the Theoretical Model

In June 2017, Beverly Tyler conducted a workshop during a regular Weekly Research Meeting (WRM; see Chapter Five), in which LAS participants were asked to reflect on and discuss many of the factors incorporated in the collaboration model and a few additional factors not in the model. Fifteen participants attended the WRM: 13 were from government and 2 from NC State. Of the 15 participants, 5 were in LAS leadership positions. Four Research Questions (RQ) guided the focus group workshop:

RQ1: Which three performance outputs do the activities and actions associated with discovery and translation most strongly affect and why?

RQ2: What activities or actions associated with factors in the model are most related to breakthrough or discovery?

RQ3: What activities or actions associated with these factors are related to translation in the intelligence security context?

RQ4: What factors (in the model or not) most hamper discovery and translation?

In the first phase of the workshop, participants were asked to review the 15 concepts illustrated in a slightly modified model from that depicted in Figure 3.1 (see Figure 3.8). Following additional literature review and experience participating in LAS, the original model was revised to incorporate more variables related to program characteristics (program design, funding, team-based rewards, and access to team members), and three new constructs revealed to be relevant to innovative output of interdisciplinary research (commitment to interdisciplinary research and development, collective identity, and shared contexts). After some discussion with the Collaboration Group, it was also decided that task, goal, and output interdependence might be hard for participants to differentiate, so only one item was included: interdependence within the team. Participants could also suggest additional constructs, although no one did. Following a short question-and-answer session about the meaning of various concepts, participants were asked to select the five concepts they felt were *most important to discovery and translation* at the lab. They were then asked to rank order the five concepts (1 = “most important,” to 5 = “least important”).

Block One Concepts: Program Superstructure and Team Project Design

☐ 1. Program design† (Program Superstructure)
☐ 2. Funding (Program Superstructure)
☐ 3. Team-based rewards† (Program Superstructure)
☐ 4. Knowledge diversity in team* (Team Project Design)
☐ 5. Interdependence within the team* (Task, goal and output not specific) (Team Project Design)
☐ 6. Location/access to team members† (Team Project Design)
☐ 7. Team members' commitment to interdisciplinary R&D** (Team Project Design)

Block Two Concepts: Team Processes

☐ 8. Communication (sharing, listening, create a common understanding)*
☐ 9. Elaboration of task relevant information*
☐ 10. Routines to structure tasks & interdependencies (descriptive of team learning behaviors)*

Block Three Concepts: Team Emergent States

☐ 11. Collective Identity**
☐ 12. Shared Context**
☐ 13. Technical Leadership*
☐ 14. Trust*
☐ 15. Conflict*
☐ 16. Other:___________

†Program characteristics
*Figure 1 concepts/scales
**New team constructs

Figure 3.8: Focus Group Worksheet.

To determine the aggregate overall importance, we recorded the number of times a concept was included in the top five by our 15 participants. We then determined the mean rankings for each construct by averaging the ranking of each construct to determine magnitude/popularity of a construct. The magnitude calculations for the top five constructs are in the graph in Figure 3.9: communication (17%), trust (13%), program design (10%), knowledge diversity (10%), and collective identity (10%). The number beside the constructs represents the average ranking each received by those that selected it as one of the five most important factors. When comparing these results with the survey results, it is important to recognize that three of the five factors weighted most heavily during this focus group—program design, knowledge diversity, and collective identity—were not included in either wave of survey data collection (2014 or 2018). It is also noteworthy that empowerment and technical leadership were not included in this list, although they were both significantly related to team productivity in the 2014 data; and empowerment was positively and significantly related to individual satisfaction in these data.

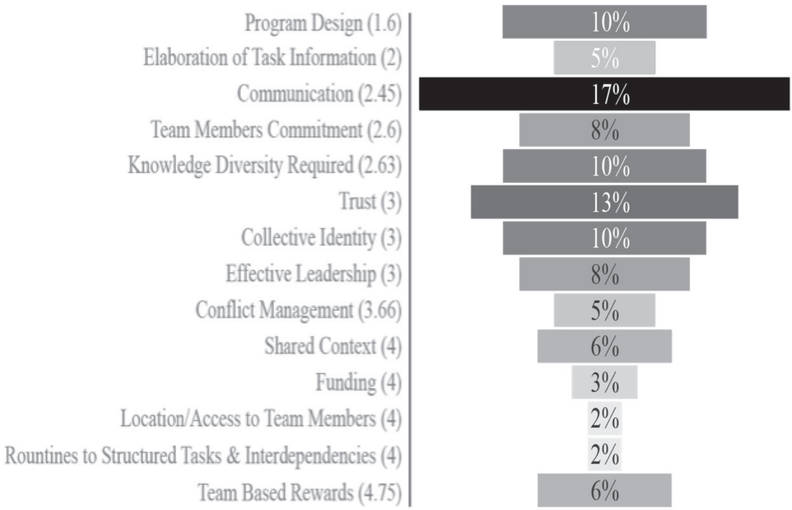


Figure 3.9: Focus Group Ranking of Top Five Constructs.

Finally, it should be recognized that the communication/cooperation and trust scales were significantly and positively related to team productivity and individual satisfaction, respectively, in the aggregated 2016 and 2017 data, although they did not appear in the models for 2014. Two explanations for this are possible. It could be that the removal of empowerment and technical leadership in the 2016 and 2017 data created the opportunity for communication and trust to become more significant in the second wave of data collection. While this could explain the regression results, it does not explain the strong weighting of communication and trust by the focus group. Another explanation is that the focus group attendees who were primarily government participants (13 of 15) might not be representative of faculty and industry participants (who participated in the surveys). Thus, the findings of the data taken from this focus group may only be generalizable to the government participants, not to LAS participants more generally.

Communication. Many focus group participants included communication in their list of top five concepts that are most important for discovery and translation at the Lab; this item also received the most #1 rankings. Comments from participants suggested that trust and conflict management were positively associated with communication. Focus group participants wrote comments to explain their ranking, and those related to communication included "Can't do anything without a common understanding"; "allows members to understand what is going on—feedback helps members share and innovate"; "without communication, people make assumptions, don't trust, don't stay on track"; and "must have communication at the beginning for the rest to work."

Trust. While somewhat less likely to be ranked as *the* most important factor for discovery and translation at the lab, trust was the second most popular factor in the list of top five concepts. Participants explained their response with comments such as: "Trust keeps people from hoarding ideas for fear of being scooped/having their IP [intellectual property] stolen"; "trust is the beginning; without trust nothing else matters"; "without trust, anyone would think the other members of the team are on a mission to sabotage the others"; and "without mutual trust an interdisciplinary R&D model falls apart—very closely linked to many other factors." The comments associated with communication and trust suggest that these factors are necessary to discovery and translation at LAS but may not be sufficient for success.

Program Design. Program design received a high number of #1 rankings, as shown by a mean of 1.60, although it was ranked in the top five concepts by only 10% of those present. Comments associated with program design appeared to be related to the importance of agreement on and understanding of the teams' goals and objectives. Specific explanations for ranking Program Design #1 in importance include "project specifications—expectations—is everyone going or think they are going to the same goal?"; "need to know what you're doing & why & how otherwise it will all fall apart"; and "Program Design to provide a scaffold."

Knowledge Diversity. During the review of the concepts included in this exercise, participants were told that this concept is sometimes defined more broadly as diversity or team heterogeneity. However, research on diversity typically includes a wide variety of different kinds of diversity related to functions, sex, race, and religion. However, in the team science literature that focuses on interdisciplinary R&D, only knowledge diversity—measured as diversity in education and experience—is typically considered (Horwitz and Horwitz 2007). In this focus group, the ranking of team knowledge diversity included only diversity in knowledge and skills based on educational training and experience, as is consistent with the term used in block one of Figures 3.1 and 3.8. In the context of LAS, the primary types of diversity are educational training and experience in government, academia, and/or industry. It is not surprising, then, that government members of a cross-sector, interdisciplinary lab would believe such diversity is important to discovery and translation. Comments associated with this factor include: “if we all think the same thing, it is not interdisciplinary”; “greater diversity equals greater potential to innovate”; “in order to create something bigger than the sum of the parts, you need all the parts”; and “diversity of thought is crucial for the success of an interdisciplinary team (otherwise it may as well be a solo effort).”

Collective Identity. While this construct is not included in Figure 3.1, focus group participants identified it as an important part of block three: team emergent processes. Specifically, participants said that a sense of collective identity “fosters working together and collective success”; “is important for successful outcome, because without it one or more of the disciplines may want to receive all the accolades (and blame the others in case of failure)”; “keeps the team moving towards a common goal”; and “builds team cohesion.” These focus group observations are consistent with previous academic research on the importance of collective team identity (Koschman 2011; van der Vegt and Bunderson 2005).

After examining the top five constructs identified by focus group participants, we looked at their responses to the four research questions.

RQ1: Which three performance outputs do the activities and actions associated with discovery and translation most strongly affect and why?

For the first research question, participants were given a list of seven team performance outputs and asked to select the three performance outputs that activities and actions associated with discovery and translation are most likely to affect, and why. The six items were “my teams meets or exceeds its goals,” “completes its tasks on time,” “makes sure that deliverables meet or exceed quality standards,” “responds quickly when problems come up,” “is a productive team, “and successfully solves problems that slow down our work.” These items are similar to those used in the 2014 and 2018 surveys (data for 2016 and 2017) to assess team productivity. As seen in Figure 3.10, when asked to rank order the seven outputs, none of the 15 participants in the focus group included “quality,” one included “project goal completion,” and two included “productivity” and “efficiency.” This suggests that the primarily government participants did not believe the activities and actions associated with discovery and translation are highly related to these commonly valued outputs. However, the focus group did believe that “individual knowledge improvement,” “collective knowledge improvement,” and “emergent innovations” are associated with these activities.

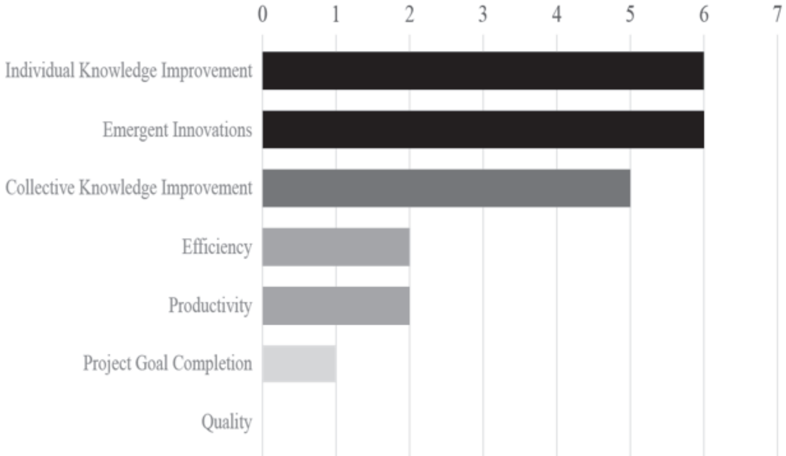


Figure 3.10: RQ1: Performance Outputs most Associated with Discovery/ Translation.

RQ2: What activities or actions associated with factors in the model are most related to breakthrough or discovery?

As seen in Figure 3.11 and described in their top five most important constructs, the primarily government participants in the focus group believe "trust" and "knowledge diversity" are the most important factors related to discovery. This suggests the importance of developing a trusting relationship between participants and fostering understanding of the ideas proposed by others with diverse backgrounds and experiences to the discovery of innovative outputs. Also recognized as important to discovery is the importance of changing up routinized processes, having sufficient resources, and having a collective identity and direction-setting goals. In addition to the comments described above, LAS focus group participants' comments explained the importance of being able to speak freely and honestly, to have access to team members, to have the ability to talk through any misunderstanding that occurred when "what was said wasn't what was heard," and the importance of humor, as one participant shared: "being able to laugh together sometimes generates that weird idea."

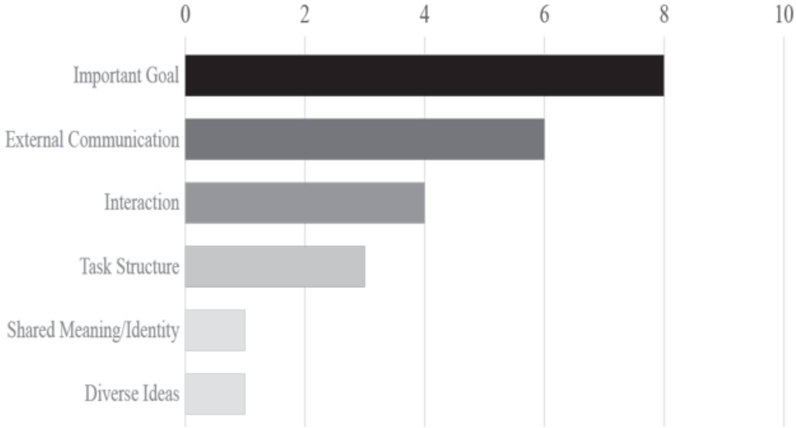


Figure 3.11: RQ2: Factors most Related to Breakthrough/Discovery.

RQ3: What activities or actions associated with these factors are related to translation in the intelligence security context?

As illustrated in Figure 3.12, LAS participants in this focus group perceived having an “important goal” and “external interaction” as the most important factors in achieving research translation to the intelligence community context. It is worth noting that “interaction” and “task structure” were also considered important by some participants, as well as “shared meaning/identity” and “diverse ideas.” Comments that elaborated on this idea suggest the importance of collaboration both inside the Lab and with external colleagues and customers. Featured explanations include: “the need to conduct focused discovery activities (FDAs; see Chapters Five and Ten) with mission personnel to do initial pilots of prototypes”; “dedicating resources to reaching out to mission partners, and understanding gaps in capabilities”; “identifying a customer up front and having frequent engagement”; “well-thought-out program design, with wise use of available funding connected to mission need”; and “making sure the project is a current priority by those higher up.”

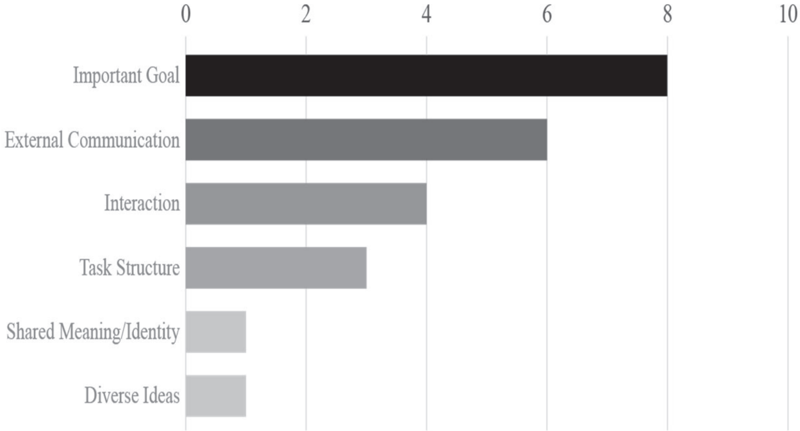


Figure 3.12: RQ3: Factors Most Related to Translation to the IC.

RQ4: What factors (in the model or not) most hamper discovery and translation?

Not surprisingly, focus-group participants indicated that the lack of factors that promote discovery and translation, such as trust, task structure, and information sharing, are major obstacles to goal achievement (see Figure 3.13). They especially commented, however, on the importance of sufficient resources, conflict management, and interaction. Others noted the lack of shared commitment, lack of shared goals, and lack of leadership. One participant described the need for better conflict management by observing that "doing the same thing over and over and expecting different results" is an obstacle. Other comments describing obstacles to discovery and translation included "unclear, poor, or ineffective communication"; "lack of individual or collective knowledge"; "individuals without leadership skills"; and "conflict (if not managed)," "collective identity (if it becomes group think)," and "team-based awards when they overtake results."

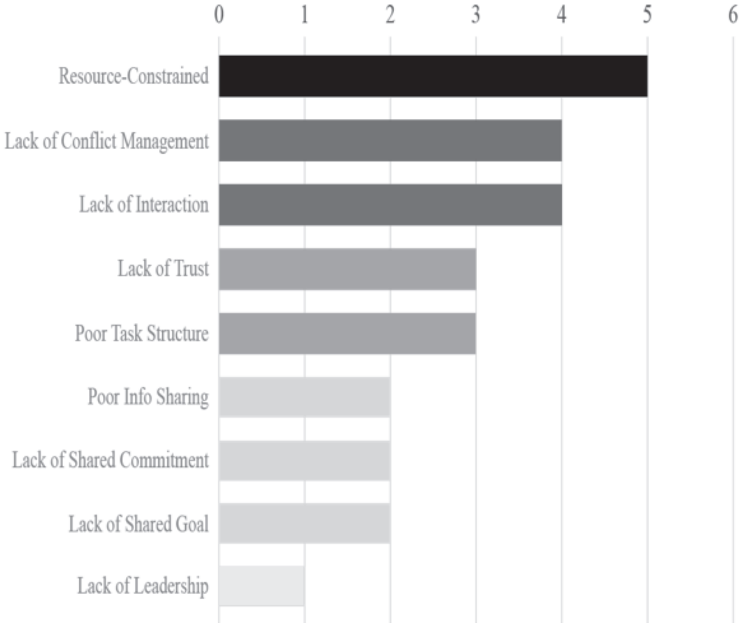


Figure 3.13: RQ4: Obstacles to Discovery/Translation.

Important Takeaways from the Focus Group Session

We learned a number of things from the discussion regarding the 15 factors incorporated into this focus group exercise. First, it appears that effective communication leads to relationship building and trust, at least for government participants, all of which are required but are not necessarily sufficient for promoting a collaborative environment. Program design, having the required diversity for the project, having a collective identity, and effective leadership are also very important to creating the collaborative environment necessary for discovery and translation in cross-sector, interdisciplinary programs and projects, according to the 15 people in this focus group. Asking questions, which enables information elaboration and improved knowledge meshing of ideas proposed by participants with diverse backgrounds and experiences, is also moderately important, as are conflict management, a shared context, and team-based rewards. Least important, according to our focus group participants, are the routines to structure tasks, ready access to team members, and funding.

When asked specifically about activities that lead to discovery, trust, having the necessary diversity, and changing up routinized processes are often mentioned by participants, although sufficient resources and a collective identity were also noted as important. In regards to activities that support translation to the high side, participants noted having important goals and external communication as the most important factors for translation, followed by integration of effort, task structure, shared identity, and diverse ideas. When asked what factors most hamper discovery and translation, resource constraints were cited as the most important, followed closely by lack of conflict management, lack of team interaction, and poor task structure. Less impactful but still mentioned were poor information sharing, lack of shared commitment, lack of shared goals, and lack of leadership.

Conclusion

The purpose of the research described in this chapter was to complement the observational and interview data described in Chapter Two to identify the factors of team collaboration perceived by LAS members to be most important to team productivity, individual satisfaction, and innovative outcomes. We grounded this work in a model depicting the LAS program and its project teams' collaborative efforts, and developed a survey instrument to measure various factors believed to predict three primary outcomes: knowledge meshing, team productivity, and team satisfaction. It is important to note that as the teams were in the early phases of research when we conducted the first study in 2014, it was not possible to measure innovation at that point, although we added knowledge meshing in the 2018 survey as a measure of innovative output. Furthermore, our survey research may have been influenced by changes in the structure of LAS teams between the original survey in 2014 and the follow-up survey in 2018 (i.e., the percentage of team members that were from academia or government changed over time). We also chose to adapt the survey instrument between 2014 and 2018 because of challenges in collecting data from individuals participating in more than one project. Finally, to provide more insight into LAS member perceptions of the model and what leads to innovation, the focus group activity was conducted with 15 LAS members, 13 of which were from government.

The preceding discussion of our findings presents a complex picture of the collaboration process, revealing—not surprisingly—that no two teams are exactly the same, and what they need for successful immersive collaboration is often both individual- and context-dependent. Nevertheless, this research supports the model in Figure 3.1, in that factors in each of the three blocks were revealed as important predictors of knowledge meshing, productivity, and/or satisfaction across the two surveys and focus group described here. Specifically, member participation in decision making, task interdependence, and goal interdependence (block one: project design); communication, information elaboration, and learning behavior (block two: team processes); and technical leadership, team empowerment, and trust (block three: emergent states). It is noteworthy that two of these factors, communication and team goals, are also reflected in the themes that emerged from our observations and interviews, as discussed in Chapter Two. Finally, there is some evidence to suggest that team knowledge meshing may serve as a mediating variable between information elaboration and team satisfaction. Focusing our attention on these aspects of the model, we conclude Chapter Three with implications for interdisciplinary, cross-sector research and development efforts at each of the three levels of analysis: program, team, and individual.

Program Level

The part of our theoretical model that program leaders have the most control over is project design (block one). Program leaders should build teams with the amount of knowledge diversity needed to fulfill project team goals (found to be very important in the focus group, even though we could not measure this in the surveys reported here). Additionally, leaders should create structured opportunities that bring team members together—either before funding begins or within the first month of funding—to get to know one another and negotiate individual tasks and goals. Early structured opportunities to engage team members in information exchange and social construction of a common understanding of project goals will help team members feel they have participated in team decision-making processes, help them see connections across their fields and interests, and support both task and goal interdependence. Furthermore, the process of negotiating team goals and tasks should encourage the development of effective and efficient team processes (block two), as well as increase perceptions of team empowerment and the ability to address conflict productively, and build trust (block three). Program leaders can also support team processes by assigning technical leaders who see connections across individual projects to help the team locate points of intersection and interdependence that would in turn foster more innovative outcomes.

Team Level

Although communication comes up as critical to effective group process in the 2018 data and focus group, it is important to be more precise about what kind of communication is needed for cooperation to enable immersive collaboration. Clearly, effective communication is required, but our study suggests that different forms and types of communication are necessary for collaborative success in cross-sector, interdisciplinary project teams. As described in Chapter Two and confirmed by the model, communication about individual and team goals and how to align them is important. For team members to feel they have participated in team decision making depends on their perceived ability to communicate freely and interactively with their team members. Goal, task, and output interdependencies require that team members establish a shared vocabulary so that communicated information is interpreted correctly.

Looking further at the team processes block, we can see how important communication is to elaborating on task-relevant information and participating in team learning behaviors. Information elaboration refers to communication that goes beyond mere sharing of information to include an interactive process, during which team members ask clarifying questions or relate the information to their own experience in order to confirm their understanding. Information elaboration thus ensures that team members look at an issue from multiple perspectives and facilitates the development of shared understanding and shared meaning. Communication is also key to the activities associated with team learning behavior: handling differences of opinion privately or offline, getting all the information you can from others, frequently seeking new information, and speaking up to test assumptions about issues under discussion. In the 2018 survey, team knowledge meshing also emerged as an important outcome of information elaboration and appears to be a mediator between elaboration and satisfaction. The actions associated with knowledge meshing all require good communication practices within the team.

Looking at block three, technical leadership, team empowerment, and trust were also revealed as important to successful team outcomes, and the kind of open communication and information sharing characterized by information elaboration and learning behavior (along with member participation and agreement on team goals) ought to help foster these emergent states. When teams are especially concerned with the translation of their products back to the intelligence community, another important consideration is to include external members in the conversation early and often. This is also relevant to information elaboration and learning behaviors, because it is not enough to consider the perspectives of co-located team members, but also the perspectives of those outside the formal team who are the customers or eventual end users of the resulting products.

Individual Level

The main implication of this model for individuals who are part of interdisciplinary, cross-sector teams is to actively participate in collaborative conversations with their team members, even when they believe their projects can be completed independently. Individuals need to be open to learning new information and engaging in information elaboration and team learning behaviors that contribute to the social construction of a common understanding, so that knowledge meshing is possible. The focus-group discussion shed light on behaviors that government members see as most helpful, such as convenient access to team members, team members who work to increase their knowledge, and clear and effective communication. Other important features of individual communication that were revealed included being able to speak freely and honestly, the ability to talk through misunderstandings, and the importance of humor.

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Appendix A: Survey Scales and Measures

I. Program Design [Block One]	
A. Job Design	
1. Team heterogeneity	(Not included in this study)
2. Participation (Campion et al, 1993	3 items (#1-#3)
B. Interdependence	
1. Task (Campion et al, 1993)	3 items (#4-#6)
2. Goal (Campion et al, 1993)	3 items (#7-#9)
3. Outcome (Campion et al, 1993)	3 items (#10-#12)
II. Team Processes [Block Two]	
A. Communication/cooperation (Campion et al, 1993	3 items (#13-#15)
B. Information elaboration (Homan et al, 2008)	3 items (#16-#18)
C. Team learning behavior (Edmondson, 1999)	7 items (#19-#25)
III. Emergent States [Block Three]	
A. Technical Leadership Effectiveness (Van de Ven & Chu, 2000)**	6 items (#26-#31)
B. Team empowerment (Kirkman et al., 2004)**	12 items (#32-#43)
C. Trust (Kirkman et al, 2006)	4 items (#44-#47)
D. Conflict (Jehn & Mannix, 2001)	9 items (#48-#56)
IV. Team Performance [Block Four]	
A. Team knowledge meshing (Tyler et al, 2014)*	5 items (#66-#70)
B. Team productivity (Kirkman & Rosen, 1999)	6 items (#57-#62)
C. Individual satisfaction (Collaboration Group-created)	3 items (#63-#65)

* Scale not included in the 2014 survey
** Scales not included in the 2018 survey

Appendix B: Survey Items

Each item below relates to your participation and the interdependence of the tasks you are involved in for the specific LAS project you have been asked to consider in this survey. Please answer the following questions on a seven-point scale, from 1, "strongly disagree," to 7, "strongly agree."

1. As a member of a team, I have a real say on how the team carries out its work.
   1 2 3 4 5 6 7
2. Most members of my team get a chance to participate in decision making.
   1 2 3 4 5 6 7
3. My team lets everyone participate in decision making.
   1 2 3 4 5 6 7
4. I cannot accomplish my tasks without information or materials from other members of my team.
   1 2 3 4 5 6 7
5. Other members of my team depend on me for information or materials needed to perform their tasks.
   1 2 3 4 5 6 7
6. Within my team, jobs performed by subgroup members are related to one another.
   1 2 3 4 5 6 7
7. My work goals for this LAS project come directly from the goals of the team.
   1 2 3 4 5 6 7
8. My work activities for this LAS project each month are determined by my team's goals.
   1 2 3 4 5 6 7
9. Most of the activities I am involved in for this LAS project are related to the goals of the team.
   1 2 3 4 5 6 7
10. Feedback on my performance on this project is integrated with how well the entire team is doing.
    1 2 3 4 5 6 7
11. I believe LAS will evaluate my performance based on how well my team performs.
    1 2 3 4 5 6 7
12. My future opportunities to participate on LAS projects will in large part be determined by my contributions as a team member to this project.
    1 2 3 4 5 6 7

Each item below relates to the team processes, technical leadership, and attitudes of team members for the specific LAS project and technical leader you have been asked to consider in this survey. Please answer the following questions on a seven-point scale, from 1, "strongly disagree," to 7, "strongly agree," to express the strength of your agreement with these statements.

13. Members of my team are very willing to share information with other team members about our work.
    1 2 3 4 5 6 7
14. Team meetings enhance the communication among the team members.
    1 2 3 4 5 6 7
15. Members of my team cooperate to get things done.
    1 2 3 4 5 6 7
16. The team members contribute useful information to accomplish the team task.
    1 2 3 4 5 6 7
17. The team members contribute unique information to accomplish the team task.
    1 2 3 4 5 6 7
18. During the task, we try to integrate all available information.
    1 2 3 4 5 6 7
19. We regularly take time to figure out ways to improve our team's work processes.
    1 2 3 4 5 6 7
20. The team tends to handle differences of opinion privately or off-line, rather than addressing them directly as a group.
    1 2 3 4 5 6 7
21. Team members go out and get all the information they possibly can from others.
    1 2 3 4 5 6 7
22. This team frequently seeks new information that leads us to make important changes.
    1 2 3 4 5 6 7
23. In this team, someone always makes sure that we stop to reflect on the team's work process.
    1 2 3 4 5 6 7
24. People in this team often speak up to test assumptions about issues under discussion.
    1 2 3 4 5 6 7

25. We invite people from outside the team to present information or have discussions with us.
    1 2 3 4 5 6 7
26. The technical leader of this team encourages individual initiative.
    1 2 3 4 5 6 7
27. The technical leader of this team clarifies individual responsibilities.
    1 2 3 4 5 6 7
28. The technical leader of this team provides feedback on individual contributions.
    1 2 3 4 5 6 7
29. The technical leader of this team maintains a strong task orientation.
    1 2 3 4 5 6 7
30. The technical leader of this team emphasizes team relationships.
    1 2 3 4 5 6 7
31. The technical leader of this team demonstrates trust in team members.
    1 2 3 4 5 6 7
32. My team has confidence in itself.
    1 2 3 4 5 6 7
33. My team can get a lot done when it works hard.
    1 2 3 4 5 6 7
34. My team believes that it can be very productive.
    1 2 3 4 5 6 7
35. My team believes that its project is significant.
    1 2 3 4 5 6 7
36. My team feels that its tasks are worthwhile.
    1 2 3 4 5 6 7
37. My team feels that its work is meaningful.
    1 2 3 4 5 6 7
38. My team can select different ways to do the team's work.
    1 2 3 4 5 6 7
39. My team determines as a team how things are done on the team.
    1 2 3 4 5 6 7
40. My team makes its own choices without being told by LAS.
    1 2 3 4 5 6 7
41. My team has a positive impact on the LAS program.
    1 2 3 4 5 6 7
42. My team performs tasks that matter to LAS.
    1 2 3 4 5 6 7
43. My team makes a difference in the LAS program.
    1 2 3 4 5 6 7

44. My team members have a high degree of trust between each other.
    1 2 3 4 5 6 7
45. My team members believe that others on the team will follow through on their commitments.
    1 2 3 4 5 6 7
46. My team members always do what they say they will do.
    1 2 3 4 5 6 7
47. My team members trust each other to contribute worthwhile ideas.
    1 2 3 4 5 6 7

For items #48 through #56, indicate how often your team experiences the following types of conflict on a scale of 1 to 5, where 1 = "none at all" or "never," and 5 = "a lot" or "always."

48. How much relationship tension is there in your team?
    1 2 3 4 5
49. How often do people get angry while meeting with your team?
    1 2 3 4 5
50. How much emotional conflict is there in your team?
    1 2 3 4 5
51. How much conflict of ideas is there in your team?
    1 2 3 4 5
52. How frequently do you have disagreements within your team about the task of the project you are working on?
    1 2 3 4 5
53. How often do people in your team have conflicting opinions about the project you are working on?
    1 2 3 4 5
54. How often are there disagreements about who should do what in your team?
    1 2 3 4 5
55. How much conflict is there in your team about task responsibilities?
    1 2 3 4 5
56. How often do you disagree about how time should be spent in your team?
    1 2 3 4 5

Each item below relates to your perceptions of the team's productivity and your own satisfaction with the specific LAS project you have been asked to consider in this survey. Please answer the following questions on a seven-point scale, from 1, "strongly disagree," to 7, "strongly agree," to express the strength of your agreement with each statement.

57. My team meets or exceeds its goals.
    1 2 3 4 5 6 7
58. My team completes its tasks on time.
    1 2 3 4 5 6 7
59. My team makes sure that deliverables meet or exceed quality standards.
    1 2 3 4 5 6 7
60. My team responds quickly when problems come up.
    1 2 3 4 5 6 7
61. My team is a productive team.
    1 2 3 4 5 6 7
62. My team successfully solves problems that slow down our work.
    1 2 3 4 5 6 7
63. Working on this team has helped me meet my personal goals.
    1 2 3 4 5 6 7
64. Working on this team, I feel intellectually stimulated.
    1 2 3 4 5 6 7
65. Working on this team has motivated me to do more interdisciplinary research.
    1 2 3 4 5 6 7
66. My team members from different disciplines were able to pool different knowledge sets to spark new insights (e.g., "riff" off of each other).
    1 2 3 4 5 6 7
67. My team members often reached a standstill because they were unable to pool knowledge across disciplines.
    1 2 3 4 5 6 7
68. My team members from different disciplines came up with new approaches to problems they had not considered previously.
    1 2 3 4 5 6 7
69. My team members learned how to interweave knowledge from their respective disciplines.
    1 2 3 4 5 6 7
70. My team found it difficult to work with members from other disciplines to generate new insights.
    1 2 3 4 5 6 7

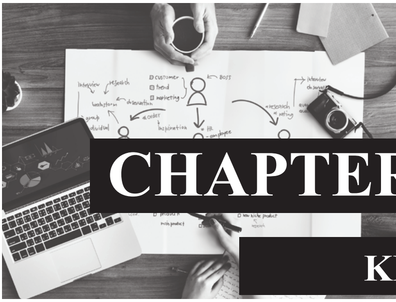
4

A SOCIAL NETWORK ANALYSIS OF COLLABORATION IN A CROSS-SECTOR RESEARCH LABORATORY

HECTOR RENDON, JESSICA KATZ JAMESON and BEVERLY B. TYLER

It is hardly possible to overrate the value ... of placing human beings in contact with persons dissimilar to themselves, and with modes of thought and action unlike those with which they are familiar. ... Such communication has always been, and is particularly in the present age, one of the primary sources of progress.

–John Stuart Mill, Principles of Political Economy, 1848, retrieved from Liberty Fund 2006 Ed.



CHAPTER 4

KEY TERMS

- **Integrative Collaboration:** Collaboration in which participants work together by sharing information and exchanging ideas throughout the task.
- **Team Cooperation:** Teammates' behavioral decisions about whether to act in promoting the objectives of the team.
- **Social Network Analysis:** The study of social structures and interactions between people, groups, or organizations to identify patterns of relationships between them. The primary components in a network analysis are nodes , individual team members and technical team leads, and ties, or the connections among the nodes.
- **Team Leader Centrality:** How connected the team's leader is to the rest of the network.
- **Team Centrality:** How connected a team is to the whole network.
- **Team Complexity:** The number of sectors represented in the team (government, academic, and industry). Greater representation leads to greater complexity.

KEY POINTS

Program: Program leaders should clearly communicate the goal of integrative collaboration across disciplines and sectors and develop integration mechanisms (workshops, training sessions, etc.) to support participants in getting to know one another and building trust to increase their comfort with an ambiguous task.

Team: Teams need to be prepared in advance that new members are likely to visit their meetings and even join the team once it is in progress. Teams would benefit from norms that include introducing new members, understanding their background and expertise and how they will contribute to the team. This would reduce the negative impact of network instability.

Individual: When building a cross-sector center, individual participants should make a commitment to meet with their teammates regularly (face-to-face or virtually as needed) so that they can begin to jointly establish a common and agreed upon understanding of the teams tasks, goals and outcomes. This includes attending program-wide events and getting to know the other lab participants to facilitate immersive collaboration.

While it is broadly recognized that multiple perspectives are needed to address challenging social issues, it is also clear that when participants have different ontological, epistemological, and methodological views and practices, embedded in different types of organizations, collaboration is no easy task (Hara, Solomon, Kim, and Sonnenwald 2003; Keyton, Ford, and Smith 2008). This chapter contributes to case studies of cross-sector and interdisciplinary collaboration through an exploratory social network analysis of LAS. Using the 2014 survey data described in Chapter Three, the network analysis examines how team network structures—team leader centrality, team centrality, team complexity, and team longevity—influence members' perceptions of interdependence (task, goal, and outcome), team communication (leader effectiveness, information sharing, and cooperation), conflict (task, relational, and process), and outcome indicators (team performance and individual satisfaction). The goal of this chapter is to provide additional insights from our collaboration survey data using a network analysis approach.

Interorganizational and Interdisciplinary Collaboration

Reflection on interorganizational collaboration research provides insights into understanding collaboration inside LAS. Stohl and Walker (2002) defined collaboration as "the process of creating and sustaining a negotiated temporary system which spans organizational boundaries involving autonomous stakeholders with varying capabilities including resources, knowledge and expertise and which is directed toward individual goals and mutually accountable and innovative ends'' (240). This definition guided our decision to emphasize a subset of variables from the model discussed in Chapter Three in the network analysis. Due to their relevance to other network analyses, we focused specifically on LAS team member perceptions of *interdependence*, *communication*, and *conflict.* A brief overview of literature relating these variables to interorganizational collaboration is presented below, followed by an overview of network analysis.

Interdependence, Communication, and Conflict

Interdependence. In Chapter Three, we described our measurement of interdependence using the subcategories of task, goal, and outcome interdependence (Campion et al. 1993). Task interdependence refers to how much team members perceive they rely on other team members to complete their task. Goal interdependence refers to how much team members perceive they rely on other team members to complete the team's goal. Outcome interdependence refers to how much team members perceive they rely on other team members to complete the outcome or final deliverable expected from their team. Although at face value it may seem obvious that if a team is expected to produce a deliverable together they are interdependent, previous scholars have made the link between types of interdependence and collaboration. Hara et al. (2003), for example, describe that collaboration falls on a continuum from complementary to integrative. At one extreme, *complementary* collaboration occurs when participants work independently and then put the pieces together to create a whole, as in a puzzle. At the other end of the continuum is *integrative* collaboration, in which participants work together by sharing information and exchanging ideas throughout the task. In practice, many collaborative efforts likely fall somewhere between these extremes, where team members share ideas or information at various points throughout a project and may or may not make adaptations or learn from this communication. While leaders may assume the level of collaboration is an objective feature of the tasks assigned to an interdisciplinary team, team members' perceptions of the type of interdependence required to accomplish these tasks affects their expectations and behaviors. For example, their perceptions of interdependence will influence whether team members spend more time working alone or together, how they choose to communicate (primarily face-to-face or electronically), and who they believe is responsible for subtasks. Importantly, all team members may not have the same preference for the type and level of interdependence that would be required to accomplish their collaborative task, because some members may be more guided by individual (or institutional) experience, training, or interests, while others may be motivated by team identity or public interest (Keyton et al. 2008; Koschmann 2013). It is therefore important to examine team members' perceptions of interdependence and how their placement within the larger social network may be related to such perceptions.

Communication. Communication is commonly described as being essential to collaboration, yet this word is ambiguous, as studies of collaboration have used "communication" to refer to behaviors (Dickinson, Viga, Lizarraga, and Castillo 2006), internal versus external targets of communication (Walker and Stohl 2012), or the media used to communicate (Gibbs et al. 2015). Incorporating previous research on group and team communication and the data we had available (from the survey described in Chapter Three), we include three dimensions of communication in this network analysis: *information sharing*, *cooperation*, and *technical team leadership effectiveness*. To achieve collaboration, team members must share relevant unique information with one another. Previous team research has demonstrated that group members tend to privilege shared information as more trustworthy, which decreases the likelihood that individual members will share unique information (referred to as the "hidden profile"; see Stasser and Titus 1985). It is therefore important to examine the level of information sharing perceived as present in collaborative teams.

Another important and related communication variable is the level of cooperation within a team. Team cooperation has been defined as "teammates' behavioral decisions about whether to act in promoting the objectives of the team" (Tyler and Blader 2000, as cited in Sinclair 2003, 75). Cooperation may be achieved in teams when individuals engage in behaviors such as offering assistance, volunteering ideas, and taking advantage of existing channels for communication, as well as creating new communication channels (Sinclair 2003). Operationally, cooperation is not the same as collaboration. Cooperation, for example, can involve providing mutual support that assists individuals in achieving their goals without necessarily integrating or meshing information as described above and in Chapter Three. Team cooperation has been directly linked to team effectiveness (Sinclair 2003), and we presume that it is a necessary but insufficient condition for team collaboration.

Team leader communication has also been linked to team effectiveness (Jung and Sosik 2002; Lee 1997). Member perceptions of leader empowerment, for example, have been shown to increase perceptions of cooperation, cohesiveness, and effectiveness (Jung and Sosik 2002). Furthermore, Lee (1997) examined how perceptions of leader embeddedness with those higher up in the organization impacted team cooperativeness. While Lee's study specifically examined how perceptions of the supervisor's influence with organizational leaders impacted group member cooperativeness and perceptions of team effectiveness, it seems logical that a team leader's communication with his or her team would similarly impact team member cooperation. Technical team leadership is largely about coordination in the context of interdisciplinary and cross-sector labs. Just as Barbour and James (2015) observed in their study of an interorganizational and interdisciplinary toxic waste storage facility, LAS team leaders had no authority to task or direct individual team members' actions, and they relied heavily on emails and reminders of team goals to encourage participation, cooperation, and collaboration.

Conflict. Also related to effective team communication and the presence of collaboration is the existence of conflict. In an interdisciplinary, cross-sector team, there should be cognitive diversity (at a minimum) that results in task-related conflict, and possibly relational and process-related conflict, as described in Chapter Three (Jehn and Mannix 2001). Whether team members engage in or avoid conflict may also be related to their position in the larger network and their perceptions of interdependence.

Because we were in the unique position of having access to the assigned project membership of lab participants and the collaboration survey data, we wanted to explore the nexus of relationships among team leaders' and teams' positions within the social network that represented the overall lab structure in 2014. Specifically, we wanted to conduct a network analysis to determine how network characteristics (i.e., team leader centrality, team centrality, team complexity, and team longevity) relate to LAS participants' perceptions of interdependence, communication, conflict, team performance, and individual satisfaction.

Social Network Analysis

Social network analysis is the study of social structures and interactions between people, groups, or organizations to identify patterns of relationships between them (Scott 2013). For the purposes of this chapter, a social network is defined as a set of interconnected persons—or groups of people—with one or several relational links between them (Marin and Wellman 2014). One underlying assumption driving social network analysis comes from theories of social capital (Carpenter, Li, and Jiang 2012). This theory suggests that network participants use their relational networks to gain access to information or resources. Therefore, in the context of cross-sector collaboration teams, social networks have important implications for collaborative effort, participants' satisfaction, and ultimately team success. The primary components in a network analysis are nodes (individual team members and technical team leads), and ties, or the connections among the nodes (Marin and Wellman 2014). To understand the patterns of connection among nodes, it is important to examine the relationships between participants and teams within the context of the overall network established by program leadership.

At the team level, common network characteristics are *team leader centrality*—how connected the team's leader is to the rest of the network—and *team centrality*—how connected a team is to the whole network (Carpenter et al. 2012). A meta-analysis of social network studies of work team performance demonstrated that leader centrality and team centrality predicted team performance and team cohesiveness (Balkundi and Harrison 2006). These authors also noted that there have been conflicting findings regarding leader centrality, as some studies have found that leader centrality negatively affected performance. It has been theorized that having a leader who is widely connected to other parts of the network may distract them from their leadership role in a given team. Therefore, we suggest that leader centrality is an important factor influencing team member perceptions of task interdependence, communication, task conflict, satisfaction, and overall team outcomes.

In their theorizing of the role of conflict in a social network, Balkundi and Harrison (2006) proposed that teams consisting of more similar members (less diverse sector and disciplinary representation) would communicate in ways that would uncover task conflict, which would allow them to address those issues and minimize relational conflict. Dickinson et al.'s (2006) study of an interorganizational ecology project consisting of scientific team members, facilitators, and community members concluded that this team diversity led to stronger perceptions of conflict within the network. Group conflict studies have supported the prediction that a moderate amount of task conflict is positively related to team performance (Jehn and Mannix 2001), although another meta-analysis revealed that both task and affective conflict were negatively related to team member satisfaction (De Dreu and Weingart 2003). In this study, we define *team complexity* as the level of diversity on the team based on membership representing different sectors (government, academia, industry). We are interested in the relationship between team complexity and perceptions of conflict at LAS.

Aboelela et al. (2007) found that networks in an interdisciplinary center became larger, more centralized, and more complex over time. Balkundi and Harrison (2006) also underscored the importance of considering time in social network studies. Their analysis found that integrative structures were antecedent conditions for positive team performance rather than something that occurred over time. They further found, however, that increased familiarity with team members over time moderated the effect of network characteristics on team performance outcomes. Group communication scholars have also noted the importance of investigating time in understanding group behavior (Ballard and Seibold 2004) and social networks (Walker and Stohl 2012). Because the LAS teams differed in terms of how long they had been working together, it was possible to explore the role of team longevity in member perceptions of team processes and outcomes.

Considering this literature on interorganizational collaboration and social network analysis in the context of teams, this study explores the relationship of four team network characteristics on four important features of LAS:

RQ1: Is there a relationship between *team leader centrality, team centrality, team complexity,* and *team longevity* and perceptions of task, goal, and outcome *interdependence*?

RQ2: Is there a relationship between *team leader centrality, team centrality, team complexity,* and *team longevity* and perceptions of *communication* (measured by team lead effectiveness, information sharing, and cooperation)?

RQ3: Is there a relationship between *team leader centrality, team centrality, team complexity,* and *team longevity* and perceptions of task, relational, and process *conflict*?

RQ4: Is there a relationship between *team leader centrality, team centrality, team complexity,* and *team longevity* and perceptions of individual *satisfaction,* and *team productivity*?

Method

As described in Chapter Three, the population for this study included all LAS participants assigned to project teams during 2014, some of whom had started in 2013, and many of whom continued into 2015. To provide context for the network analysis, it is important to note that several LAS researchers were on more than one team, and that new members joined teams as new government personnel arrived or new academic and industry participants contracted to work for LAS. The voluntary nature of team meeting attendance and the fact that newly arriving government personnel were not assigned to specific teams led to some confusion, in the early days, about who was or was not on a given team. This created some network instability that likely influenced the results of our analysis (Barbour and James 2015; Keyton et al. 2008).

Measurements and Data Collection

Our data combine a mapping of the LAS network structure according to team composition in 2014 and results of the collaboration survey described in Chapter Three. Only eight of the nine original teams are included in this network analysis: five teams had been meeting for approximately 15 months at the time of the survey, while three teams had been meeting for about six months (see Figure 4.1, repeated from Chapter Two). The individual interviews described in Chapter Two were not analyzed for this analysis, yet those data and the direct observations of the Collaboration Group provide additional information that is helpful in interpreting the results.

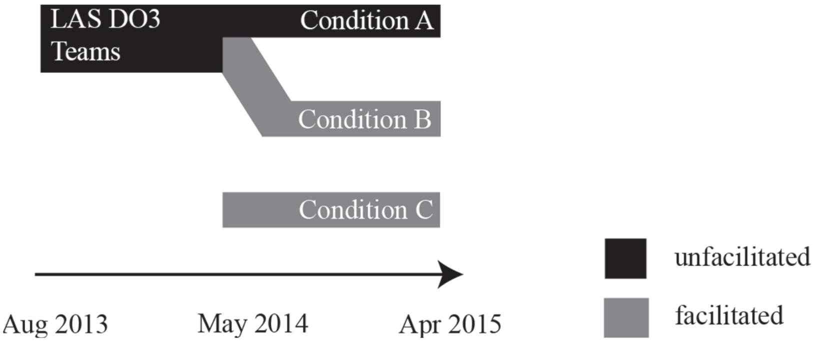


Figure 4.1: Comparison of teams to demonstrate differences in team longevity.

With the available data, it was possible to construct a map of team membership, which illustrated who worked with whom across the entire lab. A database including all the individual participants involved in LAS in 2014 was uploaded into Gephi, an open-source visualization platform (see https://gephi.org) we used to generate the social network analysis and visualizations reported. Using this approach to network analysis, we measured three network characteristics as our independent variables: team leader centrality, team centrality, and team complexity. *Team leader centrality* (Monge and Contractor 2003) was calculated in relation to three network theory measures commonly used: degree (number of direct links between one node and other actors), closeness (how easily an actor can reach other nodes in the network), and betweenness (when a node becomes the shortest path between another two actors). *Team centrality* was measured as the aggregate of the same three metrics as leader centrality, with the addition that each team member's centrality was aggregated to determine how participants' linkages positioned each team with respect to the whole network. Given the degrees, closeness, and betweenness of members in each team, each team was then coded either as being central or not central to the network. We calculated *team complexity* according to whether the team had representatives from one, two, or all three sectors—academic, government, and industry—which we coded on a scale from 1 to 3. Member sector membership was used as the basis for computing complexity because sectoral differences were revealed in observations to be the basis of important barriers to collaboration. The final independent variable in our study was *team longevity*, or whether the groups had been together a longer or shorter period of time (three groups with less time working together were assigned a 0, and five groups that had been working together for a longer time were assigned a 1).

The dependent variables were measured using the survey methodology described in Chapter Three to explore team members' perceptions of interdependence (RQ1), communication (RQ2), conflict (RQ3), and team productivity and individual satisfaction (RQ4). Details on the items and scale construction of the survey in 2014 are reported in Chapter Three, Appendix B, and Appendix A, respectively.[1] *Interdependence, conflict, individual satisfaction* and *productivity* were all measured using the same scales described in Chapter Three. Team *communication* was defined and measured differently for this network analysis, however. As described above, we were interested in three dimensions of communication: technical team leadership, information sharing, and cooperation. *Technical team leadership* was measured using the same scale described in Chapter Three (Van de Ven and Chu 1989). To capture information sharing, we developed a seven-item scale (α = .81) using the first two items in the Campion et al. (1993) communication scale (see Chapter Three, Appendix B, items 13 and 14), the three items in the Homan et al. (2008) information elaboration scale (see Chapter Three, Appendix B, items 16–18), and two items from the team learning behavior scale (Edmondson, 1999) (see Chapter Three, Appendix B, items 21 and 22). We created a six-item scale to measure *cooperation* (α = .73) drawn from the second and third items on the Campion et al. (1993) team communication scale (see Chapter Three, Appendix B, items 14 and 15) and four items from Edmonson's (1999) team learning behavior scale (see Chapter Three, Appendix B, items 19, 20, 23, and 24).

As described in Chapter Three, the survey was sent to all individuals listed as part of the laboratory at the time of this study. Participants fell into one of four main categories: (1) government staff, (2) industry partners, (3) faculty members, and (4) graduate students. The Qualtrics survey was sent via email to all 65 lab members in 2014. Participants on more than one team were asked to complete the survey separately for each team. Accounting for this, a 100% completion rate would have resulted in 76 surveys.

Results

This study generated 51 responses out of a possible total of 76 surveys for a network response rate of 67%. Five lab members completed the survey twice, for two separate teams they participated in, resulting in 46 out of 65 unique participants (an individual response rate of 71%). Of the 51 respondents, 26 were faculty members, 7 were government staff, 4 were

[1] Descriptive statistics, correlations, and Cronbach's Alpha are reported in Chapter Three in Tables, 3.1, 3.3, and 3.5 respectively.

industry partners, and 14 were graduate students collaborating in connection with a faculty member's research.

The responses were distributed across teams as follows: Team 1 had 11 out of 14 members respond; Team 2 had 5 out of 7 members respond; Team 3 had 8 out of 14 members respond; Team 4 had 8 out of 15 members respond; Team 5 had 4 out of 6 members respond; Team 6 had 4 out of 7 members respond; Team 7 had 6 out of 6 members respond; and Team 8 had 5 out of 7 members respond. Therefore, the team response rates ranged from a low of 53% to a high of 100%, with an average team response rate of 69%. The network analysis was based on known team membership, rather than survey responses, and resulted in 65 nodes representing each unique participant—each related to one, two, or three teams. Given the 65 participants, the number of possible relationships totaled 377 possible links between participants from government, academia, and industry working in the laboratory at the time of this study. Nodes are arranged in Figure 4.2 to highlight leader centrality and team centrality in the LAS network. Limitations of the software prevented us from being able to illustrate team complexity and longevity in the figure. The teams with high complexity (representatives from all three sectors) include Teams 4 and 5. Teams with moderate complexity include Teams 3, 6 and 8. Teams with low complexity are Teams 1, 2, and 7. The five teams with higher longevity (fifteen months) are Teams 1, 2, 4, 5, and 7, in contrast with lower longevity (six months), Teams 3, 6, and 8 (see Figure 4.2).

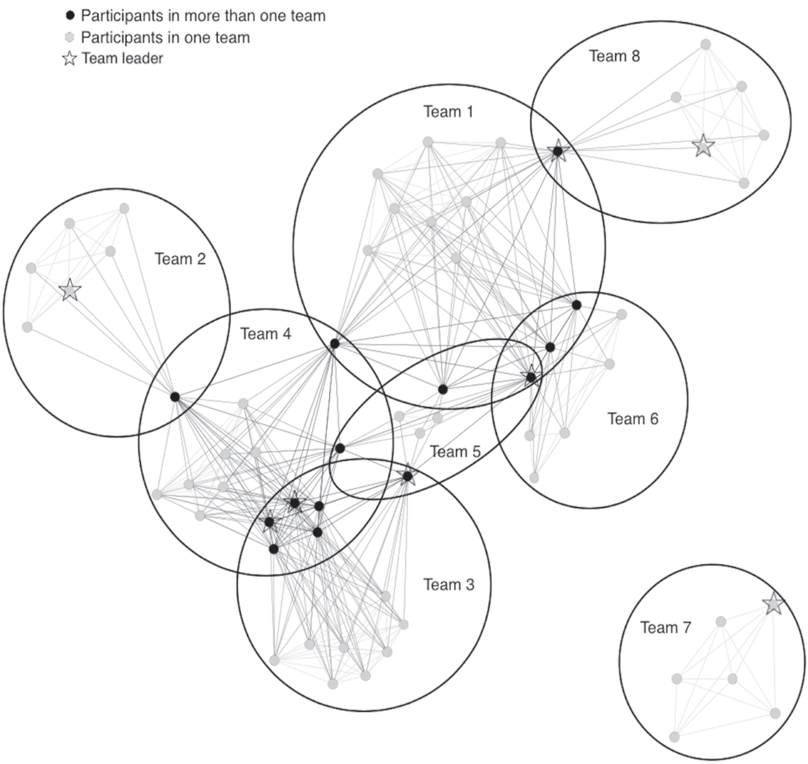


Figure 4.2: Network analysis highlighting leader centrality and team centrality.

Research Question One explored the relationship between leader centrality, team centrality, team complexity, and team longevity and perceptions of task, goal, and outcome interdependence (Table 4.1). The relationship between team leader centrality and task and goal interdependence was statistically significant. As confirmed with a two-tailed *t*-test, those with a team lead who was not central to the laboratory network had higher perceptions of task interdependence ($t(90) = 3.74$, $p = .001$) and goal interdependence ($t(107) = 4.59$, $p = .001$) than teams whose leads were central to the laboratory network. The differences in outcome interdependence were not significantly different. For team centrality, the *t*-test produced a statistically significant difference in terms of the influence of team centrality on perceptions of outcome interdependence ($t(56) =$

–2.86, p = .006). The analysis indicated that team members who participated in groups that were more central to the network had higher perceptions of outcome interdependence than those working in teams not central to the network. On the other hand, there was no relationship between team centrality and perceptions of task and goal interdependence. The relationship between team complexity and perceptions of goal interdependence ($F(2)$ = 13.04, p = .001) and outcome interdependence ($F(2)$ = 4.83, p = .01) were statistically significant. In a post hoc analysis, we found that teams with low complexity levels had higher perceptions of goal interdependence, and participants in teams with higher complexity had higher perceptions of outcome interdependence. The ANOVA test did not produce significant differences for team complexity and task interdependence. Team longevity produced significant differences in goal interdependence ($t(33)$ = –2.54, p = .01) and outcome interdependence ($t(41)$ = –2.75, p = .009). Teams with greater longevity had higher perceptions of goal and outcome interdependence than newer teams. Team longevity did not have a significant effect in relation to task interdependence.

		Leader	Team		
		Centrality	*Centrality*	*Complexity*	*Longevity*
Interdependence	*Task*	**$t(90)$ = 3.74** p = .001	***NS***	***NS***	***NS***
	Goal	**$t(90)$ = 3.74** p = .001	***NS***	**$F(2)$ = 13.04** p = .001	**$t(33)$ = -2.54** p = .01
	Output/ Outcome	***NS***	**$t(56)$ = -2.86** p = .006	**$F(2)$ = 4.83** p = .01	**$t(41)$ = -2.75** p = .009

NS = Not Statistically Significant

Table 4.1: Relationship between leader centrality, team centrality, team complexity, and team longevity and perceptions of task, goal, and outcome interdependence.

Research Question Two explored the relationships among team leader centrality, team centrality, team complexity, and team longevity and perceptions of communication (see Table 4.2). This was measured using the three scales described above: technical leadership effectiveness, information sharing, and cooperation. Leader centrality had a statistically significant relationship to perceptions of cooperation ($t(110)$ = 2.61, p =

.01). Teams working with a leader who was not central to the laboratory structure had more positive perceptions of cooperation than those who worked with a leader who had higher levels of centrality. There were no significant differences between teams with leads who were central to the laboratory structure relative to those not central, according to their perceptions of technical leadership effectiveness or information sharing. Team centrality had a statistically significant relationship to technical leadership effectiveness ($t(56) = -3.16$, $p = .001$). The analysis showed that participants in teams that were central to the network had more positive perceptions of the work of their assigned lead than teams with leads less central to the lab network. Team centrality did not have a significant impact on information sharing or cooperation. Team complexity also produced statistically significant differences in technical leadership effectiveness ($F(2) = 8.89$, $p = .001$). Teams that included members from government and academia (moderate complexity) had more negative perceptions of technical leadership effectiveness than teams consisting of either only academics (lowest complexity) or industry partners, government staff, and faculty members (highest complexity). There were no significant differences in the results between more or less complex teams and their members' perceptions of team cooperation. Team longevity had no significant relationship to any measures of communication.

		Leader	**Team**		
		Centrality	*Centrality*	*Complexity*	*Longevity*
Communication	*Technical Leadership Effectiveness*	***NS***	**$t(56) = -3.16$** $p = .001$	**$F(2) = 8.89$** $p = .001$	***NS***
	Information Sharing	***NS***	***NS***	***NS***	***NS***
	Cooperation	**$t(110) = 2.61$** $p = .01$	***NS***	***NS***	***NS***

NS = Not Statistically Significant

Table 4.2: Relationships among team leader centrality, team centrality, team complexity, and team longevity and perceptions of communication.

The third research question investigated whether leader centrality, team centrality, team complexity, and team longevity were associated with the level of perceived conflict within a team (see Table 4.3). As stated in the methods section, conflict was measured using three subscales: task conflict, relational conflict, and process conflict. In this respect, leader centrality had a significant impact on all the three conflict scales: task conflict ($t(97) = -2.98$, $p = .004$), relational conflict ($t(92) = -2.28$, $p = .02$), and process conflict ($t(102) = -2.43$, $p = .01$). In all areas of conflict, teams with a leader who was central to the laboratory structure perceived more conflict in their team than those teams with a leader who had low centrality. On the other hand, team centrality was not associated with any significant differences in perceptions of conflict between teams that were central and those that were not. There were statistically significant differences between teams that were more and less complex and their members' perceptions of task conflict ($F(2) = 3.26$, $p = .04$) and process conflict ($F(2) = 3.68$, $p = .03$). Post hoc analysis suggested that teams with members from only one sector represented lower levels of task conflict than teams with members from two or three sectors. Team complexity was not significantly related to members' perceptions of relational conflict in our sample. Moreover, team longevity was not significantly related to members' perceptions of any of the subscales for team conflict.

		Leader	Team		
		Centrality	*Centrality*	*Complexity*	*Longevity*
Perceived Conflict	*Task*	**$t(97) = -2.98$** $p = .001$	***NS***	**$F(2) = 3.26$** $p = .04$	***NS***
	Relational	**$t(92) = -2.28$** $p = .001$	***NS***	***NS***	***NS***
	Process	**$t(102) = -2.43$** $p = .01$	***NS***	**$F(2) = 3.68$** $p = .03$	***NS***

NS = Not Statistically Significant

Table 4.3: Relationship among leader centrality, team centrality, team complexity, and team longevity and level of perceived conflict within a team.

The fourth and final research question explored the impact of team leader centrality, team centrality, team complexity, and team longevity on perceptions of individual satisfaction and team productivity (see Table 4.4). Leader centrality yielded statistically significant differences in perceptions of team productivity ($t(104) = 4.18$, $p = .001$). Teams with leaders who were more central to the LAS network had lower perceptions of team productivity than teams with leads who were not central to the network. Team centrality was not significantly related to members' perceptions of individual satisfaction or team productivity. Team complexity produced statistically significant differences in satisfaction ($F(2) = 4.38$, $p = .01$) and team productivity ($F(2) = 5.66$, $p = .005$). Teams with members from government and academia (moderate complexity) had more negative perceptions of satisfaction than those teams with either only academics (lowest complexity) or industry partners, government staff, and faculty members (highest complexity). Additionally, newer teams (lower longevity) had statistically significant lower levels of satisfaction ($t(31) = –2.46$, $p = .02$) in comparison to those teams that started when the laboratory was established (higher longevity). Finally, teams that had been together longer did not have a significantly stronger perception of team productivity than teams that had been together for a shorter time.

		Leader	**Team**		
		Centrality	*Centrality*	*Complexity*	*Longevity*
Individual Satisfaction	*Individual Satisfaction*		***NS***	**$F(2) = 4.38$** $p = .01$	**$t(31) = -2.46$** $p = .02$
	Team Productivity	**$t(104) = 4.18$** $p = .001$	***NS***	**$F(2) = 5.66$** $p = .005$	***NS***

NS = Not Statistically Significant

Table 4.4: Impact of team leader centrality, team centrality, team complexity, and team longevity on perceptions of individual satisfaction and team productivity.

Multilevel Implications

This chapter analyzed the relationship between team characteristics of leader centrality, team centrality, team complexity, and team longevity with measures of member perceptions of interdependence, communication, conflict, and indicators of team performance (individual satisfaction and team productivity) at LAS. Overall, the team network characteristics with the most significant relationships to outcome variables were leader centrality and team complexity. The results show that members of teams with leaders who were more central to the lab (those working with more than one team in the lab) had lower perceptions of interdependence, lower perceptions of cooperation, and higher perceptions of team conflict. In other words, teams with leaders having low centrality (those focused on one team in the lab) had better perceptions of interdependence and cooperation, and experienced less conflict of all types—relational, task, and process.

At LAS, team centrality produced fewer statistically significant differences in comparison to leader centrality. However, higher levels of team centrality were positively related to perceptions of team outcome interdependence and technical leadership effectiveness. This suggests that teams with members who were more connected to other laboratory teams may have been more likely to see its big picture and could better understand how various team members were needed to achieve team outcomes. Furthermore, these more connected team members may have better understood what their leaders were trying to achieve, and therefore rated them more highly on technical leadership effectiveness.

Team complexity measured the impact of combining members from different sectors on perceptions of team performance. There were three teams in the lab that included only members from academia (low complexity), three teams included academics and government staff (moderate complexity), and two teams had members from all available sectors—academia, government, and industry (high complexity). Teams of all academics (lowest complexity) had the highest perceptions of goal interdependence, which comes as no surprise because they share the most similar goals (i.e., conducting research and publishing results). Teams with members of all three organizations (highest complexity) had the highest perceptions of outcome interdependence, suggesting that they best understood the collaborative outcome the Lab was trying to achieve. Not surprisingly, increased complexity led to increased perceptions of both task and process conflict, as would be predicted when team members have less shared language, are unfamiliar with some member roles, and have very different sectoral goals. The relationship between team complexity and outcome measures of satisfaction and team productivity are somewhat more ambiguous, as teams with the lowest and highest levels of complexity had more positive perceptions than those teams formed only from academics and government staff (moderate complexity); these teams had the lowest perceptions of satisfaction and team productivity. One interpretation of this is that academics and government staff may have had previous experience working with industry partners, but they had less experience working directly with each other, leaving them with few norms and expectations to fall back on and help these teams negotiate their work.

To unpack the ambiguous findings regarding complexity and team outcomes, we examined patterns in individual survey responses according to whether the respondent was from academia, government, or industry. We found that industry members tended to perceive the most conflict within their teams, followed by government staff. This may be related to the initial task given to all teams, which was to develop a grand challenge and research agenda for their focal area. This task may have been most consistent with the typical activity of faculty in an academic setting, while government and industry performers may have had more difficulty understanding and negotiating their role in this process. Graduate students reported the lowest levels of conflict, which might be a result of working closely with a faculty adviser who protected them from direct exposure to team conflict. While industry partners reported the most conflict, they also reported the highest levels of satisfaction compared to faculty and government performers. Government members reported the lowest levels of satisfaction and team productivity. This means that in teams in which faculty members had positive perceptions of satisfaction and team productivity, government staff participating in the same teams often did not have the same positive perception of what was happening regarding work in their team. Since the primary purpose of the Lab is to foster and achieve cross-sector collaboration, this finding is significant, as it supports the importance of technical leadership, communication of goals and expectations, and structural support to help teams develop shared norms, trust, and expectations necessary for collaborative work. Finally, we found that those teams that worked together longer (greater longevity) displayed higher perceptions of goal and outcome interdependence, as well as higher satisfaction. This suggests that cross-sector teams may increase their understanding of the ways in which they are interdependent and learn to work together more effectively over time. While we posit these conjectures on how one might interpret the survey data for individuals, given the small number of industry and government members in the Lab at the time of this analysis, we caution against using this evidence to make strong claims. Data from subsequent years might be more informative in this regard.

Implications for Theory

Previous research suggests that team member perceptions of interdependence are a necessary precondition for collaboration (Hara et al. 2003; Hollingshead 2001; Keyton et al. 2008). According to social capital theory, teams with more connections to other parts of the Lab (high leader centrality and high team centrality) would be expected to have access to greater resources and perhaps thus perceive greater interdependence. In our study, leader centrality predicted lower perceptions of task and goal interdependence, while team centrality was positively related to perceptions of outcome interdependence. Making sense of this finding requires some additional reflection on the teams' tasks at the start of the Lab. The earliest objective was to develop a statement of the grand challenge in the team's focal area, and then develop a three- to five-year research plan for investigating this challenge. The interviews with lab members and the Collaboration Groups' observations indicated that this task was highly ambiguous and outside the typical work of members from all three sectors. Teams therefore had to spend a lot of time orienting themselves to their tasks, and leaders who were part of other teams were addressing this same challenge with multiple groups. Furthermore, since many LAS participants had no history working with team members from other sectors or disciplines, they were unprepared for the challenges of bridging the sectoral boundaries separating them from team members. Thus, even if they were attending scheduled meetings, talking, and exchanging information about their research interests with their team, they may have been less likely to make the time to create the personal social ties that are fundamental to network productivity than teams whose members had experience with cross-sector work. As is consistent with previous social network analyses (Balkundi and Harrison 2006), this study suggests that time is an important factor, as teams that had been together longer had higher perceptions of goal and outcome interdependence, as well as higher overall satisfaction.

This study makes another important theoretical contribution regarding the importance of leader centrality and time on cross-sector collaboration. Balkundi and Harrison (2006) noted two competing theories regarding leader centrality. One is that it should increase team collaboration and performance, because the leader who is central to the network has more social capital within the network and access to resources than leaders who are not. The opposite assumption is that leader centrality will decrease team performance, because the leader's attention is not fully dedicated to any one team. Balkundi and Harrison's meta-analysis appeared to resolve this debate by concluding a positive relationship between leader centrality and team performance. However, the study of LAS supports the alternative hypothesis. As with interdependence, we suggest that task and time are important explanatory variables here. On one hand, if a team lead has not yet had time to forge relationships with members of the network outside their team, they cannot activate those resources to enhance their team's productivity. On the other hand, if they have established social relationships with participants in other network teams, they may become distracted by what other teams are doing and frustrated with their own team members who are looking to them for guidance. Over time, we would expect this relationship to change, as leaders form relationships with other members of their network outside the team they are leading, and as ambiguity in the overall objectives of the Lab decreases.

Teams with low levels of complexity had higher perceptions of goal interdependence, while teams with higher complexity had higher perceptions of outcome interdependence. This is intuitive, as teams that are more similar (e.g., all academics) have similar goals (i.e., to publish papers). Teams that were more multisectoral likely had members with different sectoral goals; yet, since they were working in a lab which values collaboration, they understand that they would be evaluated according to their ability to work with team members from other sectors (our measure of outcome interdependence). Our findings are consistent with Keyton et al.'s (2008) theory of interorganizational collaboration, suggesting that when team members have disparate sectoral (or organizational) goals, this may reduce collaboration.

Finally, this study supports Barbour and James' (2015) finding regarding mandatory versus voluntary collaboration, and Keyton et al.'s (2008) findings regarding network instability and collaboration. In the first 18 months, government members were coming into the Lab in stages, with more members arriving every month. Government participants were not assigned to a specific team, but asked to sit in on meetings to find a place where they could make a contribution. Some government members chose a team (or two) right away, while others moved from team to team for months. In either case, government members were unsure of their role, as were other team members, and this added to the ambiguity that already existed with regard to the task. Industry partners were likewise unsure of their responsibilities, although they knew that LAS leadership expected them to collaborate. As Keyton et al. (2008) found in their study, industry partners often sent surrogates, rather than have the same industry representatives attend each meeting. These features of the network structure—changes to team participants, voluntary participation, and high ambiguity—explain perceptions of low satisfaction and high conflict, especially for government members. Even though industry partners had perceptions of low levels of team productivity and high levels of conflict, it is interesting that they also reported higher satisfaction; however, this may reflect the fact that they were happy to have the contract and be a part of the Lab. Again, small numbers may have been a factor as well.

Additionally, it is relevant to highlight a few concrete implications for the practice of constructing immersive, cross-sector, collaborative programs and projects. While this experience illustrated that sometimes the ideal structure cannot be achieved (e.g., having all members join the Lab at the same time), we suggest that communication can help overcome some of these challenges and facilitate more integrative collaboration (Hara et al. 2003). We specifically emphasize communication that clearly defines the task, fosters Lab-wide understanding of all members' roles and responsibilities, and obtains member commitment to participate in collaboration.

Implications for Practice

Defining the Task and Providing Integration (Program Level)

One of the barriers to performance and satisfaction in our study was the ambiguity of the original task as defined by LAS program leadership. LAS was created specifically to develop innovative approaches to the challenges emerging for security analysis. For this reason, LAS program leadership did not begin building the Lab with predetermined problems for its members to solve. Because government efforts to engage academics and industry in cross-sector interdisciplinary innovative collaborations has historically focused on predetermined problems (Vogel and Tyler 2019), building the Lab without predetermined problems created confusion for government personnel, industry partners, and academics who had previously worked on government projects. However, LAS program leadership wanted participants to have the freedom to imagine a new set of research questions. As one government lab member put it, "if we wanted to do things the old way, we could have just stayed home" (personal correspondence).

While it has been argued that strategic ambiguity (Eisenberg 1984) can help produce creative thinking, in this case, the task was too different from the norms of members from all three institutions for this innovative thinking to emerge. In response to this ambiguity, we saw at least two different kinds of responses. First, many faculty members created individual research projects that they believed would help achieve the team goal. This resulted in complementary rather than integrative collaboration. Another response was remaining silent. Participants, especially those from government and industry, often sat away from the main table and/or contributed very little to team discussions during meetings. To prevent these behaviors, teams needed to clearly understand that the expected outcome was the generation of a new set of research questions from the integrative collaboration of ideas gleaned from the different sectoral perspectives.

LAS program leadership also learned in the early years of the program that they needed to develop integration mechanisms (meetings, workshops, training sessions, etc.) by which lab members could get to know one another—outside of team meetings—and that official onboarding activities were particularly important for new government participants' engagement and integration into the program. These program-level integration mechanisms and activities, designed to help all Lab members understand what different members were expected to contribute to the overall objectives of the program, are discussed in greater detail in Chapter Five.

Understanding Team Members' Roles and Responsibilities (Team Level)

Our network analysis results contradicted some of the assumptions of social capital theory, in that increased leader centrality and team centrality did not lead to the expected increases in team satisfaction and productivity. Poor team satisfaction may well have been influenced by the teams' lack of understanding as to members' roles and responsibilities, and the fact that teams did not appear to understand the importance of learning about their members' skills and competencies or how they could contribute to team objectives. This was further complicated by the fact that new government team members arrived unexpectedly. All the teams needed to understand that new government members might arrive at any time, and that these new lab members were expected to visit different teams and decide which ones they believed they could contribute to; only then would they become a formal member of a team.

Furthermore, we observed that very few teams asked new members to introduce themselves, and when they did, they did not follow up with discussions about how that person's background or experience could contribute to the teams' activities or goals. Going through new-member orientation activities at each meeting also took time away from the teams' tasks; teams who tried to do so became frustrated and felt they were always backtracking by talking about the task rather than making headway on completing it. Clearly explaining to all teams that new members were to arrive and what their roles would be might have helped prepare them for the resulting network instability and assisted in the development of mechanisms for navigating that challenge.

Building Relationships, Social Capital, and Commitment (Individual Level)

At this early stage of our study, most members did not yet have relationships with other people in the Lab's social network. Challenges to creating social capital included new-member arrivals, as discussed above, but also a lack of expectation that members should get to know one another. This was exacerbated by a lack of a structure for connecting people, particularly with regard to geographic separation, as faculty were located at different NC State University campuses and buildings, and even other academic institutions. Likewise, some industry partners were headquartered in different parts of the United States. Those who were geographically separated often participated in meetings via conference call, but this created challenges for the development of social capital among team members. Furthermore, the same industry representatives did not always participate, leading to a lack of consistency and inability to form relationships with team members. We therefore make a final recommendation that when building a cross-sector center, program leaders should clarify requirements of participation in the Lab so that participants meet (face-to-face or virtually, as needed) and converse regularly; in this way, they can begin to jointly establish a common, agreed-upon understanding of teams' tasks, goals, and outcomes. This includes not only consistent presence at team meetings, but also at other program-wide events, as well as a commitment to take the time to get to know other Lab participants and thus facilitate immersive, integrative, innovative collaboration.

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PART TWO:

SOCIAL AND TECHNOLOGICAL INTERVENTIONS FOR COLLABORATION

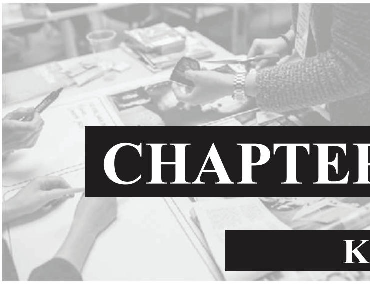
5

PROMOTING COLLABORATION

SHARON M. B. JOINES and
JESSICA KATZ JAMESON

In a single morning session, you provided us with an intuitive and re-usable framework for systematically analyzing problems, refining them into solvable propositions, and laying the groundwork for thoughtful and well-reasoned solutions.

–Government Personnel



CHAPTER 5

KEY TERMS

- **Cross-Cutting Teams (CCTs):** Teams created to bring LAS participants together to share and integrate diverse ideas and perspectives on the same theme or content area.
- **Dialectical tensions:** Coming from Relational Dialectics Theory, dialectical tensions are described as opposing needs experienced in human relationships at the dyadic, group, and organizational levels. The three most commonly described are needs for both connection and autonomy, certainty and uncertainty, and openness and closedness.
- **Focused Discovery Activity (FDA):** A collaborative session where a group comes together for a period of time ranging from two hours to two weeks to focus on a specific problem and come up with a solution.
- **Hackathon:** A series of day-long efforts organized periodically to rapidly develop tradecraft around a particular problem and/or technique.
- **Kick-Off Events:** Events held at the beginning of each new project year to bring together all LAS participants working on a common or related research theme.
- **Offboarding:** The reverse of onboarding; it involves separating an employee from a team or organization. It often includes a process for sharing knowledge with other group members and retaining institutional memory.
- **Onboarding:** "Formal and informal practices, programs and policies enacted or engaged in by an organization or its agents to facilitate newcomer adjustments" (Klein, Polin, & Sutton, 2015, p. 263)
- **Sprint:** Short, two-hour working group that uses design theory methods and techniques to explore a current analytic process.
- **Team Charter:** A team-negotiated agreement that includes individual and team goals, objectives and boundary conditions, and necessary pre-work. (EPA, 2012)

KEY POINTS

Program: Offer interventions that enable members to easily balance autonomy and connection such as networking events; provide third places where classified and unclassified members can work together; and provide workshops and activities where individuals can break out of structured routines and become more comfortable with uncertainty and ambiguity.

Team: Ensure team members collaboratively negotiate when they will work individually and together; use team charters or other tools to help members reframe their experience as individual work that helps meet team goals and/or collaborative work that supports their individual goals.

Individual: Balance competing tensions by choosing when to work on collaborative versus individual projects, when to work in different spaces, and attend networking or other program-wide events as time allows.

The Collaboration Group (CG), described in detail in Chapter Two, sought to understand how collaboration can be effectively promoted in a newly formed, complex, cross-sectoral organization with members from varied professional cultures (IC, corporate R&D, and academic research) and disciplines (STEM, humanities, social sciences, management, and design). While studying and promoting collaboration at LAS, the CG's transdisciplinary workstyle allowed us to develop and deploy interventions aimed at promoting collaborative workflows for LAS members informed by theoretical constructs from multiple disciplines (organizational psychology, communication, social science, and design). Using a mixed methods approach to appraise collaboration, we assessed impacts of structural and procedural interventions on parties at LAS, identified the barriers to and circumstances surrounding intervention success, and reflected on how collaboration can be inculcated in future complex, cross-sectoral organizations.

While the initial organization of LAS was itself a collaborative endeavor (see Chapter 1), LAS faced many challenges with the initial implementation of the research teams. A first step in addressing the barriers to collaboration was the creation of the CG. Although the formal CG's Collaboration Facilitation Teams consisting of three members each—a facilitator, a designer, and an observer—embedded in project teams lasted only one Delivery Order (approximately 6 months, in this case), the CG has continued to provide support to LAS through a variety of mechanisms, including the development and implementation of several interventions recommended as a result of early observations and experiences at LAS (described in Chapter Two). These interventions can be grouped into three categories: (1) crafting intentional interdisciplinarity; (2) connecting LAS performers to each other, to external experts, and to stakeholders; and (3) immersing collaborators in alternative methods and perspectives (see Figure 5.1). This first section of the chapter describes the rationale for and goal of each intervention, and provides an assessment of its effectiveness and current status (concluded or ongoing). The latter half of the chapter summarizes overall lessons learned and implications for the IC.

Assessment of the effectiveness of collaboration interventions occurred in several forms. Informal data were collected by members of the CG through conversations with LAS participants following various interventions and as part of our participation on LAS teams and in LAS activities. We also conducted an intervention assessment survey at the end of 2015,[1] and conducted interviews of several LAS research team members. Workshop instructors also routinely conduct evaluations of participant satisfaction and perceptions of workshop effectiveness. The different assessment mechanisms were designed to triangulate the data and corroborate findings.

Many of the interventions we developed have been handed off to LAS and have become institutionalized into everyday operations; these interventions are characterized as ongoing. Other interventions had a purpose that was either addressed, is no longer a challenge (in some cases, because of changes in LAS structure), or was not effective; these interventions are characterized as concluded.

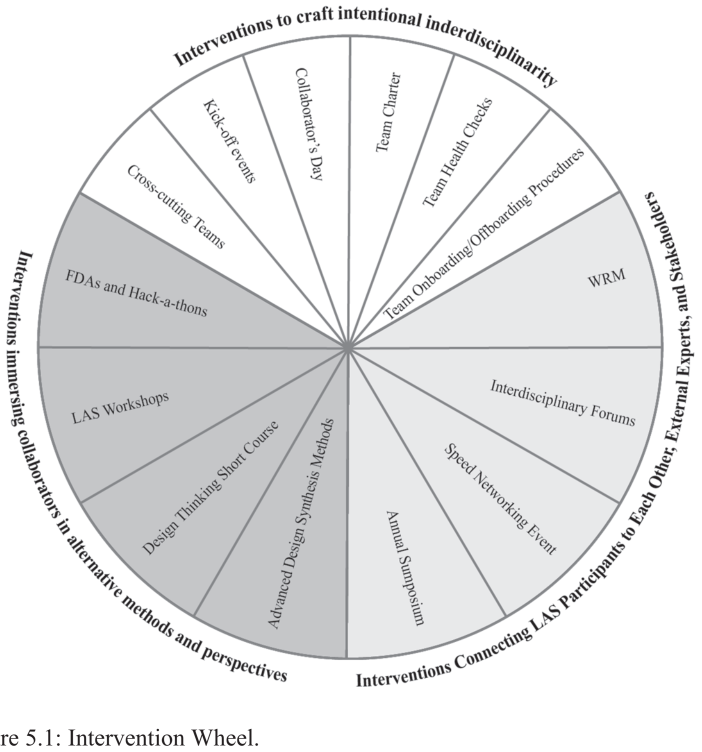


Figure 5.1: Intervention Wheel.

[1] In 2018, we collected additional assessment data on LAS participant perceptions of two interventions: the weekly research meeting (WRM) and the annual symposium. We present those results where applicable.

Interventions to Craft Intentional Interdisciplinarity

In the early days of LAS, all participants were trying to figure out their role and how they could make the best contributions to the LAS mission. A programmatic structure that required each contractor (faculty or industry partner) to have an independent deliverable, compounded by the zero history among most LAS members, reinforced a tendency toward working independently rather than in direct collaboration. Several mechanisms were developed in these early days to create and support norms of interdisciplinary collaboration. Below, we review the use of cross-cutting teams, kick-off events, "Collaborators' Day," team charters, team member on- and offboarding procedures, and team health checks.

Cross-Cutting Teams (CCTs)

Cross-Cutting Teams (CCTs) were created around a variety of LAS member-proposed themes and were required to include government, faculty, and industry members. At this time (the second full year of LAS), participants developed individual research questions and research activities but met with members of a CCT weekly or monthly (depending on team preference). For example, one CCT was formed around *Journaling* (described in Chapter Six), which brought participants together who had interests in instrumentation and measurement, as well as those trying to better understand group processes and analyst workflow. Another CCT, called *Collaborative Working Model,* charged representatives from LAS government, faculty, and industry to develop a best practices model for collaboration across sectors. This CCT produced a final report that included a list of characteristics that CCT members agreed either supported or impeded collaboration (see Table 5.1). As both of these examples illustrate, the CCTs did not directly support any individual government member's work or any contractor's specific deliverable; however, the goal was to facilitate LAS participant networking, ensure cross-sector communication, and collaboratively develop the tactical aspects of their work by sharing information, plans, and ideas, and obtaining feedback from multiple perspectives.

The CCT concept was not initially embraced with enthusiasm, as contractors in particular did not see the direct connection to their deliverables and did not feel this time allocation was included in their contract with LAS. Time was therefore a significant obstacle to the CCTs. In the intervention assessment survey, we asked LAS members about their CCT experience in three questions: (1) How well did CCT members work together? (2) How well has the CCT helped you make progress toward your goals? and (3) How well has the CCT you worked on achieved their team goal? Responses indicate that the CCT experience was positive overall, as 25 of 32 (78%) respondents indicated CCT members worked well together, and 22 of 32 (almost 69%) respondents indicated their CCT worked well to achieve their team goal. Given that the CCTs were not directly connected to individual deliverables or goals, it is not surprising that a lower proportion of LAS members (13/32, or 40%) felt their CCTs helped them achieve their individual goals (see Figure 5.2). Ultimately, we conclude that the CCTs served an important purpose at that moment in the LAS timeline, as they connected LAS members who otherwise might not have met and spawned future collaborations. Examples of the kinds of innovative and longer-term outcomes that emerged are illustrated in the case studies described in Chapters 7 through 13 of this volume. As LAS participants created sustainable relationships after 2015, the CCT intervention is no longer necessary and has concluded.

Supports Collaboration	**Impedes Collaboration**
Taking time to discuss and align language/terminology; identify the key ideas	Unclear or absent personal motivation
Understanding the value all members bring to the project (what you can learn from others)	One partner trying to dominate
Sharing cases, examples, stories to help create shared meaning/experience	Lack of communication channels
Sufficient meeting time (for task)	One partner perceiving they are working "for" the other (rather than with)
Time to build trust/get to know others (social)	Lack of collective identity - which might stem from not having the time commitment to LAS
Having a common goal that supports individual goals	Not asking for clarification or assuming we know what others "mean" and what they want or do not want to do
Clear roles and expectations	Geographic separation
Common interest in the problem/focus area	

Full-time commitment to the project	
Leader who understands the needs of various partners and can serve as a bridge (speaks both or all languages)	
Common use of technology to support file sharing and distributed interaction	

Table 5.1: Characteristics the Collaboration Working Group CCT concluded support or impede cross-sector collaboration.

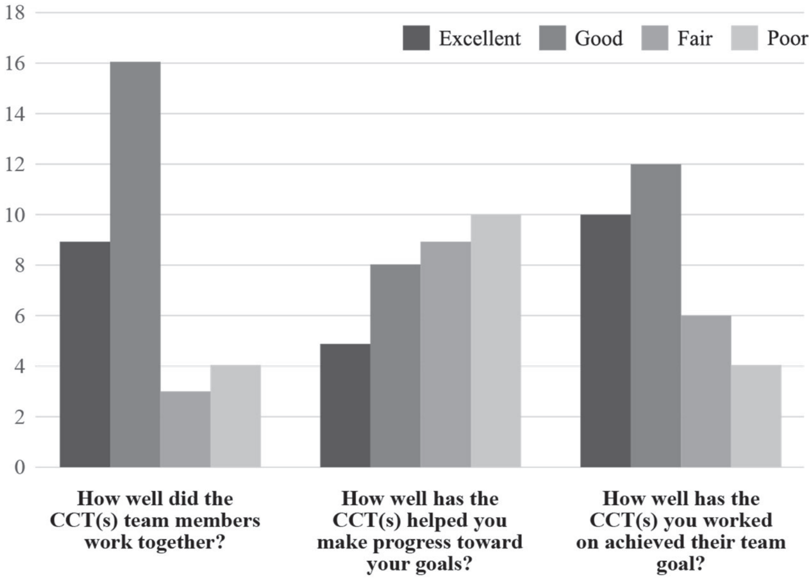


Figure 5.2: Responses to intervention survey questions about the CCT experience (n = 32).

LAS Kick-Off Events

The purpose of kick-off events is to help LAS participants prepare for their work each year by convening everyone working together or in similar content areas. Information is sent to LAS participants in advance of the event, for example, in the form of a meeting agenda. The events are typically led by LAS staff leadership with participation and support from LAS government leadership. Kick-off events have been held at the beginning of each project year since 2015, and the format has changed somewhat each year.

In 2015, the CG included a workshop during the kick-off with a twofold purpose: to introduce the new CCTs and to provide LAS team members with tools to facilitate effective group communication and collaboration, such as team charters, a team health check, and a team member on- and offboarding process (these intervention tools are each described in more detail below). As work teams tend to dive right into their tasks, and as the collaboration facilitation team structure was not continuing, LAS decided that providing some information on team dynamics and offering some best practices might help the CCTs and individual projects move forward. Workshop topics included team leadership, group member roles, the importance of clearly identifying and aligning individual and team goals, and providing feedback to team members.

The 2015 kick-off event and workshop was evaluated using informal feedback provided by LAS participants, an intervention assessment survey, and a debriefing session among CG members. Results from the intervention assessment survey (21 people responded) indicated that 93% of participants found the kick-off event helpful (rated as “extremely,” “very,” or “somewhat”), while only 7% reported the event as not helpful at all. Several participants perceived the information shared as useful, while others felt more structured techniques for group collaboration were needed (such as affinity clustering or other visual activities). The advanced communication from LAS-NCSU leadership was noted as positively preparing LAS performers for the year ahead. As a result of this feedback, the CG recommended to LAS that they continue to hold a kick-off information session, while the more specific team communication workshop could be held as a separate activity. A series of workshops has since been created, which are described in the third section on “Immersing collaborators in alternative perspectives.”

Each year since 2015, the kick-off event has had different levels of LAS leadership involvement in the planning process. In 2016 and 2017, for example, technical team leaders were responsible for conducting kick-off events that were most relevant to their individual teams, and there was significant autonomy and variation in how those kick-off events were executed. In 2018 and 2019, LAS returned to higher-level kick-off meetings during which LAS participants working on a similar exemplar or theme all came together at the beginning of the year to meet, discuss individual and team goals, and discover opportunities for additional collaboration with

LAS participants. Following the 2019 kick-off events, which occurred January 14 through 18, nine interviews were conducted to determine the effectiveness of the kick-off meetings.[2] These interviews made it clear that the kick-off events were critical to helping team members meet each other, clarify individual and team project goals, and learn about everyone's interests and contributions to the overall project. Five best-practices for kick-off meetings that came from these interviews include: (1) pre-meeting information sharing, such as agendas and previous LAS work in the content area; (2) balancing structure and autonomy, such as having clear goals for the kick-off meeting, while also allowing technical leaders flexibility in designing the meeting to best meet the needs of their team members; (3) facilitated discussions, such as paying attention to the agenda, keeping the meeting focused, and preventing a deep dive into specific details; (4) a post-meeting follow-up, including a timeline of important deadlines for interim products or status reports; and (5) continuous feedback from LAS leadership on expectations and satisfaction with the group's progress.

Collaborators' Day

As LAS evolved, it became clear that current and prospective participants needed advance notice of the call for participants for the subsequent year in order to develop proposals and identify potential collaborators from across sectors. In June of 2017, LAS introduced *Collaborators' Day,* which continues to take place in June of each year. During this event, LAS leadership describes how to partner with LAS and provides an overview of the upcoming year's focus areas. Open to current and potential government, industry, and academic partners, Collaborators' Day is a public forum for individuals to ask questions about LAS, its processes, and upcoming focus areas. For the last two years, the event has been attended by approximately 250 guests, with an additional 75 attendees participating online via live streaming. The event is followed by an invitation to write whitepapers that propose collaborative projects and activities for the following year. While we do not have specific data on the effectiveness of Collaborator's Day, anecdotal evidence supports that it has proven an important process for recruitment and retention of faculty and industry LAS partners.

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[2] Special thanks to LAS intern and NC State MS in Communication student Haddon Mackie for conducting the 2019 kick-off interviews and providing a summary of results to contribute to this chapter.

Team Charter

The purpose of the team charter is to clearly identify team members' roles and expectations, clarify individual and team goals, and discuss how these goals might be aligned to encourage goal interdependence and interdisciplinary communication. The team charter process is especially important because of the LAS program structure, in which government staff work with faculty and industry contractors, each of whom has individual deliverables, and none of whom has the authority to task others. Additionally, the charter is a place to document the group-negotiated and agreed upon procedures and norms, such as how often they will meet and where team materials will be stored and shared. While issues of data sharing and storage may seem mundane, collaborators from different sectors and disciplines often have different professional routines and norms, such as whether they use an internal (and often proprietary) data management system or a publicly available collaborative system (e.g., Google Drive or Slack).

In 2015, CCTs were required to submit team charters to LAS for review; reviewer feedback was provided, and revised charters were saved to a digital storage space accessible to all LAS collaborators to assist in information sharing and awareness of other LAS team projects. At that time, and again in 2016, charters were used to support the CCTs and new research teams.

Our assessment of the team charters, based on the number submitted and the intervention assessment survey, revealed that 19 charters were submitted in 2015, and 15 charters were accepted. Ultimately, 14 CCTs with charters were active during 2015 (several of the original CCTs disbanded from lack of activity or changes in goals). Six teams reported making changes to their charter, while four teams reported that notable challenges had emerged in their team process; they were able to revise their charters to address those challenges. Responses to the intervention assessment survey (n = 21), indicated that 63% of participants found the team charter process to be helpful ("extremely," "very," or "somewhat"), while approximately 37% reported the charter was not helpful at all. In open-ended comments on the intervention assessment survey, one participant said:

> *I admire the "team charter" idea and wonder if it should be adopted for all research teams, regardless of whether they cut across disciplines. Perhaps workshops on effective collaboration and team planning would work.* (Government personnel)

Comments such as this provided an indication that more workshops covering collaboration and teamwork would be welcome. Although the team charters appeared to serve a useful and practical purpose, they did not remain a required element after 2016, as team leaders were granted autonomy to determine how they wished to document team member tasks and team goals. The team charter tool remains available to LAS teams. Chapter 12 of this volume—The Analytic Rigor Team: Team Charters and Collaboration—recounts the experience of one team that found the team charter especially valuable.

Team Member Onboarding/Offboarding

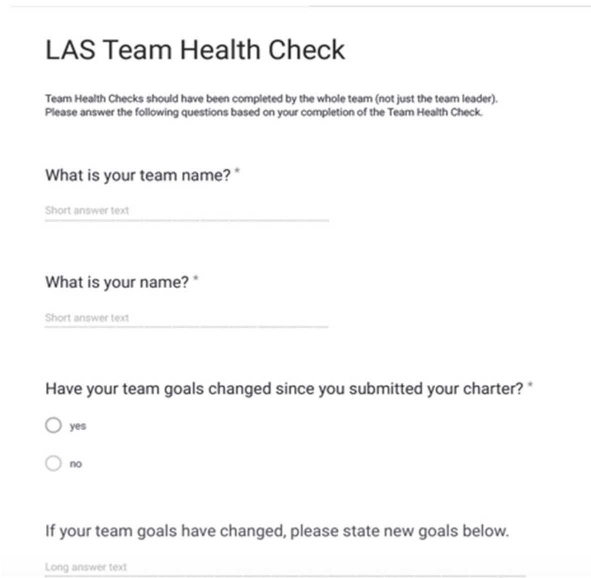
One of the challenges the CG had identified in our first year at LAS occurred when new members joined a team after it had started work, or when a team member had to leave a team. Team onboarding and offboarding processes were therefore developed to maintain team cohesion and productivity by supporting the team and its members as individuals joined or left the team. The onboarding process was intended to provide consistent communication of the operational norms to new members joining the group in order to ease their transition by answering anticipated questions about procedural matters. An intentional onboarding routine communicates the value and contributions of new members to everyone and helps new members feel a sense of belonging (Klein, Polin, and Sutton 2015). For various reasons, team members sometimes needed to leave a project team. The offboarding process was intended to capture project information from the departing member so that the team's work was not slowed or derailed by changes in team membership. The onboarding and offboarding processes were intended to be clear indicators of changes in team membership. These processes prevented some of the problems of "shadow" members (those on the roster but not contributing) and "floating" members (individuals who attended multiple meetings but took no specific task responsibility).

Assessment of team onboarding/offboarding occurred during the team health check (described next) and the intervention assessment survey. During the team health check, 9 of 14 CCTs reported a change in team membership, with only four teams reporting actual onboarding/ offboarding activities. Only one problem was reported with the addition of a new team member; five teams reported the lead having followed up with new members. Results from the intervention assessment survey (n = 21) indicated that only 40% of participants found the onboarding process to be helpful ("extremely," "very," or "somewhat"), while 60% reported the process as "not at all helpful." However, it is not clear from the way the data were collected whether the process was deemed "not helpful" because there was no opportunity to use it or because the process was used but not helpful.

As a result of the feedback, we recommended maintaining the intervention as part of the team charter process and having it available as a tool for team leaders. Our understanding is that team technical leaders take responsibility for onboarding and offboarding of team members throughout any given year, and this has not been a major obstacle or challenge for collaboration at LAS.

Team Health Checks

The collaboration survey described in Chapter Three revealed that teams did not spend much time discussing and revisiting the processes and practices they used to achieve their goals. The health check was recommended as a tool teams could use to self-audit team processes and performance, as compared to those defined in the team charter (see Figure 5.3). The intent was to facilitate a team conversation about how team processes were working, their progress toward goals, and whether any adjustments to tasks or expectations required negotiation. The team health check provides an opportunity for the team to focus and hold one another accountable; it was designed to be completed approximately every three months, or at least midway through the project year or delivery order.


LAS Team Health Check

Team Health Checks should have been completed by the whole team (not just the team leader).
Please answer the following questions based on your completion of the Team Health Check.

What is your team name? *

Short answer text

What is your name? *

Short answer text

Have your team goals changed since you submitted your charter? *

yes

no

If your team goals have changed, please state new goals below.

Long answer text

Figure 5.3: Partial example of a team health check survey.

The team health check was designed (1) to have team members review their team's performance, logistics, and culture and make adjustments as needed, and (2) to assess the team charter and communicate revisions to LAS leadership. In 2015, the CG reminded CCT leaders to complete the team health check by sending a link to a survey the team was expected to complete collaboratively during a meeting. In several cases, CG members facilitated the team health check discussion, which was an effective way to make sure project teams had the conversations and completed the health check.

The team health check was evaluated in a final question at the end of the 2015 assessment survey and in conversations with team leaders. It was completed just once during the project year, instead of quarterly, as suggested. Thirteen of the fourteen teams completed the health check, and the majority reported that it "occurred at a reasonable time" and "was easy to complete." Half of the teams indicated that it was "useful in helping our team self-evaluate," while two teams described it as "difficult/awkward." No teams indicated that the team health check "was not a helpful exercise."

Following the 2015 project year, CG members indicated their availability to facilitate team health checks for any technical team leader who might be interested. We did not receive any requests to do so, but the tool remains available for team leaders to use, if desired.

Summary of Interventions to Craft Intentional Interdisciplinarity

As LAS shifted the role of the CG from direct facilitation of teams to supporting collaboration through research and consultation, 2015 was a time of developing tools LAS teams and their leaders could use to manage collaboration on their own. Tools such as the kick-off workshop, team charters, and team health checks therefore provided useful information to LAS participants, as well as models that are available to team leaders, as needed. All the tools and summaries of what the CG learned about successful collaboration are available on a participant web portal called MyLAS. While the precise use of these tools is unknown, team leaders and members have developed their own mechanisms for negotiating individual and team goals, completing tasks, onboarding and offboarding members, and renegotiating tasks and goals, as needed. The institutionalization of these practices in any form is an important outcome of these interventions.

Interventions Connecting LAS Participants to Each Other, to External Experts, and to Stakeholders

LAS participant intervention surveys and interviews often mentioned the challenges LAS participants experienced in their attempts to learn what others were working on and connect with possible future research partners. While internal networking is critical to enacting immersive collaboration, the goal of translating LAS research and activities to IC customers also requires LAS participants to communicate with external experts and stakeholders. Programs created to support these goals included weekly research meetings (WRM), interdisciplinary forums, speed networking, and the LAS annual symposium.

Weekly Research Meetings (WRMs)

The weekly research meetings (WRMs) started as government-only meetings held on Wednesdays from 1:00-2:30 p.m. In June of 2015, these meetings were opened to include participation by LAS academic and industry collaborators. At this time, LAS staff began to recruit all LAS personnel and partners to present their work or other LAS-relevant topics at the WRM. In some cases, visitors external to LAS presented on topics such as “Introduction to Machine Learning on AWS” by Kate Werling, AWS Solutions Architect. The goal of the WRM was to create a communication channel for inter-team collaboration at LAS, as well as to help individuals find new collaborators and encourage more ongoing LAS participation from academic and industry partners.

We evaluated perceptions of the effectiveness of WRMs at the end of 2015 and again in 2018. Of the 22 WRM presentations held between June and December 2015, 10 were presented by faculty, 4 by graduate students, 5 by government personnel, and 3 by industry partners. Given the diversity of speakers and the fact that only one of these presentations was classified, the WRMs achieved the goal of including more faculty, grad students, and industry partners. Survey results (n = 32) indicate that four respondents reported they did not attend any WRMs. Ten respondents reported attending between 1 and 5 WRMs, two reported attending between 6 and 10 WRMs, and two reported attending more than 10 WRMs. Of those who attended one or more WRMs, 11 out of 14 participants indicated that the WRMs supported their interdisciplinary collaboration and LAS community building, and agreed that the topics were relevant. One survey respondent reported: “The best thing for me was presenting at a WRM, as it led to collaboration with LAS personnel.”

Questions about LAS participants' perceptions of WRMs were also included in the 2018 collaboration survey (described in Chapter Three). This survey asked participants to indicate how well they perceived their WRM participation in 2016 and 2017 to have supported their collaboration (see Table 5.2).

	Strongly Disagree	Disagree	Agree	Strongly Agree
WRMs have supported my interdisciplinary collaboration	3	3	20	6
WRM topics have been relevant to me	2	6	22	2
Time spent at WRMs supports LAS community-building and long-term collaboration	1	8	15	8
In general, the WRM is a good way to inspire collaboration and new ideas.	0	3	21	8

Table 5.2: Responses to 2018 Collaboration Survey on perceptions of WRMs as supporting collaboration (*n* = 32).

Although there are some differing perceptions on the value of WRMs, the majority of respondents found them useful. Examples of open-ended comments on how the WRMs have supported collaboration include:

> *Sharing ideas and getting feedback from the LAS community. Learning more about what it means to work in the IC from a government employee perspective.* (Faculty member)

> *I was able to learn more about NC State professors' research and it provided the opportunity for collaboration.* (Government personnel)

Those with more negative feelings about WRMs commented on the "lecture" mode they often encountered, and indicated the best WRMs were those that invited discussion and engagement with participants. As WRMs have continued, presenters have been reminded of the networking and collaboration goals of the forum; the WRM remains an ongoing activity at LAS.

Interdisciplinary Forums: Seminars and Speakers

Interdisciplinary forums were created in 2015 to help LAS keep abreast of relevant research developments beyond LAS. There were two different forums: one emphasizing science, technology, engineering, and math, and one with speakers from humanities and social sciences. As described on the LAS website:

> *The increasing complexity of newly arising problems is invariably requiring an up-to-date multifaceted approach to successfully addressing them. This Interdisciplinary Seminar Series serves as a forum to establish bridges between various areas of research and promote discussion and cross-fertilization of new ideas.* (https://ncsu-las.org/las-idss-seminar-series/)

The Interdisciplinary Seminar Series (IDSS) hosted speakers from science and engineering, such as Georgios B. Giannakis (PhD, University of Minnesota), who gave a presentation titled "Adaptive Sketching and Validation for Learning from Big Data," and Vernon J. Lawhern (PhD, Brain Scientist, US Army Research Laboratory), whose presentation was titled "Translational Neuroscience for Human-Machine Systems." There were eight IDSS seminars held in 2015, and ten IDSS seminars in 2017.

The Humanities & Social Sciences (H&SS) speaker series was a collaboration between NC State's College of Humanities and Social Sciences and LAS to increase the government personnel's exposure to ideas beyond the more traditional engineering and science research partnerships. Examples included speakers such as Noshir Contractor (PhD), a Communication scholar who conducts network analyses, and Paul Tompkins (US Army Special Operations Resistance and Force Generation), who spoke about the science of resistance. This series built on NCSU's strength in humanities and social and behavioral sciences, with particular focus on research at the interface with technology. There were a total of five H&SS seminars in 2015 and five in 2016.

Only 18 participants in the intervention assessment survey responded to questions about the IDSS and H&SS seminars; they had attended several of the seminars and felt the topics were relevant. Comments on the surveys provided evidence that some of these talks spurred new ideas and continued conversations at LAS, such as seen on Yammer, a social enterprise network. Our conclusion is that the seminars achieved their goal of bringing in external research ideas and inspiring new research directions for LAS.

These forums came to an end as those who were coordinating either left NC State or moved on to other projects. The WRMs discussed above, however, essentially replaced these seminars, as external experts have often been invited to make presentations during the WRM. This is a convenient venue, in that WRMs occur at the same time every week; this maximizes the possibility that LAS participants will have planned for it and will be available to attend.

Speed Networking Event

Another intervention created to interconnect LAS participants was a "speed networking" event. The event was held in June of 2016 in the Hunt Library, adjacent to the main LAS building. This two-hour event had three main goals: (1) to generate conversations among LAS participants, so they could get to know one another and the different projects happening at LAS; (2) to encourage new collaborations; and (3) to help participants begin to brainstorm new projects in preparation for the 2017 call for projects, which would be disseminated approximately two to three months following the networking event.

Approximately 40 people attended the event, five of whom attended virtually, through computer stations prepared in advance. Each participant was assigned a number indicating their starting point in a circle of tables and chairs. The logistics of making sure everyone maximized the number of different people they spoke to were tricky, but we designed the event in two different rounds. In the first round, the even numbers were on one side of the table, the odd numbers sat on the other side of the table, and they rotated in opposite directions every five minutes at the sound of a bell. In the second round, we created two sets of circles, so that all those with even number assignments or odd number assignments would have a chance to network with one another.

We did not formally assess this intervention, but we were pleased by the excellent turnout. Informal feedback from participants indicated they enjoyed the event. Some people sent emails asking when we would offer another such event. LAS has not held another speed networking event in this way, as more LAS participants now know one another. Opportunities for internal LAS member networking are currently more project focused, including Collaborators' Day (described above), which serves to prepare participants for the following year, and the Annual Symposium (described next).

Annual LAS Symposium

The Annual LAS Symposium is a day-long event that premiered in December of 2015. LAS participants were required to attend and share their LAS work for the year as either a poster or technical demonstration; 41 posters were displayed. The 2015 Annual Symposium also provided LAS leadership a venue where they could share the vision for the following year. Response to the symposium was very positive. The CG and LAS leadership observed high engagement among LAS participants during the symposium; 16 of 18 survey respondents reported that it supported their interdisciplinary collaboration and LAS community building. Several attendees commented that they appreciated hearing the 2016 overview at the symposium; this was especially helpful to industry partners not located in Raleigh, who therefore have little face-to-face interaction with LAS members. In our interviews, several LAS members indicated how much they enjoyed the poster session, and that this was a useful way to talk to LAS colleagues, learn about other projects, and locate future collaborators.

With the success of the first year, the Annual Symposium became a more public event, including many visitors from around the IC. We estimate that more than 400 people have attended the Symposium each year from 2016 through 2018; hundreds more have viewed the live streaming or recordings of the events. The typical Symposium agenda includes a welcome from the NC State Primary Investigator, LAS Director, and NC State Chancellor, as well as other dignitaries, such as NC Senator Richard Burr, Chair of the U.S. Senate Select Committee on Intelligence, who spoke at the 2016 Symposium.

The afternoon session features panel sessions from LAS participants on a variety of topics and continues to showcase a poster session reflecting all activities for the year from government, faculty, and industry partners. In 2016, there were 75 posters; in 2017, there were 18 demonstrations and 70 posters displayed. In 2018, 63 posters were displayed, the decline in number resulting from a more streamlined set of projects focused on a central set of exemplars (several of which are described in Chapters Seven–Thirteen). In addition to the information exchanged during the event, documents available on the LAS portal now include posters, video presentations, and a book of presentation abstracts. The event concludes with an opportunity for socializing and celebrating the year at a no-host gathering at an NC State venue.

The collaboration survey conducted in 2018 asked respondents to indicate their perceptions of how well the event supported collaboration in 2016 and separately in 2017. A total of 18 survey participants reported they had attended the symposium in 2016, and 40 had attended in 2017. The results indicate that the vast majority either agreed or strongly agreed that the Symposium supported their personal collaboration efforts as well as long-term collaboration and community.

Open-ended comments from respondents pleased with the Symposium included the following:

> *This was a great event where folks felt they got insight into LAS activities. There was much discussion and engagement. It also provided a sense of community.* (Faculty member)

> *It seemed that providing the catalog with abstracts was a good idea. People specifically came to talk about my work and asked better questions than in 2016. More than one person commented about the usefulness of the abstract.* (Government personnel)

A few open-ended comments help explain why a small number of participants found the Symposium less supportive of their own or long-term collaboration:

> *The classified session was great for talking with potential transition customers; unfortunately, we never heard anything come back from them afterwards.* (Industry partner)

> *Though I made connections at the symposiums, they did not result in follow-ups. Possibly my fault!* (Faculty member)

> *As an LAS member, the benefit I receive from the Symposium is making new connections with customers or partners. But then, we change course the next year and those connections are not always relevant.* (Government personnel)

Overall, the Annual LAS Symposium is considered a very successful event; and, as noted above, through Collaborators' Day each June, there is a greater distinction in the goals of each event. Collaborators' Day provides participants with an opportunity to network and plan for the following year's activities, while the Annual Symposium allows LAS participants to celebrate the year's work, share their projects or works-in-progress, and develop ideas, partners, or resources to support future collaborations.

Summary of Interventions Connecting LAS Participants to Each Other, to External Experts, and to Stakeholders

One of the challenges to immersive collaboration at LAS is that the participants are not, in fact, in an "immersed" environment. In fact, LAS participants are often physically separated. For example, NC State faculty offices are located in separate buildings, often on a different campus from LAS headquarters. Non–NC State faculty and industry partners are located around the state and country. Even full-time LAS personnel are separated by security clearance, as government participants are located on the third floor SCIF, while NC State staff are located on the second floor. A lesson we have learned over the last five years is that concerted efforts must be made at the program, team, and individual participant levels to meet and spend time with other LAS participants and learn more about LAS stakeholders.

At the program level, LAS has responded to this by institutionalizing the three main interventions or events described above: Collaborator's Day, the Annual Symposium, and WRMs. The former events provide structured opportunities for current and prospective partners to meet each other, learn more about LAS, and connect with potential collaborators. The WRMs allow LAS teams to share their work with other LAS participants throughout the year, and provide a space where external experts and stakeholders can share their knowledge and perspectives, and help generate new ideas or provide feedback on existing projects. Teams must be cognizant of regular meetings and participate in all structured activities, while individual members who take the initiative to attend events and immerse themselves in LAS are likely to have more successful collaborations. This brings us to the final set of interventions: those that immerse collaborators in alternative methods and perspectives.

Interventions Immersing Collaborators in Alternative Methods and Perspectives

LAS participants do not always enter the Lab with a collaborative mindset. We have learned that it takes substantial effort to get out of one's comfort zone when working independently is a more customary workstyle (and is often more efficient, if not innovative or optimal in the long-term). Several interventions have thus been introduced over the years to encourage LAS participants to be more playful, consider their own biases for preferred communication styles, and take more risks in their work practices to see things from new perspectives. Four categories of interventions created to help LAS members develop and practice a mindset of immersive collaboration include Focused Discovery Activities (FDAs) and Hackathons, LAS Workshops, a Design Thinking Short Course, and an Advanced Design Synthesis Methods Workshop.

Focused Discovery Activity (FDA) and Hackathon Series

Focused Discovery Activities (FDAs). At the request of a technical team leader, a design team facilitated guided sessions ranging in length from two hours to a full day. They called these Focused Discovery Activities (FDAs), a term government personnel knew and were comfortable with. In advance of each facilitation session, the CG member who led this effort and the project technical lead identified the activity goals, key questions to be addressed, and desired outcomes of the session.

The FDA sessions included five steps:

1. Launch and idea capture. FDA sessions began with introduction of LAS government and academic participants and the design facilitation team, followed by a review of the project. Participants documented the steps in their process, including tools, stakeholders, and barriers.
2. Mapping. The process steps, tools, stakeholders, and barriers were synthesized and recorded on a user journey map.
3. Reflection and ranking. This allowed participants to identify missing steps, stakeholders, tools, and barriers. Participants then rated the importance of the barriers as pain points in the process.
4. Action planning. The participants identified activities and barriers associated with completing their topic of interest to create a timeline for action for the following years. Sequencing, dependencies, priorities, culture, lynch pins, and tsunamis were also explored. Finally, responsibilities and resources needed to move forward were identified.
5. Debriefing/wrap-up. The findings and insights from the idea capture session, the mapping session, the alignment session, the reflection and ranking session, and the timeline were reviewed. Participant observers reported to the group the barriers in the exercise, what worked well, and which areas would require further attention and refinement.

Depending on the needs of the project team, the facilitated session documentation included photos, transcriptions of mapped concepts and activity plan into a digital form, and the physical maps and activity plans generated during the session. (The cases described in Chapters Ten and 11 include examples of the use of FDAs).

Hackathon Series. A group consisting of an LAS-NCSU staff member and two government personnel came together in 2017 to experiment with ideas for collaborative learning and transfer of knowledge back to the mission space.[3] They developed several activities, ranging from two-hour "sprints" to a week-long structured analytic tradecraft (SAT) workshop, in which government personnel devoted time to apply various SATs to domain-specific problems and negotiated understandings of assumptions to develop new tools and techniques. One of the more unique collaborative learning activities was the "Hackathon." During 2017, five unique Hackathons were held on topics such as tools for structured argumentation, alternative futures analysis, and analysis considering tweet length when using Twitter. Evaluations of the Hackathons found that 9 out of 12 participants who responded agreed or strongly agreed the activity gave them a better understanding of alternative futures analysis than they would have gotten from a traditional lecture. Overall, activities such as the Hackathon reinforce the culture of immersive collaboration expected at LAS. (See Chapter 10 for a description of how one team used the Hackathon activity).

LAS Workshops

One LAS goal was to expose its members to varied problem identification and problem-solving approaches. This exposure naturally takes place in collaborative, interdisciplinary teams, and during presentations and symposiums. Exposure can also be gained during intensive, immersive experiences such as workshops and short courses. During a facilitated strategic planning session in the Spring of 2015, LAS leadership noted that engagement with interdisciplinary teams is inherently limited by the number of faculty members and industry partners working with LAS during a given funding cycle. Further, some disciplines are underrepresented in these research engagements. LAS leadership suggested the creation of formalized opportunities for government personnel or LAS collaborators to learn more about disciplinary methods, content, and processes they would not typically be exposed to. These workshops are standalone, project independent, and offered on a periodic basis. Delivery

[3] Thank you to Devin Shackle, Matthew Schmidt, and Lori Wachter for sharing their experience and research findings in a poster presented at the 2017 LAS Symposium that contributed to this chapter.

mechanisms were driven by the content resulting in a mix of week-long short courses, full-day workshops, and multiple partial-day seminars. Workshop topics were generated through a needs assessment conducted with LAS leadership, government personnel, and academic partners. While the workshops were open to LAS partners (including faculty members and industry partners), members of the IC and LAS government personnel comprised the large majority of participants.

To date, three workshops have been delivered: "Enacting Immersive Collaboration," "Planning and Designing Experimental Research," and "What do analysts do?" (the last of these designed specifically for academic and industry partners). Development of the workshops has been a collaborative process, as facilitators from government, academia, and industry met regularly to discuss ideas and provide feedback. A description of each workshop and evaluation of responses to date are reviewed below.

Enacting Immersive Communication. The CG lead worked collaboratively with a member of the government personnel to design and facilitate a full-day workshop. This workshop covers communication that supports and creates immersive collaboration. The goal of the workshop is to have participants discuss and practice communication that builds and sustains a collaborative environment, including listening, engaging, acknowledging, building rapport, and nurturing relationships (Jameson 2014). Topics also include understanding communication styles using the DiSC inventory (Everything DiSC Workplace 2012), principled negotiation (Fisher, Ury, and Patton 1991), and unconscious or implicit bias (Payne, Vuletich, and Lundberg 2017).

The workshop has been offered twice as of this writing. The first workshop included 21 government personnel and 2 NC State graduate students, for a total of 23 participants. Evaluations from 12 attendees indicated that while the content was useful, there was not enough time provided for team activities, many of the workshop cases were too disconnected from LAS, and participants wanted more specific and tangible tools and techniques for communicating during difficult interactions or team meetings. After three months, workshop participants were asked to complete a follow-up survey to determine whether they had been able to transfer what they had learned in the collaboration workshop to their daily activities and could report any noticeable outcomes. Eight attendees completed the follow-up evaluation; while two of them indicated they could not think of anything special they had retained or used, others responses indicated that attendees felt they were betters listeners, better understood their frustration with certain colleagues based on communication style differences, thought more about establishing common ground in conflict situations, and felt they experienced improved problem solving within their teams and improved relationships with colleagues in general.

Subsequently, workshop designers added two government personnel (including an expert in diversity and inclusivity) and two communication students to the facilitation team. Twenty participants, including one industry partner, attended the second workshop. Ten attendees completed evaluations of the second workshop, which indicated most participants enjoyed the activities and appreciated the time to learn more about their colleagues, practice effective listening, and reflect on implicit biases that might impede collaboration. Ideas for improving the workshop included providing more content and practice with conflict management. Follow-up interviews with workshop participants are planned to learn whether participants are able to transfer what they learn in the collaboration workshop into their daily processes and activities at LAS. Feedback from this ongoing evaluation will help designers and facilitators continue to improve the workshop experience for participants and its outcomes for collaboration at LAS.

Planning and Designing Experimental Research. An industry partner with IC experience created a workshop to help LAS government personnel understand the research design process. A primary goal of the course was to help LAS government partners gain a deeper understanding of academic research methods, both for their own LAS research and as a means to better understand the worlds and perspectives of faculty partners. Many government personnel at LAS are engaged in research for the first time, and this workshop was intended to help LAS participants gain insights on structuring, organizing, and managing research projects to help them achieve their annual goals. This workshop was conducted in five weekly two-hour sessions.

Fourteen individuals registered for the workshop, and ten participated on a regular basis—either remotely or in person. All sessions were recorded via Webex. Based on anecdotal evidence and participant engagement, the classes seem to be valued by the participants. Several times, discussions lingered after class, and some participants compared them to graduate seminars. This could be a good foundation for continued discussion on related topics going forward. Participants were encouraged to complete the course evaluation, which included space for recommendations for future courses. Five individuals completed the evaluation; one provided oral feedback in an interview.

Evaluations provided mixed participant experiences and levels of satisfaction with the course. One challenge revealed was differences in expectations, in that some participants were expecting more in-depth training, while others were expecting a higher-level overview and exploration of academic research (as was planned). The training expectation was revealed in comments such as the following:

> *I would like exercises where we do more to develop our own research questions, initiate our own lit reviews, design our own experiments. I don't feel I have a good understanding yet of a well-designed experiment.*

On the other hand, participations reported important goals were achieved, such as increased understanding of what academics do, as noted in the following comments:

> *[G]iven I do not perform research, it was incredibly valuable to sit back and listen to my colleagues articulate their interpretations of the material and their life/professional experiences. Getting a better understanding of individual approaches is very insightful as I straddle the university/ government/performer divide.*

> *It provided useful reminders about how scholars approach their research, which I imagine will be helpful to us as we interact with academic performers in 2019 and beyond.*

The biggest limitation of this course was the timing, as travel and other obligations prevented many participants from completing homework activities and attending all five sessions. Future versions of the course will be adapted to better manage expectations and possibly use a more immersive one- or two-day format to encourage commitment to full participation.

All about IC Analysts. Just as the government personnel needed to better understand academic research faculty life, academic and industry partners expressed a desire to better understand the world of IC analysts. The same industry partner designed a workshop to help LAS participants understand the structure of US intelligence, the IC environment, analyst responsibilities, and product development. The one-day workshop has been delivered once as of this writing. Twenty people attended in person and remotely, and the entire session was recorded via Webex. Course evaluations were completed by eight attendees (40%); the responses were generally positive, and the only challenges to learning reported were related to those who attended from a distance (i.e., limitations of audio quality and personal distractions related to multitasking). The benefits of the workshop included learning more about analysts' workflow, introduction to analysis techniques, discussion about SCADA signals, and an overview of National Intelligence priorities, to see how the work of LAS directly supports mission. One open-ended comment clearly summarized the value of this workshop for academic and industry partners:

> *I thought this workshop provided an excellent background for how the IC functions. I thought it provided really valuable insights in terms of how things actually function as opposed to how agencies interact on paper.*

Given the positive feedback on the LAS workshops that have been offered to date, these are continuing interventions.

Design Thinking Courses

Two discrete short courses were created to immerse LAS members in alternative perspectives and ways of thinking. These have generally been attended by government personnel with occasional participation of academic and industry partners. These courses have been running for four consecutive years and are highly recommended by LAS leadership, as they not only expose people to valuable design thinking concepts and processes, but also provide another environment in which LAS members engage in and practice immersive collaboration. The goal is to then transfer these ideas and processes into their regular LAS activities.

Design Thinking through Design Research Short Course. One of the topics that emerged as ripe for focused training during the 2015 strategic planning session was design thinking. Thus, we developed a short course focused on utilizing design thinking and design research methods to identify, explore, and propose solutions to a specific challenge. The short course emphasized balancing primary and secondary sources of data, differentiated between inductive and deductive reasoning, utilized signals from extreme users, differentiated between investigation and evaluation, and distinguished between working in a cyclic process and communicating results in a linear report or presentation. The week-long short course (~40 contact hours for ~20 participants) was staffed by seven designers supporting four teams. The short course has been well received and has been offered three times since 2016. This ongoing effort is revised and updated each year, taking into account the feedback of current participants (see Figure 5.4) and short-course alumni.

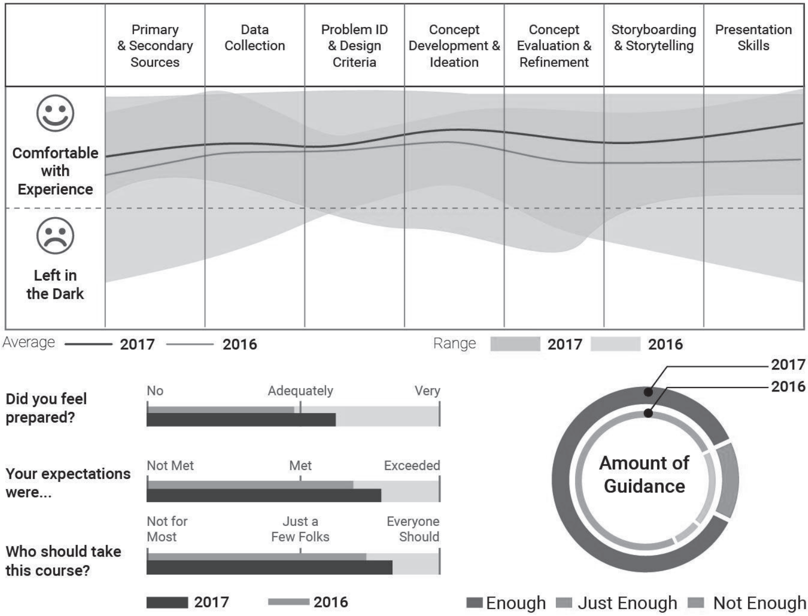


Figure 5.4: Feedback from participants in the 2016-2017 Design Thinking through Design Research Short Course.

> *I really enjoyed the class and certainly learned a lot. This should be required training for LASers. The "presentation" brief, and the other skill building session should be offered to the LAS cadre as standalone presentations. The longer lunch break was the right way to go. At the end of the day I was spent and having the break allowed me to get a mental break before the PM session.* (Government personnel)

At the end of the short course the participants reflect on the experience through a user journey map (one of the tools they use during the short course). Short-course alumni are surveyed at six months and at one year after their participation to understand which aspects of the course they have used in their project work, and whether any content should be revisited. Connections with the short course and the design thinking concepts are maintained by inviting alumni back to the short course to serve as guest critics during the culminating event, at which participants share their process and present their final solutions.

Advanced Design Synthesis Methods Workshop. Feedback from short-course alumni highlighted their interest in additional training in design thinking, tools, and techniques, resulting in the creation of an advanced design thinking workshop. This workshop provided the opportunity to examine and explore advanced methods and underlying conceptual frameworks employed by design researchers and professionals and consisted of a half-day active learning session for 15–30 participants. Going forward, topics will change with each offering and are planned to include: tools for analysis (affinity diagramming, cognitive mapping, content analysis, personas, scenarios, stakeholder maps) or tools for data collection (observation—"fly on the wall," interview, focus group, think aloud).

Implications for Interventions to Promote Collaboration: Strategic Spontaneity

One of the advantages of housing LAS at NC State University, a land-grant academic institution, is the availability of faculty with an interest in applied research who wanted to both study cross-sector collaboration and experiment with different mechanisms to support communication and collaboration. This chapter illustrates the variety of interventions attempted over the first five years to meet diverse goals of crafting intentional interdisciplinarity; connecting LAS performers to each other, to experts, and to external stakeholders; and immersing collaborators in alternative methods and perspectives. What may be obvious from this review is that there are no guarantees of what will be most effective for any specific team. Indeed, innovation is often sparked in spontaneous moments that occur in brief hallway conversations—or even in stairwells. As program leaders cannot know the precise conditions that create collaboration and innovation, the best they can do is foster an environment that provides opportunities for connecting internal and external experts and cultivates a mindset of openness to new ways of thinking about work. We call this paradoxical phenomenon "strategic spontaneity"; while it may seem an oxymoron, it actually reflects a set of competing tensions that scholars have identified as central to human relationships at all levels of analysis: program, team, and dyadic (or what we have called the individual level throughout this volume). Dialectical tensions have been articulated in the communication theory of relational dialectics (Baxter and Montgomery 1996), which has been applied to interpersonal relationships in personal (intimate, family), group, and organizational contexts. Below, we overview the theory and proceed by illustrating its implications for practice from our experience with LAS at all three levels of analysis.[4]

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[4]Author Jessica Katz Jameson presented these ideas earlier in a presentation titled "Overcoming Barriers to Internal and External IC Collaboration" at the 10th

Relational Dialectics Theory

In brief, Relational Dialectics Theory illustrates three common sets of dialectical tensions that pervade human relationships: (1) autonomy and connection, (2) certainty and uncertainty, and (3) openness and closedness. Below, we describe these three tensions as they relate to relationships among LAS collaborators. Figure 5.5 illustrates the three primary dialectical tensions.

Figure 5.5: Three primary relational dialectics (Baxter and Montgomery 1996).

Connection and autonomy. Two competing individual needs include the need to feel a sense of connection to others along with the desire to make independent decisions about one's life. We feel the need for connection at the earliest stages in our families, which provide for basic needs of security, comfort, and love; at a fairly early age we also demonstrate our desire for independence and determining our own destiny (consider the "terrible twos"). Later in life, we continue to desire connection to others, whether through intimate partners and friends or larger groups such as religious, social, or professional communities. These competing needs can create conflict or tension as we attempt to balance our desire to be with others (such as in families or in the workplace), with our need to be alone and

Anniversary Homeland Defense & Security Education Summit, George Mason University, Arlington, Virginia, March 23-24, 2017.

independent. As immersive collaboration by definition privileges the connection end of this continuum, individuals, groups, and organizations must find ways to manage the tension by also valuing individual expertise and contributions to attend to the need for autonomy.

Certainty and uncertainty. This tension is also described as the competing need for stability and change. At one end of the pole, humans like predictability. We enjoy the comfort of knowing what to expect or how others are likely to respond in different situations. Such certainty allows us to navigate our relationships and work smoothly. However, if our relationships were always predictable or routine, we might become bored. This can be true at work as well as in personal relationships. Further, when groups and organizations privilege certainty and routine, they do not easily adapt to changes in the environment, they do not take risks, and as a result, they are likely to miss opportunities for innovation and growth. Systems theorists have suggested that organizations go through cycles of relative stability and intermittent disruptions that throw the system into temporary chaos or crisis—important moments that allow systems to adapt, innovate, and thrive. Recognizing, responding to, and even generating disruptions is an important leadership role that should be attended to by all organizational members.

Openness and closedness. Relational theories often describe challenges humans experience in determining when to share information and when to keep it hidden. Self-disclosure of private information about oneself, for example, is necessary for increased relational intimacy; yet, if too much is disclosed too soon, relationships might quickly end, depending on the comfort level and expectations of each relational partner. The openness-closedness dialectic is also related to tensions about expressiveness (e.g., when to express versus suppress emotions, hopes, or dreams). It may also be related specifically to work practices, such as decisions about when and with whom it is acceptable to share proprietary information or intellectual property. Within the IC, there are clear rules about classified information—where it resides and who may see it—which continues to create challenges to collaboration in terms of comfort level when working with others who do not share clearance, negotiating expectations for shared intellectual property or patents, and creating and participating in collaborative working spaces.

Application of Theory to Practice at Each Level

Baxter (1990) described four main strategies used to manage dialectical tensions (see Table 5.3). The first is called *selection*, which involves privileging one side of the tension over the other, as when someone chooses a career or project that allows them to work completely independently (thus choosing autonomy, closedness, and often certainty). The second strategy is *separation*, which includes two subcategories: *Cyclic alternation* occurs when people or teams negotiate specific times during which partners are together or separate (such as working alone Monday through Wednesday, and working collaboratively on Thursdays and Fridays). *Segmentation* is a variation on this theme, in which certain activities are created that allow for one end of the pole over the other, such as agreeing to spend time in the SCIF to focus on classified tasks, and working in an open space at other times to focus on shared information with those outside the IC. A third strategy is *neutralization,* which involves finding ways to make the tension irrelevant. If someone spends all their time in the SCIF, for example, they reduce the concern to manage the openness-closedness tension (at least with outsiders). The final and perhaps most challenging strategy is *reframing*, which entails finding a way to see the opposing needs as integrated or aligned. This may require a shift in one's typical mindset; for example, if someone prefers independence, they may need to reframe their view of connection (i.e., agreeing that by spending some time working alone, collaborators might be better prepared to interact with and contribute to the team).

Selection	Privileging one end of the tension over the other
Separation	*Cyclic alternation*: privileging one end of the pole at agreed upon times or cycles *Segmentation*: privileging one end of the pole during agreed-upon activities
Neutralization	Making the tension irrelevant
Reframing	Shifting perspective so that the tensions can be transcended, and one side of the pole is seen as helping achieve the other side of the pole and meeting both needs simultaneously

Table 5.3: Strategies for managing dialectical tensions (Baxter 1990).

Program level. Several of the interventions we have described are intended to help LAS leadership create and support a culture of immersive collaboration. We can highlight how certain interventions specifically address dialectical tensions. For example, LAS personnel experience different levels of comfort in seeking out faculty partners, introducing themselves, and finding points of common interest that hold promise for future collaborations. Events such as speed networking, Collaborators' Day, and the LAS Annual Symposium provide both a space and a structure for personnel who might privilege autonomy, closedness, and/or certainty to engage in connecting and networking. Another example of a programmatic strategy that was not described as an intervention per se, is the availability of a *third place* (discussed in Chapter Two). A third place is not someone's home or typical work space, but a shared space in which people can come together and might be more open to new ideas. This is particularly relevant to LAS, as government personnel need to work outside of the SCIF in order to collaborate with many faculty and industry partners. The third place thus becomes an important strategy for managing the tension of openness and closedness in this context; LAS members can use the strategy of separation (see Table 5.3) to determine when to work in different spaces.

Team level. Interventions at the team level can help manage team members' expectations for autonomy and connection. This is a major contribution of team charters, for example, and the goal is to foster a conversation during which team members clarify their individual tasks as well as how their work will contribute to the team goal. This process allows them to reframe what might be seen as individual activities as those necessary and connected to the final group product. By holding semi-annual health checks, the team can assess how they are doing, in terms of balancing autonomy and connection, and can then adapt as needed. LAS teams are able to neutralize the tension of openness-closedness by finding unclassified use cases on which to experiment with different forms of analysis or activities, such as FDAs and hackathons. These activities also create opportunities for participants to step away from their routines, and to manage the tension of certainty-uncertainty by offering a "fun" space to try a new way of thinking in a low- or no-risk situation.

Individual level. One of the most important predictors of successful immersive collaboration at the individual level is coming in with the right mindset and motivation for collaboration. This includes being open to new ways of seeing, thinking, and doing, as well as to meeting and working with new people. Individual LAS members are autonomous, in that they can usually choose what activities they will participate in, where they will do their work, and whether they wish to apply for government clearance. However, working in any collaborative lab requires individuals to constantly manage the dialectical tensions we have described here. We strongly believe that the interventions held at the program and group levels described in this chapter provide structured and semi-structured opportunities for motivated individuals to engage in immersive collaboration through strategic spontaneity.

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6

SUPPORTING COLLABORATION AND DISCOVERY WITH NOVEL COMPUTING TECHNOLOGIES

KATHLEEN M. VOGEL, PAUL JONES, MATTHEW SCHMIDT, and CHRIS ARGENTA

Imagine a possible future where the techniques, the tradecraft, the technology, the user experience is all differently enabling a better product, a more effective or efficient user of the systems.

–LAS Personnel, Raleigh, NC, November 6, 2015

CHAPTER 6

KEY TERMS

- **Analytic Component System**: A new computational architecture that includes a variety of analytic components, such as automated algorithms, interactive tools, or manual techniques. These components are modular, which means that the performance of each component is relatively independent of the others, allowing new workflows to be composed by exchanging or adding components in the workflow.
- **Analytic Workflow**: The process the analyst uses to derive or discover intelligence from available data sources.
- **Collaboration Engineer**: Someone who can work with users of the collaborative technologies to integrate them into the existing work practices or to modify the existing work practices to better integrate the technology.
- **Journaling Application** (or **"Journaling"**): a collective effort across private, public, and/or nonprofit sectors.
- **U/X "Veracity"**: A virtual reality platform, a multiplayer, 3D immersive game, that allows users to insert themselves into a completely simulated world—similar to a video game or online environment (such as "Second Life").

KEY POINTS

Program: Collaboration by design should be a clear mandate from program leadership to developers in the early stages of technology development. Prototypes should be used and tested for collaboration and resources should be allocated accordingly.

Team: Collaborative prototypes need to have communication features. Several of prototypes would benefit from having some kind of internal communication feature (e.g., Google Chat) to facilitate interactive discussion amongst analysts. This could be particularly useful to facilitate communication among users who are not collocated.

Individual: There are privacy and other human factors in technology design that members should be aware of. In several LAS prototype efforts that promote collaboration, tensions exist between the desire for information exchange and the expectations about privacy and concerns about workplace surveillance. This reveals some individual- (and team-) level concerns about how these technologies are designed and implemented, and the impacts they might have on a variety of users. Concerted efforts should be made to start addressing these human factor issues as part of the continued technology design and development efforts.

The primary goal of the Laboratory for Analytic Sciences (LAS) is to find new ways for intelligence analysts to manage, share, interpret, and make sense of large volumes of data to improve intelligence analysis in the years to come. Because LAS is committed to modeling collaboration and promulgating that practice throughout the Intelligence Community (IC), it is also important to assess the extent to which new technologies developed at LAS support multi-user collaboration. As part of its larger test and evaluation effort for prototypes that would assess usability and effectiveness, LAS management had an interest in determining which of its prototypes had "collaboration" potential—in other words, the extent to which they would enable and enhance the ability of intelligence analysts to collaborate with others. Thus, this chapter discusses some early findings of LAS prototypes and their potential as collaborative technologies.

In this chapter, we use the following working definition for collaboration: two or more people working together and/or sharing ideas on a problem or project that leads to value creation, improved knowledge and understanding, increased productivity, and enhanced diversity of subject matter expertise, while supporting trust development. In the course of research, we learned that there are different kinds of immersive collaboration possible through LAS prototype efforts. Some are focused solely on information sharing (between people and/or between computer systems); others are more focused on interactive problem solving among users. To show this range of use, we focus on a description of three LAS prototypes that show different types of immersive collaboration:[1] (1) the Journaling Application, (2) the Analytic Component System, and (3) the Applied Research Associates (ARA) U/X (Veracity) system. As this chapter reveals, there are certain LAS prototypes that have significant immersive collaboration potential given their technological design and development and others in which the collaboration could be enhanced by some additional modifications.

Beyond thinking about the purely technical design and development of technologies to work in a collaborative manner, it is also important to consider how social context can shape the capacity of these technologies to be able to work collaboratively. Social scientists have shown that successful adoption of computational technologies in a work environment, including those that support collaborative activities, requires a consideration of the

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[1] The data for this chapter involved interviews with LAS prototype designers/ developers and technical leads as well as observations of demos of the LAS prototypes. These interviews occurred at NC State as well as at industry offices. The interviews and demos lasted approximately 1.5 hours each. This project received NC State and NSA IRB approval for the use of human subjects in this research study.

socio-cultural environment in which the technologies will be embedded. This chapter ends with a discussion of recommendations at the program, team, and individual levels to enable successful deployment of these prototypes into an intelligence-work environment.

Journaling Application

The Journaling application (hereafter referred to as "Journaling") is a web-based platform aimed to serve as a kind of "self-tracking" capability or "smart digital assistant" for intelligence analysts, which can gather data about a user's daily workflows. This is the process by which the user applies personal knowledge, tools, and organizational resources to perform information analysis tasks; the application then provides analytic and visualization displays of the user's individual knowledge creation patterns and collaborative work practices. It supplements passive data collection of analyst work activities via instrumentation of a worker's computer (i.e., the computer logging what websites the analyst has visited), with the active collection of user goals or tasks as the analyst is working. Because intelligence analysts have to work with big data and are increasingly doing so in multitasking and collaborative environments (Dhami and Careless 2015), Journaling helps them by providing continuous feedback on what they are doing and recommendations for how they might do it better.

Currently, Journaling achieves this goal by occasionally asking users to explicitly decide which goal or task an activity belongs to (via a customizable goal-task tree; see Figure 6.1). For the long term, Journaling attempts to help the analyst reach these goals (and provide recommendations) in a minimally invasive way using artificial intelligence algorithms, and asks the user for his or her input only when absolutely necessary. Journaling attempts to associate activities with tasks and goals to help analysts understand what resources they use for a given task and why they use them. Ultimately, algorithms running on Journaling data develop recommendations not just about particular information or sources of relevance, but also about entire workflows that could help users more accurately reach their desired goals.

Figure 6.1: The Journaling activity/goal tree visualization displayed in a web browser.

Individual tasks are made of smaller sub-tasks or stages, shown on the right. Clicking a task reveals more information about it, as well as potential collaborators.

Journaling currently gathers data from two sources: (1) instrumentation of Apple's macOS operating system,[2] which records accessed applications, URLs, and opened documents; and (2) instrumentation of Google's Chrome web browser,[3] which exclusively logs accessed URLs and the browser tabs that contain them. A user is prompted to tag a newly visited page if he or she has spent over a minute there, or has scrolled more than 50 percent of the way down the page. Use of these triggers builds on previous research (Liu 2010) on user dwell times and levels of interest in documents. New

[2] The *macOSinstrumenter* is written in Objective-C and is native to Macintosh computers. In order for this instrumentation to work on any other platform, a rewrite would be required, but similar principles could be used.

[3] The *ChromeInstrumenter* is able to gather data from any Chrome browser, regardless of the operating system. This plug-in was developed in collaboration with Renci, a local research institute in North Carolina.

triggers can be added, and the defaults can be modified according to user preferences. Known sources of information are then explicitly associated in real time with their appropriate goals in the goal tree. A summary of all activity is then displayed in a “recent-work dashboard” visualization (see Figure 6.2), which allows task tags to be added, deleted, or amended. All untagged activity is displayed at the bottom of the dashboard.

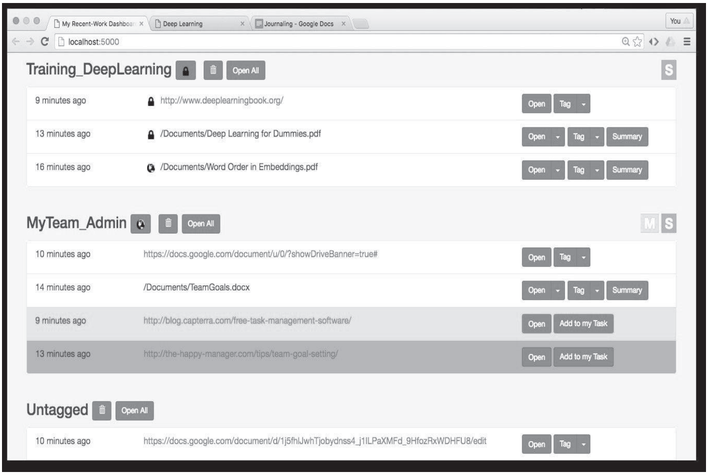

Figure 6.2: Example of part of a user’s “recent-work dashboard” in a Chrome web browser.
Image reproduced from (Jones 2016) with permission. © 2016 IEEE.

In the dashboard, information artifacts are organized according to their associated tasks, with those most recently accessed appearing first. The Open buttons allow easy opening of multiple documents, either in a file explorer or in the native application for each document type. The Tag button allows users to relabel documents with a new task (or to delete labels), as needed. The Summary button runs an algorithm to summarize the contents of documents. Collaborators are denoted by colored icons on the right-hand side—their public documents can be viewed by clicking these icons, which adds an additional colored block to the table. In this example, the collaborating users are “M” and “S.” Users can mark documents (or entire task blocks) as private to prevent documents being shared. In this example, the “Training Deep Learning” task has been marked private by default, and only one document from this block has been shared; by contrast, the “MyTeam_Admin” task has been marked public by default, and all documents in this block are shared by collaborators.

The dashboard also provides a test bed for new algorithms that can automatically learn associations between tasks, users, and documents (Jones 2017). Many clues to such associations are available, such as team-working between users, the hierarchical structure of tasks, document similarity, and grouping of activity in time. Algorithms making such associations, when combined with the dashboard visualization, provide important benefits for collaborative workflows. By displaying the work of other participants contributing to the same tasks and goals, and with the ability to access their sources and documents, a user is able to gain a better understanding of the task at hand. Accessing additional sources of information also provides the potential for increased productivity across users, as a wider variety of information is now available for quick reference (when compared to users having to collect this information separately). Moreover, being able to access others' work enables trust building between individuals working on the same task. This is possible because, as the prototype tracks the user's workflow on a granular basis, it allows others to better understand the user's thought trajectories and rationale behind activities.

One of the most promising Journaling features that could be implemented to enhance collaboration would be the ability to discover subject matter experts in a particular field and allow users with different levels of expertise and different knowledge bases to collaborate with one another through the prototype. To do this, one could add a feature that includes short bios of individual users, their years of experience, and areas of expertise. This feature might be particularly useful for less experienced or junior analysts who wish to engage with subject matter experts for general mentoring or for assistance in gathering sources. Another feature that could be developed would allow individual users to "rate" other contributors according to several different factors—one of them being contributors' expertise in the subject of interest. Alternatively, the user might rate the entirety of shared data (arriving from all users) by other useful criteria such as: relevance of data to user's work, relevance to user's overall goals or objectives, contributors' duration of time spent working on task, and the volume of contributions made to the task. This rating feature might be applied similarly to how online shopping platforms rate their products. This modification would require the development of additional algorithms, which—based on our discussions with the LAS prototype lead—would require a certain amount of technical effort. The benefit of this feature is that it would allow for increased comprehension amongst users, and reduce the daunting prospect of displaying potentially thousands of data files and/or thousands of contributors, which a single user would otherwise have to sort through. If this feature were implemented, Journaling could easily be introduced for remote work (as opposed to being limited to small teams in the same physical setting). However, there may also be the need to implement, along with the rating system, a communication system (e.g., Google Chat) within the Journaling app that would allow an individual user to easily communicate with other users. This feature would be particularly useful for attempting to ask questions of relevance, clear up points of concern or misunderstanding, or solve any other related problems.

Currently, Journaling is only available for work in unclassified environments, but the idea would be to port to classified settings once the prototype is fully developed. Given that different technologies are used to support classified systems, Journaling may need to be installed separately on unclassified and classified systems. Regarding privacy issues, users are currently able to make certain shared information private (but not anonymous). They can also opt out of sharing their own information altogether, while still accessing the dashboard for others' contributions. While this might dissipate some concerns, it also reduces the ability for other users to access data that may be relevant or important. A simple feature "requesting" access could be developed and implemented; however, this might not solve concerns of under-sharing information. As such, the potential for free riders remains an unaddressed challenge with this technology.

A related challenge is that in its current configuration, users can choose to circumvent the collaborative features of the Journaling prototype. This might happen when a particular document becomes "untagged," at which point the application automatically "un-shares" the file with others. Moreover, the developer has expressed that all collaboration features are indeed optional and the default setting is "no sharing." If Journaling is implemented into a real analyst's workspace, the developer has expressed desires that collaboration features remain optional and off by default, primarily to avoid accidental sharing of sensitive documents. We suggest that, instead, it might be more beneficial to allow for the (clearly presented) option of anonymity when contributing. This is because collaboration might be key, given the LAS's assertion that recommendations about analysis (which greatly benefit from collaboration) are essential to achieving the ultimate goals of Journaling.

Finally, end users will need to be aware of two inherent challenges associated with the Journaling effort. By design, the Journaling application is unable to capture certain types of information produced when people communicate, such as by phone, in hallway conversations, or other face-to-face interaction (even if their computers support the Journaling application). As such, while Journaling has the potential to generate a clearer picture and understanding of user workflows, it is important to keep in mind that it does not propose to capture all user workflows, or all aspects of collaboration, in their entirety. The second is that in any collaborative prototype, including Journaling, there is the potential for the negative consequences of confirmation bias or groupthink if the application shares data among like-minded users. It is possible that some users will employ the Journaling dashboard as a primary or sole means of information gathering, as opposed to leveraging the dashboard feature to enhance their own collection capabilities or seek out other kinds of expertise and data not available through the Journaling application. If so, the generation of new ideas, hypotheses, opinions, or questions might be limited, and the user may come away with a biased or constrained picture of the overall problem being studied. This could be mitigated in a variety of ways, including the development of algorithms to recommend additional documents or tasks specifically designed to counter confirmation bias—for instance, by exposing the user to conflicting information or to reports with an opposing bias.

The LAS developer of Journaling has suggested two additional areas of research for further consideration, which we echo: (1) human factor analyses ought to be considered to address privacy concerns (or other social concerns) that may arise from the use of this technology among analysts, and (2) algorithms ought to be developed that are able to most effectively display or rate the multitude of dashboard contributions from all users. Addressing these concerns will reduce the likelihood that users are overburdened or develop sensory overload from the large amount of data that could be displayed in the Journaling recent-work dashboard. Finally, as a means to reduce the possibility of confirmation bias or groupthink in Journaling, it might be worthwhile to consider a system in which users are encouraged or required to work on their own projects without access to others' contributions from the Journaling dashboard for a predetermined period of time. This requirement might encourage users to think outside the box and generate their own ideas and hypotheses before being exposed to others' opinions or findings.

Analytic Component System

Intelligence analysts must work with a variety of data sources, analytic software, and computational systems to collect and analyze classified and unclassified data. Although analysts have access to an increasingly wide variety of analytic tools and tradecraft they can draw on, applying these to a problem can require a great deal of effort for the analyst to: (1) learn about the tool/method and how to effectively use it on a given problem, and (2) adapt the analyst's workflow to efficiently incorporate it. An analyst's workflow is the process the analyst uses to derive or discover this intelligence from available data sources. Workflows rarely, if ever, consist of a single homogenous activity. Instead, they consist of many different activities performed by the analyst with the support of various tools or techniques. Also, analytic workflows are typically problem and/or analyst dependent (or, in the case of a collaborative effort, team dependent). Therefore, the association between the intelligence need and the combination of activities that make up an associated workflow is very brittle. Workflows that typically produce rigorous results may fail if the type of intelligence need or available data sources changes (e.g., flawed human intelligence in the 2003 Iraq war, need for new Arabic sources in the aftermath of 9-11). The result is that analysts are required to constantly develop or adapt their analytic workflows. The most productive analysts are able to adapt their analytic workflows to ensure accurate and relevant analytic products in the context of available data and intelligence needs. The workflow development process happens not just before the analysis begins, but also during the course of the analysis. Analysts must therefore have some decision framework that allows them to choose the activities that make up their workflow, depending on the current and desired state of their analysis. Inexperienced analysts who lack this decision framework may choose workflows that can lead to biased or irrelevant products.

At the same time, many experienced analysts become comfortable with a limited set of tools they know how to use. This leads to a multifold problem involving data, workflow, and/or collaboration factors: (1) analysts may draw on a narrow set of resources, leaving out other important tools; (2) analysts will vary in their choice from a multitude of potential analytic workflows (e.g., a nuclear analyst in one intelligence unit may use a different analytic workflow than a nuclear analyst in another unit or agency); (3) analysts may choose to delete or reconfigure certain aspects of standardized methodologies to better suit their specific problem; and (4) intelligence analysts do not always know the kind of method they will follow, who they might collaborate with, or what they might use to solve a problem. For example, what if they use different data sources or databases than they have used in the past? What if some of these data sources come from manual work or are qualitative and not in quantifiable form? What if these data sources come from intermediate steps of other workflows? Furthermore, the programs used by analysts to write their assessments and reports are of a different kind than the analytic programs they use to work with the data. As a result of these complexities, traditional computational architectures, which are built around existing applications, don't work well with this kind of analytic workflow. Enabling analysts to do more adaptive and collaborative analysis, with tools that can seamlessly communicate with one another, is not well supported by existing computational systems currently used in intelligence.

Analysts also need to know how to execute a query to retrieve the data that they want from the data stored in existing intelligence systems. For example, if an analyst needs to run a particular query (e.g., "What is the state of country X's nuclear weapons program?"), they may know what information they need but not how to get it—because there are a multitude of intelligence databases and information systems that have been set up differently over time and require different methods of query. Retrieving useful data may require the use of SQL, a programming language designed for managing data in a database. SQL queries allow one to write/retrieve data to/from a database; however, this requires that an analyst know how to write SQL queries for particular intelligence databases or find someone who does. Depending on the unit, these computation skills may not be readily available among the analysts present. Even when analysts may have access to technical support teams to help with complex computational requirements, this approach adds time and a layer of bureaucracy to an already stressful intelligence work environment; analysts often have to know how to retrieve data within hours, not days or weeks. If the data are not already accessible and in a form usable by analysts, then the analysts must do some heavy lifting to translate those data from one system to another. In many cases, analysts do not want to become computer programmers and spend their days writing code—they want to focus more on the analysis. The cost of integrating the most applicable tradecraft and technology into a multitude of workflows can quickly become a significant burden and cost in terms of time, money, energy, and cognitive overload to intelligence analysts. Thus, the burden to retrieve and/or analyze the data might be so high that they either choose not to pursue the data or expend time and resources that yield greater cost than reward—which matters when analysts are working on critical intelligence threat assessments.

To address these existing shortcomings in the interoperability of Big Data technologies and methodologies, the LAS is developing a new computational architecture, called the Analytic Component System, which includes a variety of analytic components. These components might be automated algorithms, interactive tools, or even entirely manual techniques. The key is that they are modular, which means that the performance of each component is relatively independent of the others. This enables new workflows to be composed by exchanging or adding components in the workflow; for many reasons, this is a natural way to view workflows. It has been shown that modularity is a natural response to managing complexity for the wide variety of analytic problems that analysts face—and a process that analysts already use. When analysts describe their workflows, they typically describe them as a series of steps; these steps naturally align with how an analyst breaks down work on a problem. Deconstructing workflows into analytic components allows analysts to adapt their workflow as analysis progresses, while still making use of a wide variety of analytic tools and techniques. New analytic workflows can be quickly combined and reconfigured, as needed. It also enables a single analytic workflow to be easily integrated into the analytic products of more than one analyst and or an automated analytic process. One of the main objectives of the Analytic Component System is to align the various analytic algorithms, tools, and techniques with an explicit framework that enables the capture, analysis, and support of the decisions analysts make in the development of their analytic workflow. Capturing these decisions can allow creators, consumers, and reviewers of the analytic products to assess the rigor of the workflow that produced it. Creating a repository of these workflows can provide an invaluable data source to methods that seek to recommend activities and workflows for other analytic problems.

The ACS effort consists of three distinct but related efforts (see Figure 6.3): (1) the Analytic Component Interface (ACI), which enables modular workflows that can be uniquely composed by analysts to define standard protocols and constructs, thus allowing analytic components to be interoperable; (2) the Analytic Component Library (ACL), an effort at developing a library of interoperable components using existing and novel analytic technology, techniques, and procedures; and (3) the Analytic Computing Environment (ACE), an effort to develop a service-oriented computing framework that enables a single analytic workflow to leverage multiple, independently developed analytic technologies to execute and solve a given problem. Through this combined effort, the ultimate aim is threefold: to enable analysts to more effectively and efficiently collaborate with other analysts, to permit tools to collaborate with other tools, and to help analysts collaborate with multiple tools. The intent is to automate collaboration *across* tools, rather than rely on tedious human input and direction.

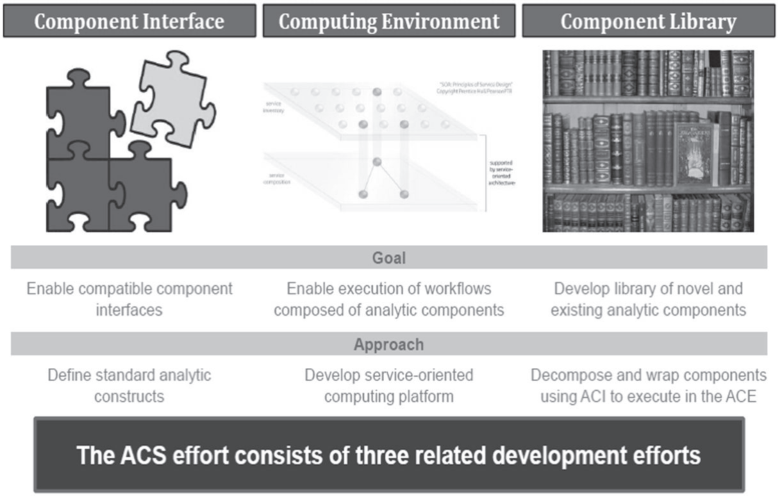

Figure 6.3: Three Elements of the Analytic Component System.

This prototype has vast potential for collaboration, albeit in a different way than commonly imagined. Because the vision of ACS is to allow different components to work together and speak to one another, one can envision collaboration occurring directly between components, rather than between people. Nevertheless, the use of these components is ultimately controlled by individuals through interface platforms. It is important to note, however, that while collaboration between components is necessary to the success of ACS, such components need not collaborate across computers or technologies controlled by *different* users. In fact, collaboration may indeed occur within different technologies (or a variety of components within the same technology platform) controlled by a single user. In such a case, interpersonal collaboration might be neither desired nor required, although the system as envisioned is able to support collaboration between individuals.

As such, the developers of the final user interfaces will be the ones deciding on the extent of collaboration and interaction between users. Creating a system that supports interpersonal collaboration requires less effort from a development standpoint, since the ACS system that bridges these components has been designed to be inherently collaborative. Once developed, the ACS would have multiple benefits to analysts. No longer would analysts need to awkwardly transition between various systems to do their analyses and write their reports; they could seamlessly integrate a variety of tools and methodologies for their analyses and workflows for their final reports. Previously captured workflows through the ACS could provide training data for the development of new analytic tools and workflow recommender systems to further assist analysts in the future. In addition, such data and workflows could be stored indefinitely and later revisited to generate valuable new insights, associations, and trends over time.

Game-Based U/X (Veracity)

At the 2014 Human Centered Big Data Research (HCBDR) workshop (Argenta et al. 2014), one of the discussion topics revolved around developing a community framework that would enable researchers to study sensemaking by putting participants into an environment that allows researchers to scale big-data challenges (e.g., studying the effects of lowering veracity of data), controlling the tools available (e.g., to compare the effects of different visualizations), the posing of tasks that attempt to elicit specific understandings (e.g., abductive reasoning tasks), and most essentially for this chapter, structuring the human element by controlling participants and their interactions with others. The general premise was that measuring performance across a sample of these dimensions would enable us to better understand the problem space of sensemaking in big data environments. Through LAS, a team of researchers decided to build a game-based user experience to begin evaluating these concepts.

"Veracity" is a virtual reality platform that allows users to insert themselves into a completely simulated world—similar to a video game or online environment (such as "Second Life"). This platform is essentially a multiplayer, 3D immersive game built by ARA's Virtual Heroes group, with the UnReal game engine.[4] We chose a space theme for this environment for two reasons: first, it was useful to provide a context that was novel to all users to suspend disbelief and avoid business-as-usual thinking; second, we could save costs by recasting art from another recently completed space-based cognitive training game (see Figure 6.4).

We designed the immersive virtual environment to be highly instrumented (e.g., all actions that users take are logged for analysis) and support multiple areas in which future tasks could be developed. We built in task-based parametric evaluation, for which we could vary some set of dimensions relevant to sensemaking for each task. For example, we

[4] Virtual Heroes is a division of ARA. The game designer of Veracity was Nik Soderstrom.

implemented a progressive goal-recognition task that asked users to predict the outcome of an ongoing series of actions. By providing multiple scenarios of differing complexity, we were able to understand the performance profiles of different users in this reasoning task with limited information (see Figure 6.5).

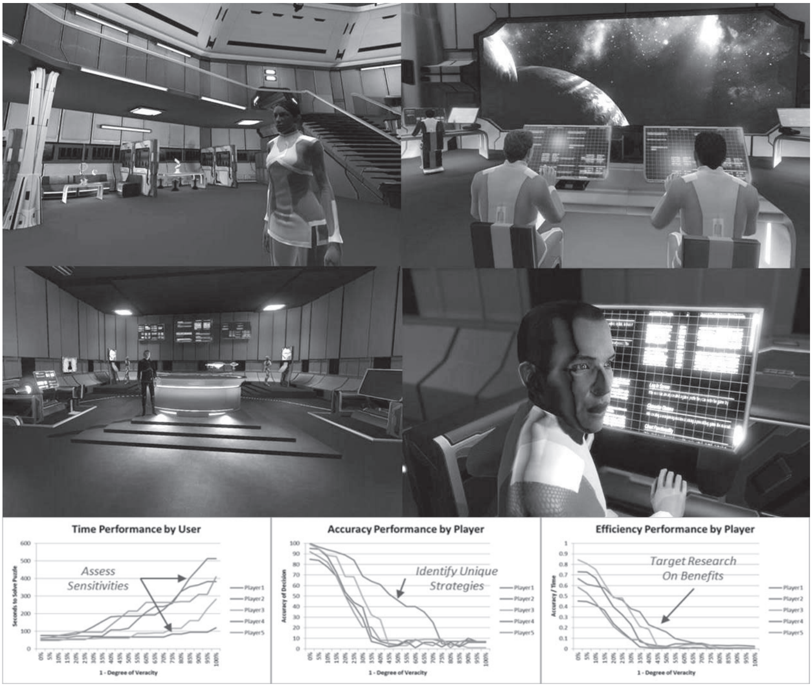

Figure 6.4: Veracity prototype with example analytic results.

Figure 6.5: A sample goal-recognition task in Veracity.

Initially, Veracity was planned to be a single-user environment for simplicity. However, as we planned out the virtual environment, LAS government staff influenced its direction to include tasks that were inherently collaborative. This significantly altered the trajectory of the research. We developed the Virtual Collaboration System (VCS) as a large multi-user environment similar to those in popular “massively multiplayer online games” (MMOs), in which multiple users interact in a shared space. We enabled both text chat and voice change with public and private chat areas. Media boards presented information/images (e.g., a slide show) in the environment. Media boards also enabled in-game presentations for training or other purposes. Finally, users were able to customize their avatar to better represent themselves (e.g., gender, facial features, skin tone, hair) and their affiliations (e.g., uniform color). The VCS environment is scalable and persistent.

Figure 6.6: Screenshot of multiple users collaborating in a shared space.

One of the most beneficial aspects of this technology is its ability to connect people working together remotely in a shared environment and on a shared task. It allows users to build trust between one another in a safe "playground" environment, in which users can be engaged in learning without real-life risk. Users can enter spaces within the virtual world to perform structured tasks or freely collaborate. For example, practicing writing queries that are compliant with policies when under time pressure can be challenging. Analysts could be given a scenario in which resolving or preventing a crisis requires executing a set of queries and acting on the resulting information. Penalties for noncompliant queries might result in a time delay during the crisis or points in an after-action review. Through spaced-practice and situational variety, analysts could improve their comfort in writing compliant queries.

Veracity's developers assert that there are a wide range of additional potential applications such as collaborative problem solving for training and team building. Future systems could include ongoing narrative aspects that engage users in activities over time to measure improvement both individually and as a team. Other potential applications include facilitating anonymous collaboration; for example, an avatar being used to avoid identifying a sensitive asset, or avoiding behavioral differences experienced with real-life presence (e.g., race, rank, gender biases).

For people with experience in 3D immersive games, Veracity follows the same mechanics and therefore requires minimal training. However, individuals who are not as familiar or comfortable with an immersive virtual environment experience the same challenges they would for games. A second significant risk of this technology is that because the environment is game-based, people treat it as a game. Users may take more risks or act less responsibly simply because they know the environment is safe. While this may be partially mitigated by instrumenting the system and reviewing user performance with them, it cannot be eliminated as a confounding variable in the research. Finally, avatars have a less natural appearance than live humans; this includes verbal and nonverbal aspects. Verbally, text chat and multiplayer voice ability could change the way players communicate. Nonverbal cues are almost completely ignored or automated—which can change the impression players get of one another.

Moreover, while in theory users would be performing the same tasks in the system as they would in reality, it is unclear whether the system currently supports a user's natural workflow. Although there is some research indicating the success of gamification in improving analytic performance (Argenta et al. 2013), it is more likely that the game would disrupt task performance. For example, to determine a good "next step," users might look for unused items in the virtual environment and use trial and error to progress. This is clearly demonstrated in escape-style games in which players must solve a puzzle using items in the environment, and it is rare to have many items that have no direct purpose. One reason for this is that it is expensive for game developers to script every possible interaction; this results in trial-and-error strategies often being rewarded and efficient compared to a more realistic process. A key challenge in the gamification of sophisticated tasks is the ability to reward the use of analysts' best practices and real-world, problem-solving workflows—thereby providing users with more appropriate experiential training, rather than merely a game that only superficially requires similar processes.

LAS has also explored alternative use of virtual environments to support collaboration for distributed teams. In these projects, the virtual world is used to extend the physical world between two geographically distant locations. Thus, the collaboration becomes the dominant factor, not the virtual environment. For example, SilverCord is a technology similar to a video conference call, except that live video is replaced with an animated avatar. Here, the user's posture is sensed using a Microsoft Kinect sensor that transmits skeletal position and limited color data to a remote workstation,[5]

[5] Kinect is a color camera plus depth sensor, produced by Microsoft and used for "natural interfaces" in games that run on the Xbox platform. It detects the player's physical movements, gestures, and speech, and uses these actions for game control and interaction. A key capability for this research is Kinect systems' ability to approximate the posture of a person (or a small group of people).

where the avatar is recreated and animated in nearly real time. Using very little bandwidth, nonverbal cues (as well as voice) can be shared over a great distance. The realism of the avatar is actually reduced to avoid eerie representations (see Figure 6.7). While clearly a very different solution, SilverCord and Veracity share the concept of using virtual representations to enhance long-distance collaboration.

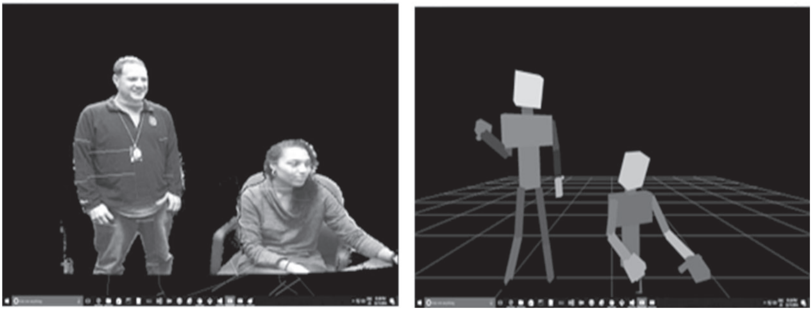

Figure 6.7: Screenshots of SilverCord, showing an actual image (left), and its virtual avatars (right) presented to a remote user.

Insights Learned from Technological Support of Collaboration

Several key themes at the program, team, and individual levels have emerged from our study of three LAS prototypes and examination of several others not discussed in this chapter.

- *Collaboration is essential*: The majority of LAS prototype developers and design-team leaders asserted that collaborative features are essential to the success of the prototype's goals and vision. Therefore, structural support by LAS is imperative as the development process moves forward.
- *Collaboration by design*: When leaders are interested in developing collaborative features in all LAS prototypes, there needs to be a clear mandate given to developers in the early stages of technology development, with resources allocated accordingly. Many LAS prototype efforts were designed from the outset to be single user systems—mostly to focus attention on problem solving and obtain tangible results in a short time frame. However, initial design and development choices can force technologies down particular tracks.

As the development process continues, it can be more difficult, time consuming, and costly to revise the way the technologies are used. However, several prototypes have the potential to develop a variety of features that are likely to enhance collaboration and are still in the early stages of development.

- *Privacy and other human factors in technology design and use for collaboration*: In several LAS prototype efforts that promote collaboration, tensions exist between the desire for information exchange and the expectations about privacy and concerns about workplace surveillance. This reveals some individual- and team-level concerns about how these technologies are designed and implemented and the impacts they might have on a variety of users. Concerted efforts should be made to start addressing these human factor issues as part of the continued technology design and development efforts.
- *Collaborative prototypes need to have communication features*: In some cases, the challenges associated with group work in a collaborative environment have not been articulated or addressed in the prototype development phase. This reflects a team-level issue. Several of the prototypes would benefit from having some kind of internal communication feature (e.g., Google Chat) to facilitate interactive discussion amongst analysts. This could be particularly useful to facilitate communication among users who are not collocated.
- *Prototypes and user identification for collaboration*: Several of the prototypes would benefit from features that allow users to identify themselves with profiles, so that others could see their subject matter expertise (particularly important for entry-level or junior analysts). At the same time, prototypes should allow users to become anonymous. This function can be useful when, for example, junior analysts want to contribute their ideas but might fear reprisal or ridicule. For some prototypes, a useful feature would be a "star rating" or other rating system for users, in order to build trust among users and allow them to recognize a reliable contributor. Addressing these issues would reflect both team- and individual-level interests.
- *Prototypes should be used and tested for collaboration*: We found that for most of the prototypes, expanded usage by a variety of users is vital to working out bugs in the system, and to inform developers about useful features that could be added or modified. To support this, a set of dedicated users should be identified for all prototypes prioritized for further development. This would require a program-

level intervention by LAS management to provide resources and personnel to support testing for collaboration and ensure the necessary training, in order to ensure that users are comfortable with these systems.

By addressing each of the above points, the collaborative prototypes being developed at LAS should reach their maximum potential.

Coda: Taking the Social into Account with Collaborative Technology Design and Development—Successful Incorporation of LAS Technologies into the High Side

In addition to thinking about the technical design of the aforementioned technologies (and other LAS prototypes currently being developed), social science literature also points to the importance of considering the socio-cultural (organizational) factors at the structural, team, and individual levels that can shape use of these collaborative tools once they are ready to be deployed into a classified intelligence environment. One important study on this issue is an ethnographic one of two intelligence units conducted to understand the culture and use of collaborative technologies in the US intelligence community (Turnley and McNamara 2016). In their study of one intelligence unit, Turnley and McNamara found that new collaborative technologies would have the potential to speed up the flow of information through the analytic chain, but that management had not considered the impact of these changes on the tempo of operations and decision making. This could create a situation in which the collaborative technology works in practice but may not work organizationally—a significant program-level issue. Therefore, there are factors beyond the technology itself that can determine the effectiveness of a collaborative technology in a particular user's organizational environment.

Turnley and McNamara went on to note that "collaboration" is actually a surrogate term for a complex mixture of issues that center around trust, information, and power, which operate in the highly politicized environment of an intelligence unit/agency. Furthermore, they found that intelligence analysts often operate within multiple relationships—to their unit, to their division, to their directorate—in producing intelligence reports. As a result, "they must negotiate their institutional allegiances with themselves as well as with others in every encounter" (Turnley and McNamara 2016, 17). Therefore, introducing a new collaborative technology into the intelligence work environment requires that analysts understand how their existing relationships (i.e., program, team, individual) may also be altered. Turnley and McNamara point out that technologies that change information flow or work practices can also impact resource allocation, ownership of information, and their associated power structures. These impacts can also shape the extent to which collaborative technologies are used—and used effectively. Because the potential ramifications of any change in intelligence practice may be significant, an analyst must trust the technology. Historically, it has also been shown that a technology must be perceived as useful and easy to use in order to have a substantial impact on organizational performance (Davis 1989). Turnley and McNamara conclude that because the analytic environment varies across intelligence units and agencies, it is important to consider the social environment within which the tool will be embedded and what existing work processes or practices at the individual and/or team level might promote or hinder use of the technology in that environment—and how these practices could be constructively modified and aligned with the new technology. Therefore, in order to promote analysts' use of new technologies, Turnley and McNamara argue that developers must consider how the socio-cultural dimensions of the user environment interact with the technology.

A set of related studies found that technologies that increase large-scale collaboration also require people to anticipate and manage conflict that can arise from resource limitations, different perspectives and routines, and competing interests and goal conflicts among participants (Xiao et al. 2007; Ren et al. 2008). They argue that in the design of new information and communication technologies that support coordination and collaboration, sufficient attention should also be devoted to identify and support the development and implementation of appropriate social processes, communication strategies, and "rules of engagement" that can handle conflicts that arise in the use of these technologies. This is also important at the program, team, and individual levels. As also long noted by Orlikowski (1992), collaborative technologies do not automatically produce collaboration in organizations unless organizational norms and incentives (structural factors) encourage it. On this point, intelligence scholar Rob Johnston has noted that the norm of autonomy in intelligence analysis makes collaborative work challenging (Johnston 2005, 73)—both a program- and an individual-level problem. Ren et al. noted the importance of having information and training sessions for workers and managers on new technologies and revisiting the organization's incentive systems before these technologies get introduced, in order to minimize user resistance (2008, 127). In addition, they advocate the appointment of a "collaboration engineer" who can work with users of the collaborative technologies to modify existing work practices in order to integrate the new technology. All of these practices would be important to address at the individual, team, and program levels within a variety of intelligence environments.

Conclusion

The new analytic prototypes being developed at LAS show great potential for increasing a future intelligence analyst's ability to work more collaboratively and to improve their analytic workflow. In addition to their technical construction, LAS prototypes will also have to be considered in light of specific socio-cultural, organizational contexts in which they are envisioned to work, in order to reduce user resistance and promote adoption of the technology.

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Part Three:

Case Studies of Collaboration at LAS

7

ANTICIPATORY THINKING

ADAM AMOS-BINKS,
CHRIS ARGENTA, AND
ABIGAIL BROWNING

Intelligence is a corporate capability to forecast change in time to do something about it. The capability involves foresight and insight, and is intended to identify impending change which may be positive, representing opportunity, or negative, representing threat.

– *Breakspear 2012*

CHAPTER 7

KEY TERMS

- **Anticipatory Thinking (AT):** The intentionally divergent exploration and analysis of relevant futures to help avoid surprise by identifying leading indicators and causal dependencies of future scenarios**.**
- **Artificial Intelligence (AI):** The science of enabling computers to perform tasks that requires reasoning a human would typically identify as intelligent.
- **AT Day:** A full day collaborative research workshop that includes AT performers.
- **Big Data:** The use and management of information at an extremely large scale.
- **Crowdsourcing:** The practice of eliciting knowledge from a large distributed group of people.
- **Future States Processing (FSP):** A set of LAS projects focused on developing the "Science of Projectors."
- **Intelligence:** The result of processing data into more actionable knowledge.
- **Intelligence Advanced Research Projects Activity (IARPA):** An element of the IC that sponsors leading edge research relevant to intelligence challenges.
- **Intelligence Community (IC):** A community of people working on various intelligence activities for the US Government.
- **National Intelligence Strategy (NIS):** A document produced by high ranking members of the IC that outlines the requirements for the near term future.
- **Platform:** A foundational system on which a large number of capabilities can be developed.
- **Scenario Explorer:** A software platform that provides imagination support for anticipatory thinking.
- **Securing Critical Infrastructure at LAS (SCILAS):** A set of LAS projects focused on developing solutions to challenges of protecting key national services.
- **Smart Cities:** Local municipal infrastructure that embeds computers to control and monitor its processes with some level of autonomy.
- **Structured Analytic Techniques (SATs):** Well-defined procedures and tools that aid analysts in performing their tasks and avoid common cognitive pitfalls.

KEY POINTS

Program: Socialize ideas into the lab: Like any new and potentially disruptive idea, introducing it slowly and getting end users involved early is key. This is particularly true in the intelligence community, who can be particularly conservative and skeptical. Many innovations have come and gone promising to make analysts lives easier, however few have approached it in the ways that are possible at LAS.

Team: Teams with a diverse knowledge base (cross-sectoral, multi-disciplinary) are rich places for testing new ideas and early prototypes because they provide a range of specific motivations, experiences and perspectives.

Individual: Be visible and approachable; ask questions and actively search for the common denominators that connect your expertise with another participant's research.

Government mandates are rarely associated with groundbreaking cross-sector creativity. But, in places of diverse knowledge, focus, and motivation, such as LAS, we saw *anticipatory thinking* become a crucial field of study for the intelligence community, as well as for academic and industry researchers.

This chapter takes a chronological look at the emergence of the Anticipatory Thinking (AT) program, from my (Adam Amos-Binks) perspective as a government employee, with contributions from my colleagues and co-writers for the years in which they participated: Chris Argenta and Abigail Browning. For the sake of clarity, my writing in this chapter primarily focuses on the programmatic and tactical side of the development of AT as a research program within LAS, while Chris takes on its technical developments, and Abigail describes our efforts to apply AT techniques and platforms, such as Scenario Explorer, which was developed through our collaboration. Although every perspective cannot be integrated into our case study, we do wish to acknowledge that many other LAS participants also worked on AT over the years.

2013: Reinventing Intelligence Analysis— A Governmental Mandate

In 2013, we were in the early days of LAS. Although the government had awarded a contract for the project in June, there was no building, no secure area, no government staff in North Carolina, and no research platform. Up to that point, I (Amos-Binks) had been in the intelligence community (IC) for a decade, integrated into various parts of the intelligence production cycle, ranging from cryptography using high-performance computing to math research for data science. However, during my years of intelligence production, the IC started to focus on where the gaps in our work intersected with developments in modern technology. The IC was ready to explore a new research platform, in the form of LAS, with an essential and challenging mandate to *reinvent intelligence analysis.*

Even without such a tall order, starting a new research lab is not a simple task. Throw into the mix that the IC has difficulty expressing exactly what intelligence is, particularly to non-IC people, and one can understand how those of us who started LAS definitely had a challenge ahead. Because I had previous experience working as a liaison between different IC communities, the Lab's inaugural director invited me to join the initial outreach team. A small group of us would travel once a month from Fort Meade to North Carolina State University (NC State), in Raleigh, where we would enter a decisively "different world" of knowledge production. Each visit offered an opportunity to build out a contact network, identify relevant research activities, and formulate NC State's relationship to LAS's mandate. At this point, we knew we needed to approach intelligence analysis differently, and the culture at NC State provided a unique perspective from which to do so.

In our monthly meetings on campus, I was struck by the different culture and, more importantly, the different definition and language of research. Despite my years as a scientist performing "research," the academy and IC were fundamentally dissimilar. At LAS, we would need to situate our goal of reinventing intelligence analysis within a more academically rigorous understanding.

Personally, I was fascinated with how engaging more deeply with academia might change our fundamental thinking about IC challenges. Very soon into our meetings, I realized that I, too, wanted to explore the academic community and navigate their research process as part of my role. I suggested that I apply for (and thankfully was later admitted to) the doctoral program for Computer Science, for a more immersive learning perspective in response to the project. Although I did not know it then, my work in Computer Science would later be useful for bridging the intelligence analysis gap between humans and artificial intelligence.

As a group, we identified that the IC lacked the technology to support the kind of future thinking it desired. To some in the government, this future thinking was exemplified by the catchphrase "left of boom"; to others, it was a fundamental element of synthesizing and producing intelligence (Breakspear 2012). The state of the art for future thinking was pen and paper, whiteboards, and structured analytic techniques (Heuer 1999), yet none of the techniques was very formal or well-studied for efficacy. There was a clear value proposition for LAS: *We needed to integrate future-thinking research into the research platform, because it supported a basic phenomenon needed for producing quality intelligence.*

In other words, before we came to the term "anticipatory thinking," we knew that imagining the future was a key research objective to serve the mandate, and it represented a gap in academic knowledge of human forecasting and prediction. Through immersive collaboration, increasingly larger investments (including a new building), and focused year-long projects in future thinking over a period of four years, LAS eventually developed a research program whose activities could cut to the core of producing intelligence and generated the seeds for the AT research program.

2014: Modeling the Future

With the contract in place and plans for the physical building set for completion in April of 2014, my role as a liaison from the early meetings expanded to include bridging the culture gap between the newly merging research communities—IC, academia, and industry—as we grappled with questions around anticipating the future. At the same time, I had started to take on dual roles as I began my doctoral program at NC State, which helped me gain an academic perspective useful for navigating needs specific to LAS partnerships.

In another effort to connect a vision across the sectors, we developed LAS's original motto, "Reflect. Observe. Imagine." This motto served to direct participants to pursue cutting edge research on analysis platforms that would help intelligence analysts *imagine* the future. This mandate aligned perfectly with an approach to identify impactful events, a more general goal in our early work of understanding anticipatory thinking.

First, we had to differentiate any future-thinking research in a substantial enough way to avoid being redundant or duplicative. Also at this time, the Intelligence Advanced Research Project Agency (IARPA) was wrapping up a major project called Aggregative Contingent Estimation (ACE) in which they crowdsourced the forecasting of future world events.[1] Of the competing performers on the project, the winning team was called the Good Judgment Team (GJT) and was led by Philip Tetlock. GJT's research—and later, Tetlock and Gardner's book, *SuperForecasting* (2015)—generated substantial interest in the IC to further focus on future-oriented analysis, although it focused only on near-term forecasting questions.

Overall, IARPA ACE focused on crowdsourcing human estimates of the likelihood for specific predetermined world or geopolitical events. Participants received their information mostly from news sources, with little structure, and updated their forecasts appropriately. Our view was that while the ACE approach was useful and had the mathematical rigor to support the results, it was somewhat constraining. The major limitation was that forecasted predetermined events were hand selected by the IC. Participants were asked to consider only the likelihood of the events occurring, not their impact or the risk involved.

However, we could easily argue that analyzing risk is an essential element of producing intelligence. Generally speaking, risk is calculated by multiplying an event's impact by likelihood. By this thinking, the impact

[1] For more information on IARPA's ACE program, see https://www.iarpa.gov/index.php/research-programs/ace

half of the risk calculation was not part of the GJT's work, or of any existing IC research program, leaving LAS free to pursue it. This included the underlying models for anticipatory thinking.

Early Work on IARPA Aggregate Contingent Estimation from an Industry Perspective

The IARPA Aggregate Contingent Estimation (ACE) program started in 2011, and my (Argenta) company, Applied Research Associates, Inc. (ARA), was one of the prime contractors supporting the program. The ACE program required the development of technologies for crowdsourcing forecasts of world events. While teams of individuals and groups of analysts had traditionally forecasted events, this program investigated how to use a large group of participants to develop more accurate forecasts. Ultimately, the program included three key research topics: (1) establishing methods of eliciting good forecasts, (2) aggregating the forecasts of multiple participants into a single more accurate forecast, and (3) communicating the resulting knowledge to decision makers.

To achieve the goals of ACE, ARA worked closely with a large and diverse team of academics and consultants. We developed a web-based system called "Forecasting ACE" (Warnaar et al. 2012), and later a gamification version called "Global Crowd Intelligence" (Argenta et al. 2013). The core of ARA's approach was to concurrently improve individual performance and effectively integrate many independent forecasts. IARPA set up the program to have performers compete, using a set of approved forecast questions and daily forecast reporting. When the events came to pass, IARPA scored each team's forecasts over time and computed program metrics to determine which teams moved forward. Ultimately, our approach was outperformed on IARPA metrics by the GJT, which focused on identifying and coordinating smaller teams of participants with strong forecasting skills (Tetlock and Gardner 2015).

The ACE program focused on "forecasting"—predicting the future values of specific features that related to world events. The second phase included "conditional forecasts," which focused on forecasting to futures, under the condition that specific criteria were met. For example, a forecast might address the question, "How many people will attend the US Open in 2019?" while a conditional forecast might ask, "*If it rains*, how many people will attend the US Open in 2019?" A subject matter expert would identify and select events that condition these forecasts according to their belief in a significant impact on the forecasted value. In the ACE program, developing forecast questions in which accuracy could be clearly evaluated was a critical task—and a bit of an art form.

LAS' Future States Processing Research

Moving forward with ideas learned from IARPA ACE, early efforts at LAS into understanding anticipatory thinking included a project called Future States Processing (FSP), which was again comprised of cross-sectoral teams from industry, academia, and government. Our goal with FSP was to develop a future-oriented analysis platform capable of projecting ("processing") future possible worlds ("states"). From these possible worlds, we could identify impactful events that researchers or analysts might otherwise overlook. In this way, we were able to build on and supplement previous IC findings. The FSP project set the stage for the underlying models we would later use in anticipatory thinking research.

Future States Processing from an Industry Perspective

Given our previous work and expertise, LAS awarded ARA a contract to create a system that reasoned over future states and leveraging crowdsourcing techniques for anticipatory intelligence. Our research complemented other FSP research performers at IBM Watson Research and NC State. LAS posed the challenge to our research group of helping analysts imagine future possible states of the world. Our goal was not to predict the most likely future state of the world (as it was in IARPA ACE), but to avoid surprise by identifying potentially interesting future states.

This challenge was deceptively simple, because only one future will actually occur but there is an infinite range of potential future states. Essentially, a person (or organization) that more successfully considers future possibilities would be better equipped in employing strategic foresight. With this challenge, LAS wished to establish a "science of projectors." The first step was to research techniques to "project" our understanding of complex phenomena and behaviors into the future. Drawing on our experience with ACE, we focused on incorporating both collaborative human cognition research and predictive analytics.

Structured techniques for documenting and communicating human imaginative processes are not new. Narratives provide one mechanism for recording and communicating human imaginings. Concept Maps and Mind Maps extend this technique by adding structure for documenting and communicating ideas. ARA envisioned a new type of system called

"Imagination Support," which would provide tools to help foster robust imagination at scale.

We asked, "How do we *imagine* a future state of the world?" The first approach people tended to consider was predicting the most likely future scenarios from their observations and reflection—essentially, predictive analytics. But a critical extension of this technique is to consider key events that influence the direction in which things change, because this provides insight into the string of causality we expect to occur. If we understand this causal trajectory, we can begin to ask, what might occur if some of our expectations prove incorrect? For example, if we forecast the most likely state of the world next year to include higher gas prices, we might then ask how conditioning events, such as OPEC's decisions or improvements in fracking technology, might impact this prediction. A structured methodology for imagining future states would include a way to model many future states and the conditioning events potentially leading up to them (Figure 7.1).

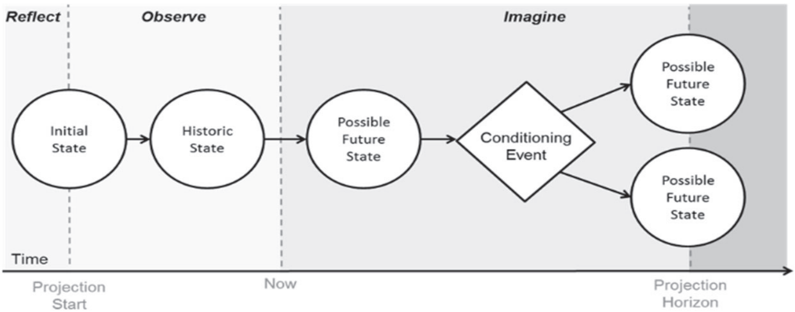

Figure 7.1: Our basic model of a futures space, consisting of a tree with branching trajectories linking past, current, and future states of the world. The key insight is that futures are not just numerically possible, but feasible (or justifiable to a human analyst), given some sequence of events that change or condition the context in which more projection occurs.

A model of future states processing would include multiple future states and the conditioning events that led up to each state, thus forming a tree structure. As time passes, the uncertainty in the outcome of a conditioning event can be resolved, allowing us to prune branches of this tree model.

We might also extend our set of possible future states by imagining how compilation of smaller events might lead to important contextual shifts. This extension requires a model that does not abstract away all of the smaller changes by summarizing only major elements. Analytic models are good at tracking data at large scales, but people are not.

Specifically, ARA invented Collaborative Intelligence for Future States Processing (CI-FSP), a collaborative tool to help analysts imagine future world states and discover potentially surprising, feasible events before they occur. We developed web-based forecast elicitation techniques, extending our earlier work with IARPA. However, in this approach, CI-FSP automatically generated elicitation question text from a model of features and used responses to generate additional questions to elicit explanations of why features might change in the predicted ways.

Our unique approach also shared a common knowledge representation between experts, distilled specific questions for an external crowd of people, and automated the analyses of forecasts to determine when more input was needed. We designed CI-FSP to leverage crowdsourcing and computational modeling to augment an expert's perception of future states of the world, discover unanticipated but feasible situations, and understand causal trajectories. Critical to doing so was the detection of modalities in crowdsourced forecasts and the ability to extract causal explanations in the form of a "conditioning event," that is, an event for which people disagree about the expected outcome, yet that outcome is a significant factor for later states. Essentially, CI-FSP provided insight into a structured technique to determine which conditional forecasts were relevant.

From ARA's industry perspective, we believed we were on to something unique and powerful. We had merged cognitive reasoning with analytic automation. However, with only a small amount of funding and time, our initial prototypes were modest and fragile. As a result, our ideas did not yet catch on as well as we had hoped. With no solid proof to compel them, the other researchers did not flock to our model. In the end, CI-FSP was viewed by others as just another projector type, albeit very odd in comparison to the models developed elsewhere.

In 2014, with the help of academic and industry partners, LAS made progress on technical contributions for future-oriented analysis platforms, which was in line with how the IC had previously engaged with research. However, most of the performer work focused on improving models of predictive analytics, instead of considering the first principles of human cognition. This is analogous, for example, to having multiple models that predict the path of the same hurricane; they may differ to some degree, but they are ultimately all built to do the same thing with similar understandings of the underlying physics.

What we learned in FSP was that our "science of projectors" was ultimately limited by the lack of basic knowledge about how humans reason and think about the future. People are able to reasonably imagine many feasible futures that the models do not predict, and world events are less predictable than the laws of physics. Without a first-principles approach to evaluating the approaches and methods being developed, it was difficult to evaluate progress and articulate value to stakeholders. *We needed to go back to basics and develop research around the human aspects of future thinking.*

2015: Defining Intelligence

The release of an updated National Intelligence Strategy (NIS) in late 2014 (Clapper 2014) validated the motivation for our approach. Within the NIS, there was a concept referred to as *Anticipatory Intelligence*, cast as one of three foundational mission objectives the IC was mandated to accomplish, regardless of threat or topic. This objective explicitly called for future-oriented methods for identifying emerging threats and opportunities. As with much of what we had learned in our FSP project, there was a significant gap between what was known about our ability to think about the future and the established practices in the IC and other industries that rely on calculating risk.

We at the LAS were not the only ones to notice the word "anticipatory." IARPA had invested heavily in their anticipatory intelligence programs,[2] and many rebrandings of existing technology followed suit. It seemed that most of the community had also conflated "anticipatory" with "prediction" or "forecasting." Our view was that many of these efforts would suffer a similar fate to our FSP program—providing technological gains but without the necessary appeal to our intelligence analyst community.

Thus, the NIS prompted a deeper question at LAS. If we were to focus research effort on understanding the basics of future thinking, we needed it to support the IC's ability to produce intelligence. But what exactly is intelligence? Mass media and popular culture emphasize and sensationalize the cloak-and-dagger perceptions of intelligence work. Yet the reality is that most intelligence is produced in nondescript government buildings by a diverse demographic of bookish analysts—not the remorseless "über-athletes" typically portrayed in popular entertainment.

As it turns out, despite our efforts to leverage the vast network of intelligence analysts across the IC, we could not develop a common working definition of intelligence—other than to observe that intelligence analysts go to work every day and do it. This is perhaps a highlight of government-academic-industry partnership. Even though we would seem to have been

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[2] As of this writing, they have had 12 active programs.

in an excellent position to answer this question, the government team could not do so. Only after we turned to the academic community—those who study the IC—were we able to find a definition of intelligence with which few disagreed:

> *Intelligence is a corporate capability to forecast change in time to do something about it. The capability involves foresight and insight, and is intended to identify impending change which may be positive, representing opportunity, or negative, representing threat.* (Breakspear 2012)

Defining intelligence was a breakthrough of immersive collaboration for LAS. For the emerging AT focus, Breakspear's definition was successful because it was able to capture both critical thinking ("forecast change") and action ("do something about it"). The definition resonated with the government perspective, which is that good intelligence entails action at some point—otherwise intelligence is simply a thought experiment.

Using a concept of intelligence that conveyed what LAS was trying to achieve, we finally had a compass to guide our research on what would become anticipatory thinking. With an understanding of the current state of the art in future-thinking science, we began to investigate how we might address the limitations that existed in understanding human and artificial intelligence (AI) approaches to AT.

2016: Methodology of Anticipating Surprise

I (Amos-Binks) began 2016 by leading a small team of government and academic partners in an investigation of how to use classical planning, a method from AI. One of the unique characteristics of LAS is its ability to bring together expertise from a wide variety of academic, government, and industry partners. Typically, this is done under a common project and shared goal, with a clear deliverable at the end. However, our main unifier was, instead, the original mandate from LAS (to reinvent intelligence analysis) and the mission objective from NIS (anticipatory intelligence).

The extended LAS contact network pointed us to an excellent resource on the gap between science and intelligence. Agrell and Treverton (2014) outlined historical accounts of intelligence diverging from the traditional scientific method. Perhaps the most relevant insight to our project was their characterization of the IC as being predisposed to collecting data and forming hypotheses from the collected data, rather than using the canonical scientific method that reverses the order (hypothesize, then collect data). They attribute this fundamental difference to the early days of the Second

World War, during which radar surveys for hostile aircraft created data at a rate greater than that with which officers could analyze them.

Certainly, given the current emergence of Big Data, one can relate to the experience of an overwhelming influx of information these officers experienced in the 1940s. In addition, it is important to recognize that *forming hypotheses in advance of having data requires a sophisticated level of domain or methodological expertise* if one is to perform a rich simulation (including independent and dependent variables). In contrast, having data and then forming hypotheses is a process that shapes and constrains mental simulation—potentially to its detriment. Our view was that the “data first, hypothesis next” approach limits the future-oriented divergent thinking needed to anticipate surprise. At a very coarse-grained level, we viewed forming hypotheses as a combination of domain and methodological expertise.

Given the often sensitive information and its associated expertise in the IC (along with the notoriously difficult task of studying expertise), we sharpened our focus on methodology. Auspiciously, methodologies used by the IC circulate in the public domain.[3]

Because we now had grounded experiences in the limitations of the FSP project, definitions of intelligence, and methods that purport to aid in intelligence production, we began an investigation of our own. At the time, several high-profile security incidents marked Smart Cities as an important topic in public discourse. Our goal was to determine how entities in three key sectors (water, transportation, energy) identified by the Department of Homeland Security (DHS) would be affected by varying degrees of government oversight and access to secure communications in future Smart Cities.

Building on extensive prognostic reports by the Atlantic Group (Healey and Barry 2015) and McKinsey (Manyika et al. 2013), we delved several levels deeper using future-oriented SATs to infer the dynamics between our entity’s motivations and its intentions. We developed a planning domain to experiment with generating outcomes using AI planning. Our findings are available in a longer white paper, but three key insights from this participatory experiment stood out:

- SATs are better understood as a flexible collection of steps than a formal methodology. It is difficult to know the circumstances under which a particular SAT will work best.

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[3] In fact, the book (Heuer 1999) used to introduce new analysts to *structured analytic techniques* (SATs) is available as a free download from the CIA website.

- To operationalize Breakspear's definition of intelligence (Breakspear 2012) at an organizational level would take nothing short of a full technological disruption.
- Evaluation criteria for anticipating surprise, strategic foresight, and intelligence are sorely lacking.

With these findings in mind, we were eager to pursue anticipatory thinking methodology in regards to a bounded problem.

Persistence in Discontinuity in AT from an Industry Perspective

From ARA's perspective, the 2015 and 2016 research supported our view that the AT approach was the correct model on which to build a unifying platform. While some LAS performers continued to work on interesting predictive analytics, ARA had moved on to different research projects with LAS (some of which are described elsewhere in this book). This demonstrates an ongoing challenge for LAS, because as funding, politics, staff, and interests change each year, research efforts can easily become discontinuous.

However, ARA had the fortune of being physically located near LAS, in Raleigh, NC. Thus, we were able to continue discussions and recommend approaches to those working to understand the nature of AT and intelligence. Simply put, we thought we were onto something important, so we persisted in improving our understanding of it and advocating for LAS to continue the research.

One thing we did accomplish during this time was to develop a clearer understanding of what differentiated AT concepts from, for example, predictive analytics, forecasting, and scenario analysis. As shown in Figure 7.2, how one chooses to make a tradeoff between the precision (how close a given answer was to the correct answer) and recall (if the correct answer[s] is [are] in the given set of answers) is an essential differentiator in these types of reasoning. This is particularly true in cases with only one true positive (i.e., only one future will actually occur).

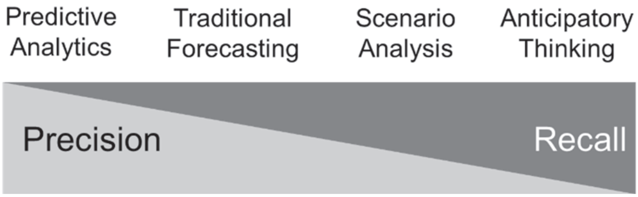

Figure 7.1: One key thing that needed to be understood and communicated to the community is how AT is different from Predictive Analytics. Both try to address questions about the future. An important difference lies in how we make trade-offs between accuracy and completeness of information.

At its core, the precision-to-recall scale addresses how tolerant one is of false-positive answers. Predictive analytics often excels at giving a few answers that are close to the right answer. Forecasting is useful for answering specific questions about the most likely answer, and it slightly increases the diversity of answers considered (particularly with conditional forecasting). Scenario Analysis focuses on a few diverse but feasible scenarios, with the hope that the correct answer is among or some combination of those scenarios. Further right on this scale is AT, which very intentionally widens the range of answers it includes.

If the challenge one is trying to address focuses on being right most of the time, with little cost to being wrong occasionally, then predictive analytics might be ideal. On the other hand, if one's objective is not to be surprised, then one will likely be tolerant of possibilities that eventually turn out to be incorrect, as long as the uncertainties keep them feasible. Despite the discontinuity in the LAS structure, both our efforts on the government side and the persistence of previous performers gave us the foothold to make AT an even more deliberate focus for the next year. Thus, I felt I had the backing and clear trajectory to lead an AT team.

2017: Focusing In with Smart Cities

For the AT group, 2017 was an important time for transitioning theoretical concepts of AT to localized problems. As our first attempt, we wanted to continue to focus on the ways in which increased technological connectivity could prove a threat to cities. Therefore, LAS decided on the exemplar of "Securing Critical Infrastructure at LAS" (SCILAS).

Our goal was to apply AT-inspired methods to the potential (and looming) security nightmare of Smart Cities. We envisioned city planners who were already charting the course for cities into the digital age with robust methods and tools we could use as a starting point. However, we quickly learned that city planning is often reactionary to the needs of its constituents. After conversations with leading experts, we found an important gap in AT research: the measures of future thinking were lacking. We needed to get down to a basic science level of investigation and build—from the ground up—the ability to assess and measure AT.

This first major AT challenge of assessment and measurement would underpin three additional research objectives. First, the LAS team developed early definitions of AT: "The deliberate and divergent exploration of relevant possible futures." A second objective, AT Support, would capture the methodologies employed (whether empowered by pen and paper or AI) that push our mental states into the divergent and creative space needed for strategic thinking. Once we established assessment and measurement for AT methodology, our final goal would be to utilize them to design training programs to help analysts improve their performance on AT tasks.

Ideally, we needed a better way to communicate and test our ideas in a focused platform. Because LAS is on a university campus, we had a special connection to graduate students and professors, who could apply and hone our theoretical suppositions. We developed a structure for the research team that emphasized both the domain expertise and IC methodology for AT (see Figure 7.2).

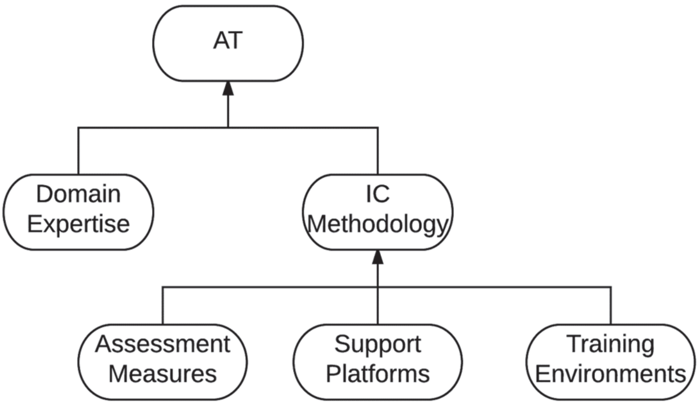

Figure 7.2: Plan for AT Research team for SCILAS exemplar.

Imagination Support for AT from an Industry Perspective

The Smart Cities focus provided an interesting domain in which to study AT, and ARA attempted to embrace it for our use cases. In this new funding year, the performers had changed again; this time, ARA was back, leading the platform development for AT and building on our previous work with CI-FSP. In working with the SCILAS team, it quickly became apparent that there were two main approaches: those focused entirely on the challenge of supporting city planners in their decision making, and those looking beyond city planning, towards IC applications. We felt our objective was not to turn AT into a decision support tool; instead, we wanted to invent a new class of systems—an "Imagination Support" system.

Over the course of the year we designed and developed our Imagination Support platform, which we eventually named Scenario Explorer. Scenario Explorer is a web-based collaborative tool for elicitation, integration, and reasoning over a large number of potential future trajectories. In concert with government researchers, we identified some of the ways in which AT related to IC tradecraft and products. Where possible, we attempted to fit with existing IC concepts while concurrently introducing changes designed to enable analysts to better and more systematically imagine futures. We identified some key needs for the AT platform:

- To enable multiple analysts to work together in order to converge on a common model of the features and timeframes relevant to a given project, domain, or topic
- To elicit known, expected, or previously imagined future events and scenarios while expressing those events and scenarios consistently with respect to the common model
- To place analysts in a mindset of imagining feasible future events that might have significant effects on the features in the common model
- To combine the elicited scenarios, automatically composing the events (potentially created by different users) to generate novel, but sensible, scenarios
- To explore manipulations of the scenarios and observe cascading multiple orders of consequences, in order to understand the sensitivity and uncertainty in accumulated knowledge
- To intelligently query the combined scenarios to discover key events and potential leading indicators that might help determine which scenarios are likely to occur

To address these aspects, we developed four new Structured Analytic Techniques (SATs) that operated on top of a shared data model and analytic platform. These focused on different methods to elicit, integrate, and reason over future trajectories and conditioning events. However, in a collaborative team of researchers, everyone brings unique perspectives, challenges, and insights. One of the key challenges for this year's research was simply to explain the concepts that had been stewing in our heads for the last three years. Because performers in the AT group came from different sectors and departments, terms used in discussions around AT were inconsistent among members. Thus, doctoral student (at the time) Abigail Browning joined our team to help us work together to clarify the theoretical language that defined AT.

AT Glossary, Tools, and Training from the Perspective of an Academic Performer

In the spring of 2017, I (Browning) learned of an opportunity to work as a graduate student on the Smart Cities project at LAS. My doctoral research at the time also focused on anticipating the emergence of collective action events, so I was eager to apply my knowledge to the goals of Securing Critical Infrastructure at LAS.

As an LAS Graduate Extension Assistantship (GEA) awardee, I joined the Anticipatory Thinking (AT) research group that summer. After one of the first AT Days (a workshop that included the different AT group performers), my mentor, Adam Amos-Binks, encouraged me to work more closely with the team at Applied Research Associates, Inc. And, although the sections of this chapter suggest, perhaps, a compartmental experience with AT at LAS, I must stress that I felt equally included and respected by both government and industry performers as I worked on this team. With an office at ARA, I was strategically able to catch up with all of the previous progress in the AT domain. I learned that Chris (Argenta) had been working on a platform (Scenario Explorer) that employed SATs to AT—in this case, one that could extend to city planners for SCILAS.

The platform was still in its theoretical stages, needing a comprehensive lexicon that could appeal to stakeholders across a variety of domains (specifically government, academia, and industry). One problem Argenta and the AT Group at LAS articulated was the lack of a standard language for talking about anticipatory thinking in general. As a result, I saw the need to develop a glossary, not only for the Scenario Explorer, but also for use in cross-sectoral discussions about AT as an emerging domain. Argenta's platform, as a lynchpin for expressing AT methodology, would rely on internally consistent terms that appealed to experts and analysts in many disciplines, and LAS was the perfect place to test an AT glossary's fidelity and usability.

Combing through research, I collected the most important terms associated with Argenta's prototype and challenged their clarity and ability to be understood across domains of expertise. To test comprehension, I drafted an AT glossary. During the next AT Day, I requested that each participant offer feedback, such as notes about terms that conflicted with important terms in their domains, as well as unfamiliar words from the glossary. My goal in assessing the feedback was to edit the glossary to improve adoptability by a general audience. I analyzed the written feedback and then met with the team at ARA several times to discuss edits for the next iteration. The semantic discussions were useful in situating myself in the emerging field of AT as well as with the IC and industry communities. More importantly, after we decided on key terms for the glossary, the words became used with increasing frequency at LAS and in more global conversations about AT.

ARA had both the technological and the visualization side of Scenario Explorer in development; another concern Argenta and Matt Lyle (ARA software engineer) articulated was not having a realistic scenario to use as a test or demonstration. I proposed, as an example, consumer electric vehicle (EV) adoption as a complex scenario with interesting qualitative and quantitative features in relationship to Smart Cities. Combined, the glossary and demo would be influential in my next work with ARA and NC State: (1) implementing the prototype into a classroom setting, and (2) instigating a research study observing AT training through Scenario Explorer.

Scenario Explorer and MBA 580 from the Perspective of an Academic Performer

One of the collaborations that demonstrated the value of industry-academic partnerships was in place before I (Browning) joined LAS. Dr. Beverly Tyler sought out analytic tools she could include for a course at the NC State Poole College of Management with her MBA students, and Chris Argenta had offered the ARA Platform, Scenario Explorer. Given my experience teaching at the university level, my role was to work with Beverly Tyler and the main course instructor, Kevin Wright, to integrate the tool into the course structure.

MBA 590 was a practicum course in which NC State graduate students worked with community stakeholders to provide recommendations on a specific project. For the assignment that semester, Tyler and Wright asked their class to focus on Smart Cities and engage with city planners (among other invested professionals). With approval from the institutional review board, we developed a research protocol to test the efficacy of Scenario Explorer as both a decision-making and a pedagogical tool. I then taught workshops for the groups to use Scenario Explorer as a tool to support their anticipatory thinking on the project. By the end of each workshop, the students were able to apply SATs for AT using Scenario Explorer as well as utilize key glossary terms. In our AT chronology, this was one of the first tests that demonstrated Scenario Explorer's ability to support imagination and pointed us toward the need for clearer assessment, measurement, and training for AT.

2017 in Review: Cross-sectoral Value

As Browning and Argenta deployed Scenario Explorer in the MBA classroom to investigate decision support for AT, other performers focused on what became AT Assessment and Training. Dr. Jing Feng (Applied Cognition Program, NC State) led the assessment effort, with a goal of developing a task that captures the cognitive phenomena required for our AT concept. One of the great successes of this effort was its tight integration of LAS government staff. James Campbell (government) was instrumental and effective in designing the task (inspired by the Scenario Planning course at The Sherman Kent School for Intelligence Analysis), aiding with deploying the experiment and analyzing its results. As we refined the task at our quarterly AT Collaboration Day, we began to socialize other government staff to the AT concept. Feedback was overwhelmingly supportive of both the task and our pursuit of operationalizing Breakspear's definition of intelligence (2012).

A jointly proposed complement to the AT assessment task was Dr. James Lester's (Center for Education Informatics [CEI]) adaptive training for AT. CEI has made great scientific progress using intelligent tutoring systems and game-based learning to provide personalized experiences that improve learning outcomes. Having CEI intimately involved in the design of the AT assessment allowed ideas for training to be influenced at a very basic level. Most notably, this collaboration began to tease apart the contributions of expertise and methodology (such as structured analytic techniques) to AT, and how to leverage intelligent training for the latter. This aligned well with opportunities within the IC, as most training is traditional schoolhouse attendance style, which is difficult for operationally driven analysts to dedicate time to. Intelligent learning technologies can be delivered in a more scalable way to an analyst's desktop in a just-in-time manner.

Lastly, Dr. Michael Young's Liquid Narrative Group investigated the theoretical overlaps between intention, a mode of prospective cognition, and planning, an artificial intelligence method used by the Liquid Narrative group to generate stories. Key to this research is that the agents in the generated stories are goal-oriented and take actions toward achieving them. When readers of the stories identify an agent's intention, this forms an expectation of future behavior and is an example of prospective cognition. The research focused on developing computational models to violate that expectation and compel the reader to think divergently about how the agent may react in response to their new reality. This idea was explored in several publications at mainstream AI conferences and was the subject of Amos-Binks's dissertation, a direct outgrowth of the AT work at LAS.

At LAS, the partnership among three institutions (academia, government, and industry) often struggled to produce significant value for all three in any one activity or program, as the different currencies (publications, operations, and customers, respectively) are misaligned. Despite this, in 2017, the AT concept was beginning to produce value for all three partners. As we began shaping the vision for the next year, we were able to recruit more LAS staff integrated with partners, academics who wanted to be involved in a rich publication area, and industry partners willing to invest their own internal research and development funds to put their AT concepts in front of customers.

2018: Assessment, Support, and Training

The AT research focus of assessment, support, and training we had developed in 2017 laid the groundwork for a 2018 with very high potential. More government staff engaged, paving the way for observational studies to investigate support tools and assessment. After presenting our AT work at academic conferences, we found that AT was not only a phenomenon essential for intelligence analysis but the underlying cognitive foundation of strategic foresight and risk analysis. We were able to garner more financial support from the IC by pivoting from Smart Cities to focus on concrete problems in clinical care and cybersecurity for AT research. These positive signals perhaps best exemplify what LAS can be—a place where significant gaps in knowledge can be pursued, both at a basic scientific level, and with concurrent, real-world experiments, each approach informing the other.

The AT team composition for 2018 was both specific and strategic. We had learned that LAS needed both cognitive psychologists and AI researchers as our academic partners. We accepted several joint cognitive psychology and AI proposals (Feng and Lester, Magliano and Young, Cardona-Riviera and Davies), along with an individual proposal from Gene Brewer (Arizona State University). As a leader of the AT group, I (Amos-Binks) was inspired by Gene Brewer's insights on counterfactual reasoning and divergent thinking. In order to flesh out these ideas, he and I decided to collaborate on how humans recognize and perceive intention revision in others. Feng and Lester continued research into assessment and adaptive training, while Magliano and Young's efforts focused on how intention dynamics between agents affect our expectations of future behavior. We also were able to work with Jim Davies from Carleton University, whose expertise on the science of imagination proved informative to steps of SATs. Importantly, we endeavored to have at least LAS government staff engaged with each proposal. Although this goal proved to be too aspirational, we did have a major increase in the number of LAS government personnel actively working with industry and academic partners.

Our industry partners also included ARA, and later in the year, the Mayo Clinic. ARA continued development of their Scenario Explorer platform. Most notably, they established and demonstrated an innovative SAT (Smart Query) for analyzing many sets of futures to extract and quantify key indicators and warnings. This exhibited, for the first time, the loop between eliciting and analyzing AT knowledge. They led workshops using Scenario Explorer, connected their work to our other academic performers, and provided access to the platform for us at LAS and for the Mayo Clinic.

I had previously collaborated with the Mayo Clinic on a large-scale graph-analysis research program, for which they had produced some excellent work. Their AT angle was to analyze the clinical decision process of the Mayo Spine Clinic. Clinicians have numerous options for patient diagnosis and treatment, yet the actual options and their second-order consequences are not always apparent. Clinicians were therefore identified as an interesting group of highly trained decision makers to study in terms of their AT.

Another industry partner, SoarTech, had previously developed an analogical reasoning platform that we thought might support AT. We designed an observational study to socialize the AT concept to those who would be using and benefiting from it most, which is an advantage of LAS. SoarTech valued this, insofar as they were willing to invest their own internal research and development efforts to refine their original prototype for the study and receive direct feedback from intelligence analysts. The results of the study have been accepted for the Association for the Advancement of Artificial Intelligence 2019 spring symposium.

Supporting AT with Scenario Explorer from an Industry Perspective

At ARA, we viewed 2018 as both a very productive year for us to push our research with Scenario Explorer forward and to collaborate with a wide range of other multidisciplinary performers. With the new round of performers, there were also some casualties. For example, funding changed for Abigail Browning's group at NC State, so we offered her an internship with ARA to help keep her involved in AT research. She has continued to be a key asset in maintaining strong collaborations within the team. The takeaway here is that although LAS can put together the collaborative teams, the relationships and reputation developed working in them can often outlive the funding.

On the technical front, we continued to improve our software. Particularly, Matt Lyle developed the Scenario Explorer from a simple prototype into a cloud-based system. We also revamped its entire user interface. We developed a new SAT that enabled analysts to extract knowledge from the AT models they developed, in the form of automatically identifying key indicators for clustered sets of futures. While we initially conceived of this outcome back in CI-FSP, there was insufficient knowledge in the earlier models, and it was not clear how the analytic would rank the value of potential indicators. From our perspective, figuring this all out represented a major milestone for AT, because we could now extract real and novel value to the knowledge analysts provided. Additionally, indicators and warnings are well established in the IC, so demonstrating how AT supported the automated generation of useful indicators bridged the basic research with current tradecraft.

Additionally, we worked closely with AT researchers developing the metrics and training aspects. Together, we looked at how they had designed their assessment instrument, and how aspects related (or didn't relate) to characteristics of the data model underlying Scenario Explorer. We coordinated to design an experiment that could help link these views of AT together. We also worked to identify points of integration for training and targeted recommendations. Our plans for the future call for both translation of our platform to the IC and further enabling it to be leveraged for AT research. We are particularly excited about integrating the metrics and training for improved AT capability that LAS performers have studied over the past few years. Not only do we see the opportunity for Scenario Explorer to become a tool for better decision making, it also may serve as a training and research platform to observe the ways that experts engage in future thinking.

As we made progress in our experiments and observational studies, more insights about AT began to emerge, particularly those tied to our original mandate of reinventing intelligence analysis. Specifically, in risk assessment, we learned that AT must be evaluated irrespective of the actual outcome. Like AT, insurance is still viewed as a good investment, even if it is never needed. Rigorous and systematic AT could change the way we prepare for and prevent surprise in the future. The progress we made in 2018 helped close the gap of assessing AT through experiments, while observational study provided the inspiration to engage a broader community of scientists and practitioners.

Impact and Implications for the AT Project at LAS: A Five-Year Summary

Over five years, LAS gave us the intellectual flexibility and resources to identify, define, assess, and then create tools, techniques, and training platforms for anticipatory thinking. The AT program followed typical social science investigations from a definition of intelligence analysis that was generally agreed upon (by both academics and professionals, in our case). First, we developed the AT concept as a combination of creativity, divergent thinking, and anticipation. Second, we developed an operationalized definition. Lastly, we developed variables we could measure in the AT assessment.

Importantly, although our research into AT is starting to show tangible benefits in the form of a converging research community, a platform to provide imagination support, and a strong theoretical basis, there is still much to be done. We were asked to "reinvent intelligence analysis." In our pursuit of this goal, we succeeded in opening a rich new research area that is of interest to the IC community. As our teams of government, academic, and industry researchers continue to reinvent intelligence analysis, we anticipate increased attention on avoiding surprise.

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8

AGENT-BASED MODELING OF ILLICIT NETWORKS AND CONFLICT ECONOMIES

CONOR M. ARTMAN, ZHEN LI, ERIC B. LABER, and ROB JOHNSTON

The social sciences deal with massively entangled, co-occurring phenomena. No progress could be made if sociologists needed a perfect model of the economy before proceeding, or if economists needed perfect models of cognition before abstracting to macroeconomies. Consequently, our team prioritized projects that would improve communication between content specialists and computational specialists.

–Quoted from Invitation to 2016 LAS Symposium

CHAPTER 8

KEY TERMS

- **Agent**: Individual or collective entities taken to be the smallest autonomous unit of interest in an agent-based modeling simulation.
- **Agent-based models:** a computational model for simulating interactions of multiple autonomous agents within a predefined environment to generate or predict complex relationships.
- **Application programming interface (API):** A system of tools and resources to facilitate software development.
- **Illicit networks:** Any collection of individuals coordinating to produce illicit or illegal goods or services.
- **Inverse reinforcement learning:** A set of techniques for deducing the rules governing an agent's behavior over a sequence of choices.

KEY POINTS

Program: Easy and flexible access to related working groups can provide essential insight into methodological development. Program leaders can create opportunities for cross-team communication and make information about teams available to all Lab members.

Team: Forming a team with content area specialists, technical specialists, and bridge members who can translate across members makes for efficient communication. Multidisciplinary collaborations focused equally on project deliverables and establishing common language across different areas of expertise pays high dividends in rapid research progress. Dividing working meetings into technical meetings and full group meetings productively optimizes the team's meeting time.

Individual: Individual team members such as modelers and content specialists see the utility of using ABMs based on their field's methodological training, Fruitful discussions about these differences opened their eyes to new ways to use ABMs while giving us a clearer picture for how they wanted to answer their research questions.

Modeling the complexity of human decision making and group behavior is inherently a difficult and interdisciplinary task. Understanding and describing human behavior crosses multiple disciplines from anthropology, cognitive science, economics, political science, psychology, and other social sciences. Modeling those behaviors requires computational statistics, computer science, and mathematics.

A large part of undertaking a task like this is developing a core interdisciplinary team that can speak and understand one another's professional jargon and come to a shared mental model of the work as well as a common language for the shared effort. Developing a simulation platform for a highly complex modeling environment to accommodate the scale of human behavior and decision making has led the team to the creation of an "OpenABM gym": a platform, or environment, wherein social scientists from any discipline can begin to run simulations to test and explore extant theories—an environment in which these simulations can result in new theory building.

Problem Definition: Illicit Networks

Illicit networks—from sex trafficking to arms trade to drug cartels—offer a uniquely difficult challenge for traditional methods of empirical study. Actors within illicit networks are unlikely to provide reliable data on their operations, and systematic study by outside investigators is generally not feasible. Intelligence analysts, researchers, and policymakers are therefore limited in their ability to construct evidence-based, data-driven, predictive models or decision support tools.

Ideally, analysts could design experiments to learn causal relationships between illicit network behavior and experimental factors (i.e., policing strategies or legislation). In general, it is impractical to run experiments on illicit networks. Analysts cannot generally track or measure illicit network behaviors, and they usually have no reliable way to isolate or manipulate the right experimental factors. Additionally, results from these experiments could not be replicated. Illicit networks are non-stationary and heterogeneous, so exposing a network to an experimental manipulation can cause it to become unresponsive to future manipulations, and results from one network need not replicate in another. Experiments on illicit networks can also have catastrophic unintended consequences. For example, a state-specific policy that is harsh on one drug might cause a spike in the use of another more harmful drug, further causing a downstream increase in drug-related deaths (Fishburne 1993). Consequently, the limited data that are available for illicit networks must be augmented by scientific theory to make progress.

When experimentation is not possible or not feasible, high-fidelity simulators are a standard tool for studying complex phenomena (Heermann 1990). Agent-based models (ABMs) can be used to build high-fidelity simulations for topics of study that have constraints similar to illicit networks. In particular, ABMs rely on a framework informed by scientific theory, allowing other rich sources of information (i.e., expert knowledge) to guide the construction of the simulator. Analysts can then calibrate ABM simulations to suitable data to explore conditions similar to those in the real world.

ABMs simulate the interactions of multiple autonomous actors within an environment for the purpose of studying emergent macroscopic patterns. ABMs are comprised of a set of agents, a set of behavioral rules for guiding and optimizing behavior, and an environment in which the agents operate. An *agent* is generally the smallest autonomous actor in a simulation (e.g., a cubic foot of gas in a weather simulation, a person purchasing goods in a macroeconomy, an ant foraging for its hive). Agent behavior can be static (e.g., follow a fixed set of if-then logical rules) or dynamic (e.g., each agent follows an internal utility function it attempts to maximize). The environment encodes system dynamics that specify if, how, when, and to what effect individual agents can interact with each other and with other objects in the environment.

ABMs have been used in several domains related to illicit network studies: Tesfatsion and Judd (2006) applied ABMs to study economic systems. Reis, Melo, Coelho, and Furtado (2006) created an artificial environment using ABMs and simulated the influence of different police patrol routes on crime rates through genetic algorithms. Groff (2007) built an agent-based model for testing variations on a common baseline model of crime called Routine Activity Theory (see below, Innovating Agent-Based Models for Intelligence: The Bottom-Up Approach). And Gerritsen (2015) applied ABMs to the study of the bystander effect (see also Gerritsen 2010; Liu and Eck 2008; Liu, Wang, Eck, and Liang 2005; Van Baal 2004).

Because ABMs can be made as complex as warranted by the problem under study, analysts need methods for clearly understanding when their simulation results are reliable. Unfortunately, guidelines and protocols for screening ABMs vary from field to field. Additionally, there are no general standards for producing high-quality ABMs. ABMs can be computationally expensive to develop, and once developed, the code and computational resources needed to analyze their data can be greater than the resources and code it took to develop the ABMs.

The lack of formal standards for ABMs also makes them difficult to reproduce. Two competing models may have significantly different agents, behavioral rules, environments, and starting conditions, but they may produce qualitatively similar results. In cases like these, analysts struggle to distinguish between models, because they do not have access to other researchers' code for comparison, nor do they have unified metrics for comparing the models. Finally, the level of coding skills required to handle complex ABMs can be a high barrier to entry for using them. When analysts do not have the time or skills to code complex ABMs, they may rely on software that makes running them easier. Popular platforms include NetLogo (Wilensky 1999), Repast (North et al. 2013), and MASON (Luke, Cioffi-Revilla, Panait, Sullivan, and Balan 2005). Masad and Kazil (2015) established a Python package called Mesa that provides various tools to build an ABM flexibly, and demonstrated the benefits of writing it in Python, in contrast to traditional ABM tools. Depending on the choice of platform and the goal of the ABM, some ABM software can constrain the complexity of the model. This can effectively reduce the model to a "toy" version of its original form, and may render it useless for studying complex phenomena.

Complex ABMs require interdisciplinary teams. Content specialists, such as anthropologists, economists, sociologists, and psychologists, contribute by addressing multiplex components of the larger problem. Because each field holds its own collection of problems and solutions, it is rare for one person to be knowledgeable enough to synthesize and operationalize so many theories into high-level machine code. Computational specialists, such as statisticians and computer scientists, contribute by assessing the best ways to translate rich and nuanced theories into statistical models and computer code; this requires effective communication. Experts rely on their field's communicative norms and background knowledge for fast and exact communication, so communicating between fields without any machinery can be slow and imprecise. As an example, economists refer to a specific market incentive and risk structure when talking about "moral hazard," but a psychologist may interpret this phrase as "situations that threaten an individual's moral identity." Translating theoretical ideas into code can be equally erroneous and misleading. Unless the content specialists have enough background to understand the code, the team may run their simulations and never understand why it produces poor results. Consequently, the theory rather than the coding error may be dismissed as "inconclusive"; or possibly worse, the coding error may produce strong-looking results that have no bearing on reality.

Under this motivation, avoiding this type of error was a top priority for the team. Finding a way to ensure that the social scientists and computational statisticians had a shared mental model required unpacking each theoretical concept and identifying its underlying hypothesis. This took the form of detailed regular meetings to describe individual elements of the theory and find ways to make those elements computational. Ideally, the team would have a fully functional interdisciplinary, or transdisciplinary, set of tools for translating academic concepts, such as a Unified Modeling Language (UML) diagram in computer science (see below, Innovating Agent-Based Models for Intelligence: The Bottom-Up Approach). In the absence of such a tool for this level of complexity, the team undertook an effort to create one for the OpenABM gym.

We propose an open-source benchmarking platform called OpenABM Gym (in homage to OpenAI Gym in the reinforcement learning community).[1] OpenABM Gym is a Python-based, plug-and-play framework for ABMs that would provide common environments for testing and comparing ABMs. Making a plug-and-play platform would allow researchers to design ABMs faster and without loss of complexity. Giving researchers an application programming interface (API) for tools made to analyze ABMs can improve the quality of ABMs. Using commonly accessible environments provides researchers with the same starting place, allowing for direct comparison between ABMs in shared environments. Open-sourcing the code allows the broader research community to compare code between ABMs while also allowing other researchers to improve the existing tools and libraries. Together, these improvements can help make complex ABMs more reproducible, comparable, and transparent.

Communication across ABM and Domain Specialties

Our group had the following goals: to design a repository of agent-based modeling environments that social science researchers could pull from or contribute to, to provide an API for social science ABMs that would allow

[1] OpenAI Gym is an online repository for reinforcement learning environments. It provides a common set of environments in which researchers can experiment with new algorithm and tracks the performance of these algorithms in commonly shared environments. One example environment is the "cart-pole" task, a simple task in which a learning algorithm attempts to balance a pole sitting on a cart in order to keep it from falling over, by moving the cart left and right. After a researcher downloads this environment and tests out their new algorithm on the cart-pole task, they may post its performance on cart-pole leaderboards for direct comparison between algorithms.

for flexible yet quick creation of ABMs, and to develop tools for improving the comparability in ABMs. Owing to the breadth of our goals, we needed team members whose backgrounds and experiences spanned numerous areas of expertise. Two government personnel, a statistics faculty member, three statistics graduate students, and one NC State staff member comprised our core team. Importantly, half of our team had complementary proficiencies apart from their disciplinary fields. These members acted in part as "bridge" members of the team, who often facilitated discussion between content specialists, practitioners, and researchers. Together, our team's specialties spanned anthropology, economics, psychology, machine learning, high-performance computing, statistics, and intelligence work in government (such as the NSA, FBI, and NASA). With adequately broad backgrounds suited to our project, and with members who could aid in communication between content specialties, our team focused on eliminating inefficiencies in our collaboration process.

From the outset, to set goals and monitor our progress, our team recognized that we needed a way to discuss software development and domain-specific social science theories while assessing results. We arranged two weekly meetings: one to discuss implementation (e.g., code, computation, and development) and one to discuss operationalization (e.g., normative descriptions for our product's output, discussion of simulation results, and translating verbal-linguistic theory into code). This allowed us to prioritize and flag discussion points for one meeting or the other, which made for more efficient generation of ideas and communication of problems. Additionally, we recognized that the audience for our product consisted of teams similar to our own, so that the tools for our meetings could translate to how we should construct our ABM platform. For example, Rob Johnston holds a doctorate in anthropology, worked with NASA during his degree, and worked in the intelligence community after earning his doctorate, which helped us better translate theoretical assertions into code and understand how government personnel would use our platform.

A team with such diverse proficiencies ensured two things: first, that no topic or idea would be couched solely in one content specialist's domain; and second, that when we found a topic that was hard to communicate across the team, we were able to rely on the secondary proficiencies of our "bridge" members in order to identify exactly why friction existed in communicating the concept. Each week, we reviewed the output of our previous week's goal, discussed issues around implementation and operationalization, and set next week's goal. During phases focusing on software development, this entailed high-level changes in the software's architecture, challenges associated with those changes, and interpreting social science theories in terms of code logic for creating true-to-theory implementations. After software development, each week's meeting focused on a succinct presentation of proofs of concept (e.g., simulation results); we used these meetings as opportunities to compare the expectations and needs of content specialists with the software we produced and as brainstorming sessions for further software development needs. Our goal was to build the minimum viable working example of that week's target, show output, and iterate. As we iterated, in operationalization meetings, we would focus on how to improve or generalize our minimum viable example in the next iteration. Finally, once we were satisfied with the stage we were working on, we would repeat the process for the next stage of development.

While collaborating with domain specialists, we noticed a massive inefficiency in communication between ABM specialists and domain specialists. ABM specialists need precise rules and logic for developing code for a domain specialist's question, while domain specialists have theories, rules, or hypotheses which may only exist as qualitative assertions (e.g., "When X happens, Y should increase/decrease" or "All else constant, A should be more prevalent than B"). Consequently, collaborators can become stuck in circular discussions around establishing terminology and common language, usually in a free-form and largely undirected way. The modeler then must learn what *exactly* the specialist has in mind for their auxiliary or environmental variables for hypothetical phrases such as "all else equal." For instance, many social science theories do not assert what constitutes a meaningful unit of time: Are we looking over a scale of seconds? Days? Years? And if so, how many actions, decisions, or consequences should happen per unit of time? What should the order of decisions be? On the other hand, content specialists *rightfully* do not think about such details; their theories are tailored to a carefully narrowed line of questioning meant to provide the clearest possible conditions for observing their phenomenon of interest. The social sciences deal with massively entangled, co-occurring phenomena. No progress could be made if sociologists needed a perfect model of the economy before proceeding or if economists needed perfect models of cognition before abstracting to macroeconomies. Consequently, our team prioritized projects that would improve communication between content specialists and computational specialists (see the next section for more details).

Aside from improving our team's efficiency, prioritization of multidisciplinary communication motivated new directions in our research. After noticing common methods for describing social science theories, we sought to integrate our observations into a principled and precise process. Concurrently, one thrust of our research involved developing methods for multi-agent optimization and reinforcement learning in ABMs, as well as making these methods accessible to social science content specialists who might not have seen these methods previously. Because of the integrated structure of the teams at LAS (i.e., government personnel, faculty, and LAS staff), we were able to quickly survey content specialists and assess our observations on norms for expressing ideas in social sciences (e.g., political scientists, forensic psychologists, anthropologists, and economists). In tandem, we could take critiques from social scientists and bring them to industry and government practitioners in order to further develop which of these ideas and observations were the most accurate and useful to people who needed to both understand and apply social science theories. We took our insights back to our software and theoretical development and were able to improve on it until we found a workable direction for a novel method that suited the intersection of needs among social scientists and government personnel.

Innovating Agent-Based Models for Intelligence: The Bottom-Up Approach

Previously, researchers had approached building complex ABMs by taking a "top-down" approach, in which researchers posited a working model of ABM structures and tried to apply it to produce insights about ABMs. In contrast, we work from a "bottom-up" approach, in which we start with simple cases— develop software, frameworks, and communication tools— and make progress by repeating this process in harder cases. By building from simpler to more complex applications, we could observe the gap between current analytical methodology and content specialists' needs. This approach let us gauge content specialists' needs for different levels of sophistication in ABMs while finding workhorse models that content specialists and government personnel have found useful.

We chose to start with simple applications grounded in criminology and sociology. Theories in criminology and sociology motivate hypotheses for illicit network behaviors, and both fields have workhorse models that have been closely studied using ABMs (Anderton and Carter 2009; Block 1983; Griffin 2003; Humphreys 2003; McIllwain 1998; Potter 1994). This gave us benchmarks for comparing our ABMs to those of the criminology and sociology literature, so we could run simulation experiments on our ABMs while providing relevant use cases for illicit network applications. We chose Routine Activities Theory (RAT) for our first example. RAT asserts that a class of routine activities (e.g., street robbery) is characterized by a suitable target, a likely offender, and the absence of guardians (Cohen and Felson

2016). It also asserts that in order to prevent crime, the absence of one of these conditions is sufficient. Broken Windows Theory (BWT) posits that making an environment less appealing for lesser crimes (e.g., vandalism, selling cigarettes without a license) should cause a decline in the prevalence of serious crimes (e.g., murder, rape, trafficking) (Wilson and Kelling 1982). We chose BWT as our second example because it provides a natural transition from a broader, simpler theory to one with additional complexity (while still maintaining relevance to the interests of government personnel).

Although simple to describe, RAT is difficult to code because of how broad it is. It does not specify the types of crimes it deals with, characteristics of the actors in its model, or exactly how crime should change if you remove one of its three components; so many different descriptions can count as a RAT model. This situation is common for ABMs. For instance, many social science theories do not have a precise time component, so it is unclear what constitutes a meaningful time step in the simulation. Similarly, many social science theories do not posit a utility function or a criterion for updating an agent's utility over time. It is also common for social science theories to rely on observable proxy measures (e.g., money) or unobservable measures (e.g., happiness). In all of these cases, social scientists must work closely with the code developer to translate between the original theory and the simulation code.

This process pushed our team to prioritize methods for improving communication between social scientists and computational specialists. In doing so, we generated simulation experiments that addressed social scientists' needs. For example, we found that simply tweaking the starting locations of agents, under the right conditions, could produce complex-looking shepherding behaviors in which police agents seemed to corral and protect civilian agents from criminal agents, when in reality this behavior was unrelated to any theory guiding the ABM. So, by choosing a broad initial theory to start with, we were pushed to find ways to communicate nuanced ideas between fields, which led us to design experiments that informed high-fidelity simulations.

Motivated by this process, we started a second communications-focused project inspired by Unified Modeling Language (UML) diagrams in computer science. UML diagrams visually map the dependencies, components, and core functionality of a piece of software without requiring the observer to pore over thousands of lines of code to understand it. In this way, UML diagrams allow software developers to critique and discuss software at a higher level without making the team read and understand every piece of code. We applied the idea of UML diagrams to create a series of documents to help facilitate communication and to serve as scaffolding for discussing how theory should be converted to code. We interviewed other LAS working groups and content specialists in marketing, political science, computer science, and forensic psychology about their field's research needs. Through these interviews, we found fundamental insights for how content specialists and modelers should interact in order to productively identify whether ABMs are relevant to their problem, and if so, in what ways ABMs could be applied to their needs. We found that most content specialists' views of ABMs were strongly influenced by their field's methodological training. For example, specialists working in fields that rely heavily on generating data in the wild or in lab experiments viewed ABMs mostly as a tool for thought experiments. Fields that rely on mathematically grounded theories—but which were fundamentally constrained by their ability to collect data—viewed ABMs as a way to generate synthetic data. Although both fields were right to use ABMs in these ways, they were also unaware of at least a dozen other ways they could be used productively (Epstein 2008). This proved to be a fruitful point of discussion in meetings with content specialists, as it opened up potential research directions they could take while giving us a clearer picture of how they wanted to answer their research questions.

We synthesized our observations into a "UML template," a survey document that walks content specialists through their own theory to see if their project comports with ABMs, and if so, how to precisely express their ideas in a way that a computational specialist can understand. Providing the UML template before meetings with content specialists expedites the collaborative process, clearly identifies gaps in understanding between collaborators, and quickly segues collaborators into operationalizing theory into code. Computational specialists also gained a better understanding of what analyses content specialists needed. By having a structured way to critique the ABM, our team quickly improved default analyses (Figure 8.1) to match what our government personnel NC State staff said they needed (Figure 8.2).

Our new tools provided scaffolding for our team's next steps. With social scientists, government personnel, and computational specialists communicating clearly, social scientists were able to provide theories germane to the practical interests of government personnel. After developing the RAT ABM and basic accompanying software, we moved to BWT. As mentioned, BWT builds naturally on top of RAT and BWT is a common baseline model for simulation studies. In addition, some debate still exists regarding BWT, which provides an academic motivation for exploring our simulation. As described above, Wilson's theory (BWT) posits that making an environment less appealing for lesser crimes (e.g., vandalism, selling cigarettes without a license) should cause a decline in the prevalence of serious crimes (e.g., murder, rape, trafficking) (Wilson and Kelling 1982). Yet Wilson's theory does not explicitly assert *why* serious crimes should decline (Harcourt and Ludwig 2006). Serious crimes could decrease because citizens become empowered to change their neighborhood when petty crimes drop, because it discourages criminal behavior generally, or because recidivism for low-level crime is less likely than for high-level crime, or even because halting petty crime causes a generational break between escalating crimes. Alternatively, the economist Paul Krugman (2011) asserts that stopping lower-level crimes only shuffles crimes from one area of a city to another, with no real effect on overall criminal behavior. (Of course, the third option is that neither of these perspectives is correct.) Comparing these hypotheses suits ABMs well: to justify one theory or the other, one must take into account concepts that are dealt with in abstractions rather than according to data in existing models. Moreover, these hypotheses are similar to the types of hypotheses analysts must work with in illicit network studies.

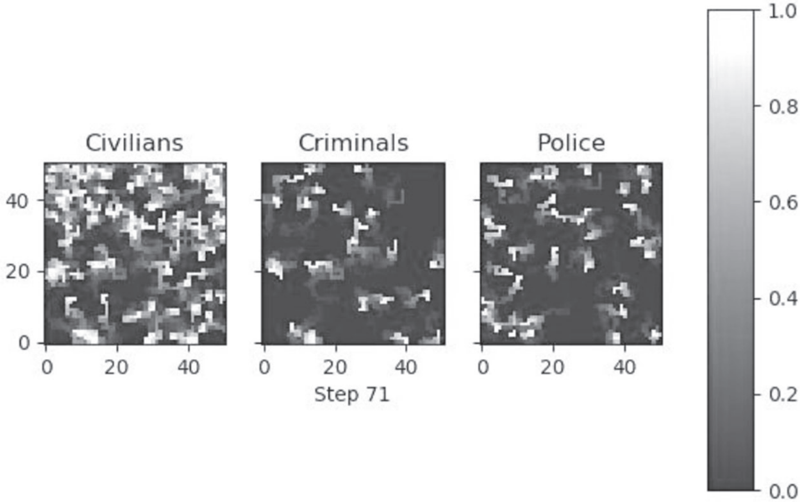

Figure 8.1: Initial style of output for watching agent behavior in Routine Activity Theory example.
Each square represents all locations an agent can move to in an environment; this output is supposed to let the user view the most recent locations by the "type" of agent (e.g., "Police"). In this output version, users can only view snapshots of agent movement (indicated per "Step" below), and it is hard to glean average agent location.

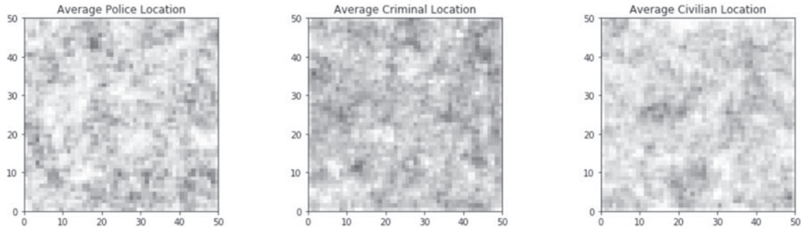

Figure 8.2: Updated heat maps for summarizing agent movements in RAT example after feedback from specialists.
We primarily changed the color scheme to be easier to read (here only shown in grayscale) and changed the normalization of the heatmap so that users could see darker and lighter regions easier (darker regions correspond to more frequently traveled regions in the map). We also relabeled the plots to reflect that these agent locations are aggregated over the simulation and separated by agent type.

To demonstrate the practical potential of agent-based modeling for the IC, we present an abridged description of our results for the BWT simulation. One set of simulations addressed the average crime rate in a simulated city as a function of recidivism (Figure 8.3). Recidivism rates followed a time-to-failure model that generated the probability of an agent committing a crime *after* they had been arrested at least once.[2] If the probability of recidivism was higher than a certain threshold, criminals would relapse; otherwise, they would transition to behaving like a law-abiding civilian. In support of Wilson's theories, we observed that if the rate of new criminal entry is lower than that of criminals renouncing crime, then stopping lower-level crimes causes a drop in the overall crime rate.

Although more detail and analysis are necessary before drawing any conclusions, we suggest how an analyst could use these results by treating the simulation as a sufficiency condition. If one observes emergent behavior during the simulation, then one might conclude that the conditions in the model are at *least* sufficient for generating the macroscopic patterns of interest (for more details on this logic, see Epstein 2006; 2008; Axtell and Epstein 1994). So, if an analyst were investigating BWT, the simulation would suggest what kinds of conditions might be sufficient for observing

[2] A time-to-failure model estimates the probability of an event or a "failure," given a set of independent variables that influence the time to an event (i.e., the probability of someone being arrested again, given the characteristics of that person; or, the probability of a lightbulb going out, given its type and energy consumption). We apply a time-to-failure model called a Weibull model, using parameters suggested by Broadhurst's study of re-arrest probabilities (Broadhurst and Loh 1995, 289-313).

the same phenomena in reality. Generally, there are many ways to choose covariates and models for a particular hypothesis, but by operationalizing a theory into an ABM, analysts formally incorporate their theoretical beliefs into the ABM. Accordingly, for all simulations that yield similar macroscopic behavior, analysts have a set of suggestions for the conditions that may be sufficient for observing their phenomenon in real life, the covariates they could focus on, and possible trajectories of outcomes for the systems they observe.

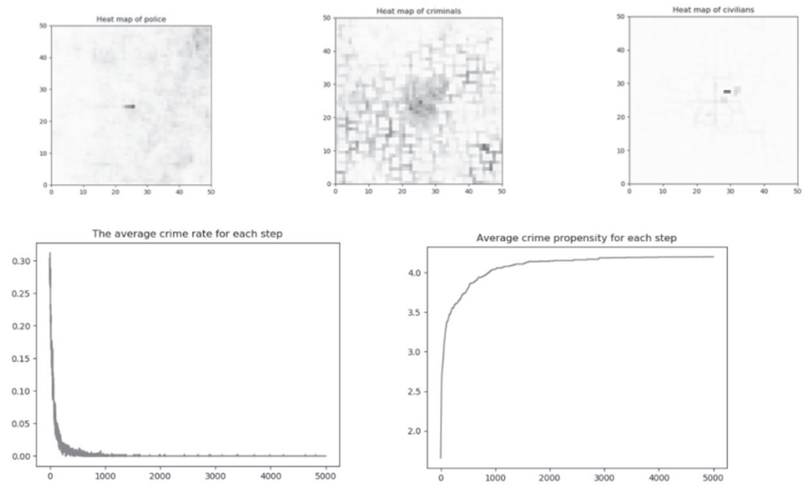

Figure 8.3: Top: Heat maps for movement across our simulated city environment for civilians, criminals, and police. Bottom: Average crime and average crime propensity of criminals per time step. From Figure 8.2 to Figure 8.3, we tailored the standard output of our simulations to reflect the common checks specialists perform after running their simulations. At the top, we have heat maps that reflect an urban city structure and the average location of an agent by type of agent. At the bottom, we have the average crime rate per step in the simulation, and another metric called "crime propensity," also reported per step in the simulation.

Limitations of ABMs

While our work provides a first step toward better standards in complex ABMs, many interesting open problems remain. Large ABMs can be computationally expensive, and few frameworks offer scalable solutions (e.g., built-in GPU compatibility). Workflows for planning and analyzing ABMs still remain costly for organizations, as compared to other forms of analysis, making ABMs a niche method reserved for particularly complex modeling scenarios. Consequently, analysts commonly let the constraints of their ABM dictate their analysis. Being unable to capture and fully utilize the rich structure in an ABM usually defeats the purpose of constructing one. In particular, academics and intelligence analysts alike have expressed a need for new analytical tools that could work with ABMs in the same way that standard statistical tests work for routine data analyses (e.g., t-tests or z-tests for comparing two normally distributed samples). Otherwise, the onus is on the analyst to select what analyses are appropriate. Analytical approaches for an ABM range from descriptive statistics to complex time series analyses, and would effectively require statistical expertise. This expectation is unrealistic, given that a single analyst must also be knowledgeable enough to navigate the content specialties guiding their ABM.

Methods for analyzing an ABM as its own class could lead to standards for screening and assessing ABMs, as the analytical tools could give some baseline measure for comparison for ABM performance. As an example, our group is pursuing methods that incorporate reinforcement learning (RL) into ABMs. By borrowing the RL literature's notational conventions, we can precisely describe ABMs in mathematical notation. RL is flexible enough for guiding agent-level behavior, as it has been applied to decision-making scenarios from video game agents, to chess-playing robots, and even to decision-support systems in medicine (Barto, Thomas, and Sutton 1998). Taking this idea as motivation, our statistics and machine-learning members noticed that the many research hypotheses can be expressed as statements about optimal behaviors in a simulation; such decision rules are formalized as policies in RL. This dovetails with ongoing research in RL that seeks to find optimal policies (or choices) for groups of autonomous agents, rather than for individual agents. Once complete, our methodology will allow content specialists to express their hypotheses in terms of policies, find individual- or group-based optimal policies for agents, and construct hypothesis tests based on those data. For instance, we can observe which hypothesis (expressed as a policy) comes closest to an optimal policy for an agent's or group's decision making, or find an optimal policy, and then see how perturbations in an ABM lead to deviations from that policy. Further, this method will also allow researchers to observe optimal policies for adversarial decision making between groups, which could in turn allow government personnel involved in security or intelligence work to better anticipate possible actions from criminal networks.

Conclusion

With a basic framework and API in progress, our team will continue developing environments in a process similar to the one described above. This will let us iterate our API by finding out more needs that analysts, modelers, and academics face. Simultaneously, we plan to add each completed environment to our initial release of the OpenABM Gym. Another direction for future work lies in calibrating ABMs to real-world data and extracting optimal policies from the ABM through a technique called "inverse reinforcement learning" (Abbeel and Ng 2004). By working with groups internal and external to LAS, we will be able to get real-world data on conflict economies, calibrate an ABM's parameters to those data, and provide methods for simulating contingency scenarios that will allow analysts to make critical forecasts for threat assessment. Through our interdisciplinary collaborations with social scientists, government personnel, academics, and NC State staff, our project helps bridge longstanding gaps in analytical processes and methodology between government analysts, social scientists, and AI researchers. In taking full advantage of the collaborative structure among our team members and others at LAS, our work has the potential to improve computational social science research by creating a common system for evaluating, replicating, and developing new methodologies for complex agent-based models.

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9

LEARNING FROM ONE ANOTHER

JOANN KEYTON, PAUL JONES,
and CHRIS ARGENTA

In other words, despite significant technological advances and solving a formidable puzzle, it was the collaboration itself that proved to be the thing of most value here.

–Joann Keyton

CHAPTER 9

KEY TERMS

- **Black Box**: In science, computing, and engineering, a black box is a device, system or object which can be viewed in terms of its inputs and outputs without any knowledge of its internal workings. Social scientists often use this term to refer to conversations for which researchers cannot predict what communicators will say, how they will say it, or what the result will be.
- **Dwell Times**: The length of time that a user spends on a page.
- **Microsoft Kinect Sensors**: a line of motion sensing input devices that was produced by Microsoft for Xbox 360 and Xbox One video game consoles and Microsoft Windows PCs.
- **Test Captures**: Pre-deployment activities of hardware and software to ensure that the audio/video capture meets the need of the research objective.

KEY POINTS

Program: Leadership must communicate that failure is an acceptable outcome of collaboration.

Collaboration membership may change over time, especially when the collaboration task goals change.

Team: Technology can be an initial catalyst for a collaboration, and it can be used as the common touch point for collaborators from disparate disciplines.

Relationships matter: Collaborators must feel comfortable with one another to offer new ideas, and to work in new ways.

While email is useful for keeping team members up to date, it is a poor channel for providing detailed explanations and developing detailed knowledge in others' disciplines.

Individual: Working with a discipline other than your own can be uncomfortable, but also challenging and enriching.

Interdisciplinary collaboration starts with a common problem—and flourishes when all parties can contribute uniquely to the solution. Without unique perspectives that converge toward problem solving, the problem remains, well, a problem. This chapter presents two short cases that illustrate interdisciplinary collaboration between communication and computer science.

In both cases, the computer science collaborator needed to develop software or programming to collect data the communication collaborator could empirically evaluate for publication. In our situation, the types of data collection were new to communication; likewise, the types of data analyses were new to computer science. Without each other, each had a unique problem. But together, the team members could integrate their disciplinary knowledge to solve a puzzle.

Case 1: Communication Is Introduced to Computer Science and Big Data Collection

In one of the regularly facilitated meetings of NC State faculty and government personnel, Keyton (communication faculty) and Jones (government researcher) found common ground about how to design more advanced experiments to elevate what counts as data, as well as how those types of data might be analyzed. Working with the underlying premise that communication is comprised of symbols, messages, and meanings, Keyton was comfortable with traditional quantitative methods of data collection and analysis (e.g., online surveys, audio recordings of group discussion for transcription and analysis) but recognized that what happened before and after group discussion might reveal how and why group members make certain arguments in group discussion. While Keyton and other social scientists have opened up the black box of discussion by studying what discussants say (and how they say it), much less is known about what influences or shapes the ideas discussants reveal in their interaction with one another.

As Keyton explained and explored the experiment with Jones, Jones offered that he (with help from other government personnel) could create a PC-based program that would capture (a) every URL the participants visited during their search time and the time spent on each page; and (b) a screen image every 10 seconds (or each time the return key or left mouse button was pressed). These types of data are unprecedented in social science, as they create an interdependence between faculty and government as well as between social science and computer science. Over time, the team evolved to include other government and university personnel. About 10 individuals worked in pairs or small groups to create and test the different forms of data collection. In these arrangements, members from each side were customers of the other, as social scientists were driving the need for data collection and computer scientists were driving the development of new data collection tools.

While team members' goals were already integrated, we enhanced our collaboration by meeting regularly and consistently to listen to and learn from one another. At times, Keyton gave tutorials on social science data collection and how data are quantitatively analyzed. At other times, Jones and other government personnel gave Keyton and her team members tutorials on the type of data the new data collection tools could produce.

In addition to Keyton and Jones, other team members came in and out of the project as needed. Often, other computer scientists stood in for Jones while he attended to other duties. Many times, we recognized just how rigorous and eye opening our conversations were; in many ways, our discussions were like doctoral lab sessions. Both sets of knowledge and motivations were necessary to ultimately put the new data gathering techniques into action. Because we were working against the deadlines imposed by funding, our pace was sometimes hectic but never frantic. On the first day of data collection, everyone was on hand to help, debug, or assist in any way they could. As a result, the first data collection session produced data as expected.

With data collection ongoing for several months, a turning point in the team's activities developed. Not only did we need to continually monitor the equipment and the resulting data; we also needed to figure out how to analyze the data. At this point, the central competing values of the two disciplines became very evident. As a practice, social scientists do not collect data they cannot analyze. Conversely, computer scientists tend to be technology driven and may collect data without any clear vision of its subsequent analysis.

At this point, the hard work began and several issues needed to be solved. For the nearly 200,000 URLs captured, how should the data be presented for social science analyses? What kind of coding scheme should be developed to identify URL types? To answer the latter question, we developed a coding scheme for the URLs that related to what task participants were asked to do and we calculated website dwell times for each coding category. These data and results were presented at a social science conference (Keyton, Harned, Jones, Streck and Schill 2016), and later published (Keyton, Harned, Jones, Streck and Schill 2018). For the screen images, the question then (as now) remained: What should we do with them? Jones provided the lead, studying how evidence from web pages was used to justify claims in a piece of writing, which resulted in a conference presentation (Jones et al. 2017). Even at this stage, we had disciplinary standards to balance. For example, most social scientists first present their theoretical essay or empirical manuscript at a conference, and *then* work towards publication in a scholarly journal. After all, journal articles are what "count" for social scientists. Alternatively, conference papers are what "count" for computer scientists. Across social science and computer science disciplines, conference papers are evaluated and are given a public presentation, but what ultimately counts is different for these two groups of scholars.

In the course of this project, Keyton and Jones sent and received over 600 email messages. These were in addition to the hundreds of emails exchanged with other government employees and more than 50 meetings. We found that email kept us up to date on what we all were doing, but it was a poor channel for providing detailed explanations and developing detailed knowledge in others' disciplines.

Despite the number of meetings, Keyton did not mind attending the meetings. As a team, we remained positive, friendly, and helpful to one another. Meetings allowed the "I got it!" moments to occur. Keyton even looked forward to these meetings: the other members were friendly, and often funny; the conversation resolved data collection or data analysis problems; and Keyton left most of these meetings with new information or knowledge. There was no formal structure to them; most consisted of only two to four people. However, we believe this informality helped us learn from one another and encouraged us all to feel equal yet different.

As a team, we had idealized a large problem space; we ultimately came to understand that every success—even the little ones—helped us gain momentum toward our goals. In essence, we saw few problems as failures, as we were able to leverage and learn from them. Ultimately, the team succeeded in capturing and analyzing URLs; and the team is still working on the second problem of analyzing screen shots. Both URLs and screen shots are types of data important to the IC as well as to analysts across many domains.[1]

[1] Data collected from this project are described and can be requested for analysis at https://sites.google.com/ncsu.edu/cic/home.

Case 2: Computer Science Creates a New Type of Data for Communication Analysis

Technology is improving at a fast pace, yet many social scientists have failed to leverage these new opportunities for studying human behavior. As a Communication scholar, Keyton studies how groups and team members interact. The standard procedure is to audio record, and sometimes video record, group members interacting. Audio recording has become more sophisticated with the use of digital recording techniques (e.g., lapel mics capturing each person on a single track, software to integrate the tracks), but video recording remains technologically static. Video recording a group's interactions for communication analysis is typically done in one of two ways. In the first method, the group, seated around a table, interacts, while one video camera captures the interaction from a distance, thus allowing all group members to appear in the visual field. The resultant video is similar to viewing the group's interaction at some distance, as if they were actors in a situation comedy. This also places group members in an unnatural communication setting. Team members talk to one another, not to an audience; views of interactions are thus frequently blocked, because there often is not a single, fixed perspective from which every interaction can be observed directly or seen in any great detail.

In the second method, multiple cameras are used. A camera is trained on the face of each group member. This results in four faces looking at the camera, usually spaced equally in a four-block square. This approach is good at creating close-up views of individual faces, but it misses nonverbal bodily cues and obscures who is talking to whom. Both methods of video recording have distinct disadvantages for communication analyses and represent an ongoing research dilemma.

One day, in a LAS meeting, a technical director asked, "What do you need to do your research better?" Responding to that question stimulated a collaboration among Keyton, government employees, and computer science students. The team identified an alternative approach to video recording that used multiple Microsoft Kinect sensors to capture different perspectives of the scene in real time. These sensors would capture 3D points from different directions and combine them into a 3D point cloud (see Figure 9.1). The resulting data could be played back as video, while allowing the viewer to change their perspective and move "within" the scene. There were plenty of examples of capturing a 3D point cloud of people and faces with Kinect cameras. However, there were no examples that combined them into an interactive video. This team worked on prototyping such a system—with partial success; however, the major problems were:

(1) Maintaining a 30 frames-per-second capture speed for nontrivial durations, because communication research sessions can vary from 30 minutes to two hours
(2) Automatically determining the positions of the sensors in the space because the systems needed to be portable and easy to set up for communication research
(3) Integrating the four streams of point-cloud data into a single image that could be viewed like a video (with interactive perspective changes), and thus allow for the coding of nonverbal cues

Figure 9.1: Screenshot of the ARA prototype, showing a 3D point cloud video, for which the view perspective and location can be dynamically changed, in real time.

While the initial team clearly made progress (Keyton, Keiser, Graffius and Primus 2015), these challenges continued to prevent the technology from being usable for communication research. To help with this problem, LAS introduced Keyton to Chris Argenta, an industry partner at LAS (see Chapter 7). We started collaborating; and early on, this included another industry collaborator. This created a situation in which non-tech Keyton was explaining both the need and the technology to a technically oriented Argenta, and the industry partners proved critical for bridging the social and computer science domains. Initial discussions focused on the industry collaborators making suggestions to students on the software approach, and making technical recommendations for the existing system and team of students. Over the summer, Argenta even hosted a student developer at the Applied Research Associates, Inc. (ARA) office to facilitate this collaboration and monitor progress. Unfortunately, while the process was improved upon, the student could not solve these challenges before his contract with LAS ended. Keyton and Argenta, who leads a team of experienced software developers at ARA, discussed other options. Together, we determined that the best approach was to redesign the system and for ARA to develop its own code implementation from scratch. In a relatively short time and with minimal LAS funds remaining for the year, ARA completed an implementation that addressed all of the challenges in a more cohesive, albeit prototype-level, tool. However, having a working prototype turned out to be just the beginning. We continued to meet regularly to perform test captures of group experiments, produce materials for conferences and demonstrations, and pursue approaches to transition the working prototype to a larger community.

Over the next two years after LAS funding ended, we met periodically to keep the collaboration active and our efforts moving forward. We met in a variety of places: our offices, on campus, and in a local pub. During this time, we also attempted to collaborate with others: potential commercialization partners, other academics, NC State's Technology Transfer Office (TTO), and several rounds of MBA student teams that TTO arranged to have study commercialization options as class assignments. NC State and ARA considered patenting the research, but in the end neither was willing to make the initial investment without a clear commercialization path. Each of these experiences of "collaboration within a collaboration" ultimately proved unsuccessful. We believe the other parties were either not as committed or perhaps did not share in our vision.

Additionally, other risks—including others developing similar technologies with the same or better sensor equipment and the end of Microsoft support for its Kinect—were realized. These risks were foreseeable, but we were unable to mitigate them. Ultimately, we received approval from our respective organizations to pursue this research independently as an open-source project.[2] In other words, despite significant technological advances and solving a formidable puzzle, it was the collaboration itself that proved to be the thing of most value here.

[2] To request the code, email Keyton (jkeyton@ncsu.edu) or Argenta (cargenta@ara.com).

What We Learned about Collaboration

Our notes about our collaboration indicate that *collaborations don't just happen*; rather, they need a push from someone—even an introduction by a third colleague or funder will do. Thus, the personal and professional networks of each contributor must cohere in such a way as to find the other contributor. It is not an issue of matchmaking, with some third party manufacturing the connections among collaborators. Rather, the collaborators must develop a working relationship that can exist without the matchmaker. Further, the problem the collaborators are working on must be interesting and engaging enough to maintain their interest. We thus learned the following principles:

1. Successful interdisciplinary collaboration is a give and take. The collaborators must be the *right* combination of personalities, communication styles, working styles, and—most importantly—have interest in a problem to which each collaborator can contribute and, at the same time, need the expertise of the other collaborator. A systematic way of linking people as collaborators is not enough; collaborating partners must find the *glue* that keeps them together. Too often, we believe, matchmakers focus on the task. Alternatively, we believe that the personal relationships created among collaborators are as important as the task to which each contributes. When beginning the collaboration, we believe that the relational aspect of interdisciplinary collaboration is more important than the task. Then, with relationships at least partially developed, the task becomes one of *the collaboration,* rather than belonging to a single collaborator. Everyone must benefit, though not necessarily to the same extent; but everyone must *get* something from working together.
2. Interdisciplinary collaborations work when collaborators *get one another* (i.e., think well in tandem) to benefit from working together. This collaboration began when a member of the executive team asked, "What do you need to do your research better?" My response triggered an "aha" and then an introduction. From that point on, the collaborators, not the matchmaker, must work at getting to know one another, agreeing to the work that needs to be done, and keeping up their end of the agreement.
3. We believe that collaborations would be more productive if potential collaborators spoke to one another prospectively (e.g., "Wouldn't it be cool if ..."), rather than instrumentally (e.g., "What's your

expertise?"). More specifically, collaborators must find a common goal that is engaging, mutually beneficial, and mutually interesting to each collaborator. And, they must leave the process a bit open-ended. We allowed questions to surface. We stopped and reconfigured. Just as importantly, we allowed for failure. With this collaborative process, we built a common culture that was a rapid feedback cycle of build-measure-learn. In doing so, we also struck a balance of social science theorizing and the concreteness of seeing it done from a computer science perspective.

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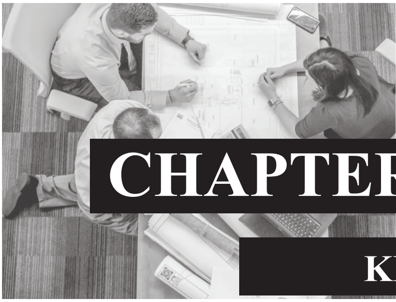
10

OPEN SOURCE KNOWLEDGE ENRICHMENT – A MULTIYEAR COLLABORATION EFFORT

JOHN SLANKAS

For the strength of the pack is the wolf, and the strength of the wolf is the pack.

-Rudyard Kipling



CHAPTER 10

KEY TERMS

- **Open Source Intelligence:** "Intelligence produced from publicly available information that is collected, exploited, and disseminated in a timely manner to an appropriate audience for the purpose of addressing a specific intelligence requirement." (ODNI 2011)
- **Publicly Available Information:** "Information that has been published or broadcast for public consumption, is available on request to the public, is accessible on-line or otherwise to the public, is available to the public by subscription or purchase, could be seen or heard by any casual observer, is made available at a meeting open to the public, or is obtained by visiting any place or attending any event that is open to the public." (DOD 2016)
- **Tradecraft:** specific techniques and methods used to perform intelligence analysis.
- **Geospatial Intelligence (GEOINT):** "Intelligence derived from the exploitation of imagery and geospatial information to describe, asses, and visually depict physical features and geographically referenced activities on the earth." (ODNI 2011)
- **Signals Intelligence (SIGINT):** "Intelligence derived from signals intercepts comprising, individually or in combination, all communication intelligence, electronic intelligence, and/or foreign instrumentation signals." (ODNI 2011)
- **Entity Extraction:** Identifying terms in natural language text into pre-defined categories such as persons, places, organizations, and money.
- **Hackathon:** An event, lasting for a short duration – typically 1 to 5 days, in which participants concentrate on developing solutions for a particular problem.

KEY POINTS

Program: Provide and encourage use of tools appropriate for their designed capabilities.

Team: Constant, ongoing communication is essential in order to discover and leverage individual team member strengths and take time to understand customer needs.

Individual: Be open to participating in and applying design thinking methods to explore problem spaces and find solutions with your team.

Open Source Knowledge Enrichment (OpenKE) is an ongoing project at the Laboratory for Analytic Sciences (LAS) to retrieve, organize, and analyze open-source information. As part of this project, we developed tradecraft to guide analysts through using open-source information to answer relevant intelligence questions as well as the technology to implement that tradecraft. A number of the other project teams have used, and continue to use, the system for their research efforts. The OpenKE work began in the fall of 2015 and continued to evolve through 2019 as we plan to formally release the tool as an open-source project for others to use and enhance. A number of individuals have been involved with the project, including government personnel, NC State staff, academics, graduate students, industry partners, intelligence community members, and contractors. This chapter first covers the initial problem and motivation, the project history, and the different people involved in the project. The chapter then presents the different collaborative techniques and tools utilized. Finally, it concludes with a discussion on collaboration and OpenKE.

Problem and Motivation

LAS has been established to improve the science of analytics through performing mission-oriented, translational research. As part of LAS's research efforts, both NC State staff and LAS government personnel identified the need to mirror analytic processes within the lab, as well as the need to utilize publicly available information (PAI) to perform open-source intelligence (OSINT). PAI provides a rich set of data that can be used to answer a wide variety of intelligence questions. Additionally, PAI provides information that can help solve problems in a vastly changing world landscape. Although two superpowers dominated the world scene from the 1950s to the early 1990s, the current situation remains significantly more challenging with the emergence of a wide number of threats, including nuclear proliferation in a variety of nations, military actions, and a number of emerging technologies, such as cyber warfare. Cyber, in particular, forms a unique threat because of its low barrier to entry as well as the ability to cause significant harm. By leveraging PAI, analysts can discover both emerging technologies and attacks. They can then develop methods to mitigate possible threats. The overall goal for the OpenKE project was to create a methodical approach to collect PAI and then to derive information of value to the analyst. This approach can be compared to the "DIKW Hierarchy" (Rowley 2007), through which we collect data, then find and extract relevant information, then tie that information together to form knowledge, and finally apply information back to answering a question (creating wisdom).

From a tradecraft perspective, the project team began to explore how using OSINT to solve an analytic challenge differs from using other intelligence types. For other intelligence types (e.g., signals or geospatial), data and information may have already been collected, but for OSINT the analyst may also need to decide what data to collect and where to locate that data. Another question is whether or not the workflow for OSINT differs from other methods, and if so, then how? This workflow looks at how analysts start with an intelligence question, perform initial discovery in the problem domain, determine appropriate search terms to use for Internet search engines and databases, discover appropriate sources, validate those sources, collect and organize the data, analyze the data and information, and, ultimately, answer the intelligence question. From another motivating perspective, OSINT is generally used concurrently with existing analysis. However, in many situations, OSINT is the primary methodology for performing intelligence (Schaurer and Störger 2013).

Given the potential methods of tradecraft being developed, we also looked to see how we might develop tools and technology to support the tradecraft. One of the key challenges within analytic processes is to perform collection, an activity that intelligence agencies have always performed. However, once those data are collected, they must also be organized and analyzed, so that analysts can make sense of the information. From a technical standpoint, this challenge relates to similar challenges posed by big data (Chen 2012). The collected information quickly becomes Big Data itself, but also poses questions specific to analysis: How much data do we need to collect? How do we store and process large amounts of data? What data are important? What does the data look like? What are the different data sources available? How quickly can we acquire the data? How do the data change? Are the data accurate and correct? Are the data free of bias? How do we extract information from the data? In some cases, the data may be unstructured, such as images and text. What can we extract from the data? Do the data and extracted information provide value? From a technical standpoint, we also examined what technical capabilities exist and how we could build upon those capabilities.

In addition, the project team explored several challenges from a policy standpoint. What were the basic policy implications of using publicly available information?[1] Our team explored the questions: How does open-source collection adhere to existing National Security Agency (NSA)

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[1] David Kris presents many of these issues in his 2017 blog post (Kris 2017).

policies? What data can we collect? How can we form our search queries? What questions need to be answered as we adjudicate (i.e., decide on the appropriateness of) particular jobs to collect data? We also looked at the complexity of maneuvering between the unclassified and classified domains.

Project History

In September of 2015, LAS began work on OpenKE. Initially, the project team self-selected among government personnel and NC State staff members. Several government staff members had proposed the project to assist with data collection on various lab projects. From this initial concept, others added the ability to study OSINT tradecraft and technology. Through September, participants held several meetings to gather the initial requirements and capabilities. We also held more technical meetings to examine the potential system's architecture. Figure 10.1 presents the initial system diagram developed during one of those technical meetings from September 2015 on the left; on the right is an illustration of the actual implementation of that system as of December 2017.

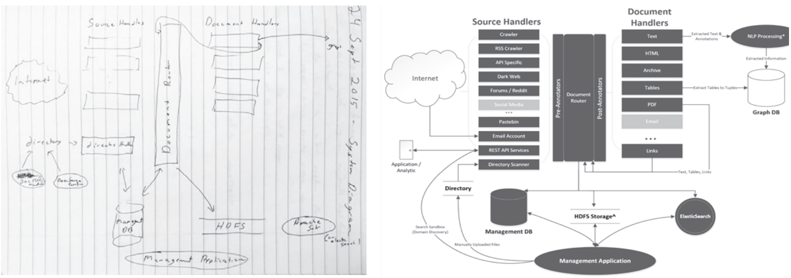

Figure 10.1: OpenKE System Diagram.

During these initial meetings, we also identified and invited partners according to their capabilities. For instance, we approached Pacific Northwest National Laboratory (PNNL) because of their experience with knowledge graphs. We also recruited local professors from NC State's Department of Computer Science to work with us because of their existing and continuing research efforts with relation extraction from natural language texts. We brought in another faculty member who had experience using PESTLE analysis (Cadle, Paul, and Turner 2010) to examine the different factors that might impact a particular intelligence analysis and use those factors to extract relevant facts from unstructured texts.[2] In October, we began development with one NC State staff member and two graduate students. In December, we deployed the initial version application and began to collect information on drones.

With the start of a new project year in 2016, we formally brought on the faculty members and their research graduate students. The OpenKE team largely spent the first half of 2016 preparing for a focused discovery activity (FDA) held in May. The FDA activity included LAS government personnel as well as approximately 20 participants from a variety of US federal government organizations. Participants used the OpenKE prototype and tools from other industry partners, such as SAS and PNNL. We formalized the partnership with PNNL so that OpenKE would provide the data and PNNL would produce a knowledge graph with that information.[3] The resulting knowledge graph and search capabilities would be available to participants for their evaluation feedback. Participants were also exposed to several different tradecraft methodologies that might be useful for OSINT. In addition to implementing tradecraft and technology feedback from the FDA, we added the ability to monitor RSS feeds from a variety of foreign news sources, and then filter the collected data by specific keywords. Another major development area included the ability to start a "domain discovery" session so that the analyst could quickly become cognizant of a particular subject area. Figure 10.2 shows this section of the application.

[2] During later portions of the project, we added another category, "Security Forces," as factors such as police, militia, and weapons did not fall cleanly into existing PESTLE categories.

[3] PNNL's knowledge graph framework has been open sourced and is available at https://github.com/streaming-graphs/NOUS.

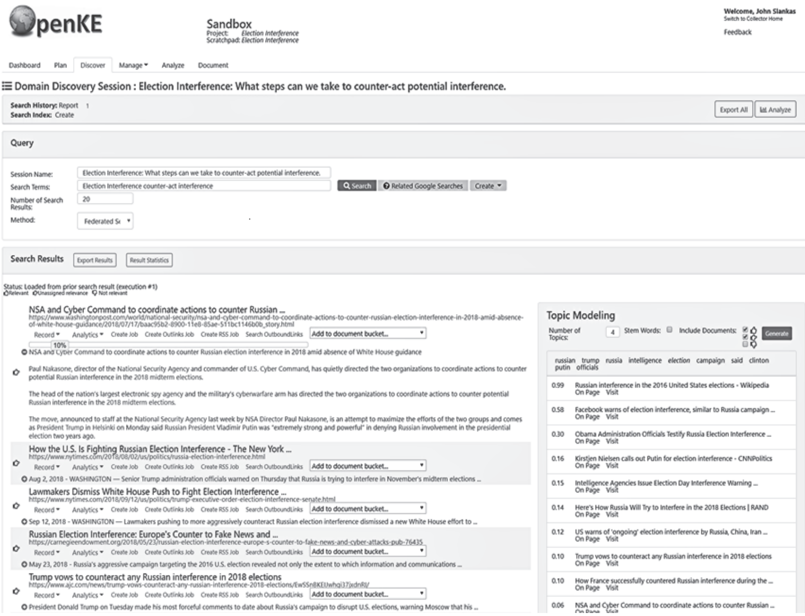

Figure 10.2: OpenKE Domain Discovery.

In 2017, we continued to evolve our approaches to open-source tradecraft and the tool. We partnered with another researcher to use OpenKE as a data source for veracity research. We made the tool available to an MBA class at NC State to use as a research platform in their class projects. In June, LAS utilized OSINT as the topic for a week-long “Design Thinking through Design Research” course led by Sharon Joines, a professor in NC State’s College of Design (discussed in Chapter Five). This course utilized the Design Council’s “Double Diamond” design process (Design Council 2005), which has four phases, in which participants (1) *discover* possible problems and insights, (2) *define* a specific area and problem to focus on, (3) *develop* potential solutions, and (4) *deliver* a solution to meet the defined problem. One of the issues identified with OpenKE was that the user interface was too narrowly focused on the collection aspects rather than on providing an interface for analysts. From these phases, we decided to define a new home page and navigation scheme for users. As part of the third phase of the design process, we created the sketch in the left side of Figure 10.3 as a potential new home page for OpenKE. The right side of the figure shows the finalized home page that was delivered to users (i.e., the fourth phase). The OpenKE team also partnered with a professor in NC State’s

College of Veterinary Medicine to research ways to utilize academic literature for OSINT. While substantial research has been performed on academic literature and bibliometrics, we considered how we could augment standard data extracted from articles with additional technical tools (e.g., entity extraction) to improve analysis and tradecraft (the PESTLE analysis). The OpenKE team participated in a Structured Analytic Techniques FDA that was conducted in August 2017. For this effort, we partnered with Johnston Analytics to use their Analysis Engine tool as a reporting device for evidence gathered within OpenKE. For several of the other research groups at LAS, OpenKE was used during day-long "hackathon" sessions, in which participants gathered to quickly generate new capabilities and methods that could be beneficial to intelligence analysts (hackathons are also described in Chapter Five).

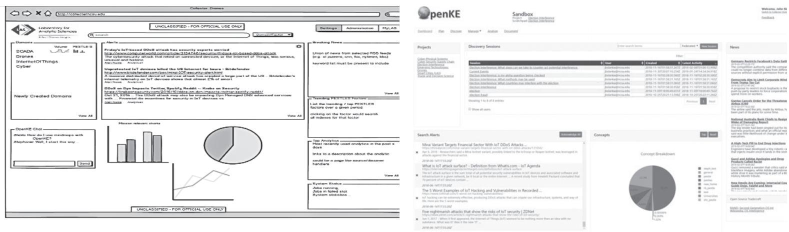

Figure 10.3: OpenKE Design Sketch and Final Implementation.

For 2018, our efforts surrounding OpenKE centered around improving the system's analytic capabilities, formalizing an OSINT tradecraft process, performing a pilot deployment, and open sourcing the system.[4] To decide which analytic features to implement, we surveyed LAS government personnel and then prioritized the requests according to the expected utility of the analytic and the implementation cost. We also partnered with a visualization expert on staff to define several visualizations to implement. For tradecraft, the system developers and analysts worked together to decide upon features to add and how to structure the system's navigation to support the tradecraft process.

For the pilot program, we deployed OpenKE into an environment available within the NSA so that we could get feedback from remote participants as they used the tool to solve operational problems. We worked

[4] In this context, we use "open source" as making the software freely available to anyone under a license that allows those users to use and make changes to the software without any constraints.

with several different groups to gain the necessary approvals for the pilot program and to structure it to maximize benefit to all participants and minimize risk to the agency. Finally, we made substantial progress to make the OpenKE system open source so that others could use and modify the system. This process required partnership with NC State's Office of Research and Innovation as well as NSA's Office of Research & Technology Transfer Applications. When this process is complete the OpenKE system will be available at https://github.com/nationalsecurityagency.

Project Members

The OpenKE team relied on a vast number of participants to achieve the project's goals. The guiding factor among these different participants was the ability to utilize their strengths to contribute to the project. Foremost has been the LAS government personnel, who initiated the project and helped guide its progress over the past three years. These individuals functioned as subject-matter experts for intelligence analysis, technical advisors, and test users. They also assisted with policy development. The NC State staff primarily developed the application. To assist with the development, we hired both undergraduate and graduate Computer Science students on an hourly basis. Additionally, for larger portions of the project (the academic literature and analysis development work), we hired external contractors with significantly more development expertise than the students—who could focus exclusively on the project for a defined period. To perform specific research, we partnered with several faculty members and their graduate assistants. Faculty members also provided expertise in related subject areas, such as business analysis techniques (e.g., PESTLE analysis) and supply-chain analysis. The OpenKE team partnered with over 50 government individuals not directly associated with LAS, many of whom participated in FDAs conducted at LAS. Others answered policy questions. Another group approved the ability to make the system open source. Finally, the OpenKE team partnered with several companies. We leveraged PNNL because of their existing expertise with knowledge graphs. With SAS and Johnston Analytics, we examined how we could integrate OpenKE's collection abilities with their product sets to provide further value to analysts. Without these different individuals and teams, the project never would have been a success.

Collaborative Techniques

The OpenKE team employed a number of collaborative techniques throughout the project—most notably, by simply encouraging communication whenever and however possible. We held regular weekly meetings to discuss current progress and direction. We utilized a number of design thinking techniques in addition to the Double Diamond design process presented earlier. In both 2016 and 2017, we used "affinity clustering" and "visualizing the vote" (LUMA 2012) to determine our strategy and priorities for those years.

In affinity clustering, participants write possible changes and activities on sticky notes (one item per note) for five minutes. After those five minutes, they place the sticky notes on a wall, and discuss their motivation and goals for the particular item. As the notes are placed onto the wall, they are also clustered into similar groups. Once all of the notes have been placed, further discussion occurs to finalize the clusters and apply labels to each cluster (See Chapter Two for another example of affinity clustering or diagramming). In visualizing the vote, participants are given a limited number of points to vote on their top priorities. The OpenKE team frequently used meeting rooms in the James B. Hunt Library on NC State's Centennial Campus. These rooms have floor-to-ceiling whiteboards, thus providing an ideal space for brainstorming and sketching user interface possibilities.

Collaborative Tools

In addition to the collaborative techniques, the project team used a number of different tools to foster collaboration. As NC State leverages Google's G Suite for Education for the university,[5] we leveraged those tools to provide email, chat, phone, and videoconferencing capabilities. These capabilities were especially critical to bring together remote participants. To augment the chat and conference capabilities, we have also begun to use Slack,[6] which provides better historical records of the communication and allows participants to join and leave conversations, as necessary. We leveraged Google's office suite capabilities for word processing, spreadsheets, and presentations. Although Google's office capabilities are not nearly as extensive as those found in Microsoft Office applications, they were sufficient for our project work and allowed for dynamic collaboration,

[5] https://edu.google.com/products/gsuite-for-education/.
[6] https://slack.com/.

as multiple individuals could edit a document simultaneously. We also leveraged Google Team Drives to store and share documents. Team Drives provide several advantages over normal Google Drives, in that files are owned by a central account; and they provide the ability to centrally define access control policies for the drive. With central account ownership, we no longer have issues with files disappearing when individuals leave the organization.

Another online collaboration tool that we used extensively was Coggle,[7] used for creating mind maps. As with the Google products, Coggle allows for online collaboration with multiple users able to create and edit a mind map concurrently. Figure 10.4 demonstrates one of the mind maps analysts created while breaking down different factors for the PESTLE-S analysis.

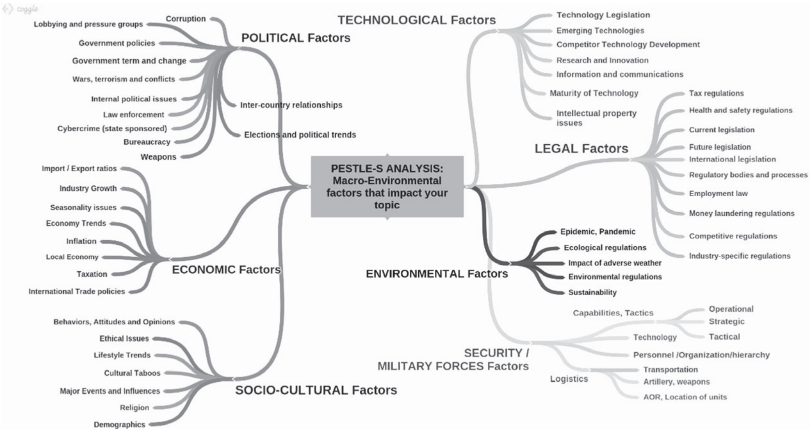

Figure 10.4: PESTLE-S Mindmap Created Collaboratively through Coggle.

Discussion

Without the partnership, teamwork, and collaboration, OpenKE never would have been a successful project. No one person could have performed all of the work or produced as rich a final system, in terms of both the tradecraft and the technology. The primary lesson learned from this experience for collaboration is to leverage people for the strengths and skills they apply to a project. We leveraged faculty members and graduate assistants to perform research on emerging technologies. Additionally, we

[7] https://coggle.it/.

partnered with companies to integrate OpenKE with their existing solutions. By holding FDAs, hackathons, and other workshops, we could quickly bring multiple participants into the project to gain their perspectives. We found that collaborative tools greatly facilitated communication and our work. Design methods greatly enhanced our ability to discover and focus on specific problems as well as develop solutions to solve those problems.

Not every aspect of the project was successful. We did have communication breakdowns, especially in early 2018, as we began work to make the project open source. Some individuals made incorrect assumptions about the project's direction while others questioned motives for making it open source. This derailment would not have occurred had the project team met regularly during that time. As an example of another failure, we attempted to use a wiki to create the user documentation for the system. However, only two individuals regularly contributed to the wiki and eventually the effort was removed. Ideally, someone should be held responsible for ensuring the accomplishment of specific tasks. All these efforts serve as an important part of the learning process, however, and teams should try new procedures until they find those that work best for their members.

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11

INNOVATION AND COLLABORATION IN THE INTELLIGENCE COMMUNITY: BUILDING A RESEARCH INITIATIVE FOR THE INTERNET OF THINGS

DEB CRAWFORD, KIM KOTLAR, and JUSTIN SHERMAN

"By failing to prepare, you are preparing to fail."

-Benjamin Franklin

CHAPTER 11

KEY TERMS

- **Internet of Things (IOT):** A global system that enables advanced services by interconnecting physical and virtual things through information and communication technologies.
- **Low power wide area networks (LPWAN):** A wireless telecommunication network designed to allow long range communications at a low bit rate among things (connected objects), such as sensors.
- **LoRaWAN:** a Low Power, Wide Area (LPWA) networking protocol designed to wirelessly connect battery operated 'things' to the internet in regional, national or global networks, and targets key Internet of Things (IoT) requirements such as bi-directional communication, end-to-end security, mobility and localization services.
- **Smart City:** a municipality that uses information and communication technologies to increase operational efficiency, share information with the public, and improve both the quality of government services and citizen welfare.
- **Smart Power Grid:** an electrical grid which includes a variety of operational and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficient resources.
- **Software Defined Radio (SDR):** A radio communication system where components that have been typically implemented in hardware (e.g. mixers, filters, amplifiers, modulators/demodulators, detectors, etc.) are instead implemented by means of software on a personal computer or embedded system.
- **War Room:** a room used to host meetings to develop strategies that address/overcome problems.

KEY POINTS

Program: Encourage teams to devote sufficient time to early planning: up-front planning made it easier to adjust goals, objectives, and outcomes as circumstances, funding, and the environment changed. Planning also laid the foundation for articulating mission objectives to potential partners.

Team: One of the most important things team members can do is celebrate one another's achievements. The small act of acknowledgement will help build and grow trust.

Use of formal and informal communication—as well as a variety of modes and channels—is critical to attracting partners, keeping collaborators, and expanding the body of research. Use of specific mechanisms to support collaboration, such as focused discovery activities, shared websites, VTC's, and regular meetings was also important to cultivate a sense of shared ownership in the project, its development, and its ultimate outcome.

Individual: The first few conversations with a prospective collaborator were awkward. It's best to acknowledge that and move forward. Many people are cautious about trusting someone they have never met and/or worked with before, which means the first few conversations are likely to be stilted and transactional. Be fine with that, and remain open and collaborative. Who you are and what you represent will usually overcome this resistance.

Nonverbal cues can hamper collaboration, shut down lines of communication, and stifle open exchanges. Thus, it is often helpful to approach meetings with nothing more than a broad outline of what you want to achieve. Often, it is not the path but the objective that matters; therefore, be willing to take a leap of faith when someone comes up with a novel idea or approach.

Collaboration is an essential element of military planning and successful mission execution. LAS includes individuals with prior military experience who bring their expertise to bear by adapting military planning methodologies to an environment that includes lessons and best practices from academic and industry partners. This case study describes the organization and implementation of a successful year-long pilot research project to improve technical understanding of certain elements within the Internet of Things (IoT). The IoT is of growing interest and importance to the Department of Defense (DoD), the Intelligence Community (IC), and industry. The methodology used in this endeavor has implications for leaders and managers of other interdisciplinary and multi-stakeholder projects.

Military planning approaches are codified in military publications that describe an *operational design framework* to determine "how (the ways) to use military capabilities (the means) in time and space to achieve objectives (the ends) while considering the associated risks" (Joint Staff 2017, xi). This *operational design framework* guides military planners through a structured design thinking process that flows across four major activity areas listed below (IV-1–IV-7):

1. *Planning Initiation*: Establishes a common understanding of the situation and describes the outcomes to be achieved.
2. *Mission Analysis*: Describes the problem, how users propose to address/solve the problem (what success would look like), and how participants will receive feedback to focus (or re-focus) work.
3. *Plan Development*: Develop and assess Courses of Action (COA) to achieve mission objectives within established boundaries and guidelines.
4. *Plan Execution*: Execute selected COA.

In 2017, a small LAS Team, co-led by a Senior-level Computer Science Researcher and a Senior-level Technical Specialist, used the above four-step process to establish a collaborative research effort into the IoT. This methodology helped to identify tasks, define goals, and develop a plan to achieve those goals. To document the course of the effort while highlighting collaboration, this chapter is organized into five major sections. Section 1 outlines how the LAS IoT Team used the first three steps of the military operational design approach—*planning initiation, mission analysis,* and *plan development*—to establish and execute the project. Section 2 describes results of the project. Section 3 offers a collaborator's perspective. Section

4 outlines the lessons learned during the process, and Section 5 provides a brief conclusion.

Section 1: Military Operational Design

Planning Initiation

In 2017, the LAS received direction to perform research to "reduce the complexity of the Internet of Things (IoT)." During the first month, extensive research was conducted on the technical and policy elements of IoT to assess DoD direction that specifically focused on low-power, long-range, wide area networks (LPWAN) designed to wirelessly connect battery-operated "things" to and control them via the Internet. These LPWAN networks usually communicate over distances at least the size of a city block and are usually deployed in large-scale systems such as smart cities and smart power grids. Since one of the LAS missions is to create novel tools, techniques, technologies, and tradecraft (including analytics) to support analysts, this task was challenging because there are no obvious connections between certain IoT systems, national security, and the DoD missions. After performing initial research, it was still unclear that comprehensive analytics on the IoT even existed.

Additionally, the Government Accountability Office's reporting on weaknesses and vulnerabilities of Federal Systems (2017) helped reinforce the need to develop analytics around IoT cybersecurity and data privacy as well as tools to better convert those analytics into effective decision making at operational and strategic levels. Although some research could be addressed internally by LAS Staff, other challenges would require the IoT leadership team to collaborate across other elements of the federal government.

Information Gathering. After an initial assessment, research goals developed for the project included the need for diverse, interdisciplinary collaboration on technical, privacy, security, and compliance research into low-power, long-range devices. As IoT is a broad technology space with many different elements, the primary author collected extensive data to identify both current activities and gaps, performed market surveys to determine the leading technical solutions, conducted open-source research to gain familiarity with the issues associated with IoT, and spoke to a number of commercial companies developing and fielding IoT solutions. The team then kicked off its technical research effort, bringing together a small, focused group of signal engineers, computer scientists, and data scientists from a pool of government and academic experts within the LAS.

With preliminary research underway, it was now time to begin identifying what other federal government entities were working on this problem. At this point, the focus shifted to finding ways to identify partners and encourage collaboration by identifying potential common interests and ensuring all partners could achieve some or all of their individual goals.

Revising Scope (An Iterative Process). Once engagement began, many of the offices viewed the development of policy and standards to be the most difficult aspect of the project's initial research goals—not, as some might otherwise think, the research into (IoT) analytics themselves. As one expert put it, "One of the most challenging aspects of security for IoT is its breadth—primarily of the vast diversity of the devices and services that are available" (Ziring n.d.). Better understanding security gaps could therefore help secure federal IoT systems, which meant that research objectives needed to be modified. The leadership team proposed a scope increase to the LAS Director and received approval to broaden the research focus to include five additional areas to improve trust and security of IoT: standards,[1] privacy, compliance, policies, and security measures (e.g., data security, link security, information security). Informal and regular coordination and collaboration with the office sponsoring the research and the LAS Director made it a fairly simple task to obtain approval to revise the project goals. Once the change was approved by the sponsor, the planning initiation phase was complete, and development of an operational approach to achieve project objectives began in earnest.

Mission Analysis and Plan Development

One team objective was to establish an environment where collaborators helped each other achieve their own missions and goals, while also contributing to LAS goals. The Office of Personnel Management website described a collaboration relationship continuum that included networking, communicating, coordination, cooperation, and collaboration (Fisher, Rayner, and Belgard 1995). Since LAS works virtually and with many partners, the leadership team agreed that most contacts would be included in "networking and communicating." For these partnerships, LAS would share information via formal and informal channels. Of course, the authors'

[1] We began by looking at IoT standards that could be used to develop techniques to identify "normal" and "abnormal" activity within IoT systems. The result, as referenced, was mapping out an ecosystem that had very few standards altogether. This issue could have a potentially significant impact on our efforts to develop analytics to identify abnormal behavior; after all, how can one tell if something is abnormal without a "normal" baseline from which to make an assessment?

goal was still to grow all relationships to the greatest extent possible, even if those relationships did not lead to formal research collaborations (e.g., co-writing papers, co-presenting at events).

The original visualization of this collaboration network resembled a flower, where each of the petals in turn represents an individual organization that overlaps a number of other petals. Some overlaps are very dense, while others are very small, but they are all linked to each other in some manner. This was the collaborative environment the authors aimed to design: all of the elements of the ecosystem would have the ability to touch each other, they would all be linked by common interests, and whether they had strong areas of mutual interest or not, they would all have the ability to reach out to any other element of the ecosystem.

The initial network concept had only a few petals: the LAS, NC State, academic and commercial collaborators, and IC partners. Given that these relationships would be mostly virtual, the authors also had to consider how far—literally, in the geographic sense—partnerships could be built to include people who might very well never meet in person during the course of their work. The team began defining what might constitute a productive partnership by posing four questions:

1. Who can benefit from the research?
2. Do potential collaborators have data, information, equipment, research findings, personnel, or funding that can be shared?
3. What can LAS do to foster collaboration?
4. What are potential barriers or impediments to collaboration? (Rubin, 2009, 9-12, 46)

Potential collaborators were approached using a variety of methods. Cold calls were especially challenging, especially because the government team normally did not engage externally. Initial calls were—to put it mildly—awkward. As initial conversations were reviewed, the team realized they did not make a compelling case when explaining the value of partnering with LAS. Putting themselves in a potential partner's shoes allowed them to realize they could build trust by offering access to preliminary research findings as well as access to the software-defined radio (SDR) we were developing as part of the project.

Sharing LAS IoT research goals and any related information yielded positive results with potential partners. Members of the team spoke of the challenges they had seen and they listened as potential partners did the same in return. They explored areas of mutual interest (or frustration) and offered to share anything they could to help. If potential partners asked what they could do in return, the government authors' first response was always a request to add them to the virtual community of interest (COI) the LAS was building. This entire process felt very awkward and uncomfortable, but it quickly became apparent that it was working. Simply having a conversation and offering to share information generally resulted in agreements to join the COI and offers to share information in return. By fall 2017, the team identified approximately 28 organizational points of contact for federal departments and agencies working on IoT.

Plan Execution—Growing Collaboration

How do you build rapport and trust with people you never see? Throughout the research effort, the government team leveraged existing technology to share findings via sending emails, contributing to an online blog, and posting monthly reports and technical papers for working groups. They were careful not to overuse group emails, setting a goal of no more than two or three mass emails per month, as they learned that a daily *update* all too often would become a daily *delete*. The team leveraged online collaborative tools by using Google documents to build reports in conjunction with others, share those documents with collaborators to provide them a voice as products were being developed, and host conference calls and WebEx meetings among collaborators. In this way they continued to discuss areas of mutual interest between the LAS and the community they had created.

Consistently sharing results reinforced the community's collaborative mindset, lowering organizational barriers and increasing the amount of information received from others. In one instance, the contact information for two of this chapter's authors simply appeared on the membership listing of an IoT-focused discovery activity being led by someone with whom they were working. The government team also began receiving queries from analysts working on other IoT efforts who had seen LAS reports and wanted to ask questions about relevant aspects of LAS research.

The IoT Team hosted one large-scale collaboration meeting in December 2017. Approximately 20 entities sent representatives to discuss IoT needs, efforts, and challenges. This meeting resulted in an important agreement to establish a common lexicon of IoT terms and an unclassified IoT device database to build a shared corpus of knowledge from which other researchers in the community could use data for their own mission needs. LAS then coordinated and shared a common template to document and share IoT findings.

LAS also coordinated and hosted video teleconferences and virtual meetings to facilitate in-depth discussions into technical IoT research topics. As a result, LAS was able to narrow the scope of its analytic approaches while providing a new sponsor with a contrasting perspective on their work. Following this collaboration, the new sponsor provided funding to LAS to develop novel signatures for the detection and characterization of IoT devices.

The LAS IoT Team also attracted other collaborators from previously cultivated relationships. LAS was able to leverage ongoing relationships with several organizations to learn more about their efforts to develop predictive analytics for intelligent command and control and battlefield services. LAS researchers attended the Science of Security Conference in April 2017 and approached another attendee, the National Institute of Standards and Technology (NIST), regarding NIST IoT standards for the US government. From these collaborations, LAS was able increase its own expertise as well as advocate and promote the work of NIST to a broader audience. LAS delivered some of its research findings to the IC in June 2018, transitioning to a study of prototype IoT SDR and operating instructions—which provide technical mission personnel with the ability to test and evaluate the effectiveness of the SDR and provide feedback on its performance. Engaging beyond the IC, LAS provided the prototype SDR to partners for evaluation. As a result of this engagement, a sponsor funded several enhancements to the SDR to be shared with the IC as no-cost upgrades.

Section 2: Results

By June 2018 the team’s research increased the government’s understanding of LPWAN, producing analytic techniques and research papers and fielding a prototype capability to generate and acquire data. These findings were openly and completely shared with the growing IoT community, resulting in numerous subsequent technical exchanges. One of the offices that received the SDR decided to separately fund—and subsequently share—additional prototype enhancements, thus increasing the collective ability of the team to identify, isolate, process, and analyze data. This collaborative development of a technical solution by multiple government offices is one example of LAS success.

Another measure of success was additional funding and research based on strengthened linkages and trust among partners. An additional collaborator was the Department of Homeland Security’s Academic Engagement Partnership (AEP), which was sponsoring six-month research efforts into related topics. LAS proposed research into industrial IoT (IIOT) systems used in critical infrastructure, with the understanding that LAS would not lead the effort but would work within its IoT community of collaborators to find a sponsor or champion. After AEP selected IIOT as a 2019 research focus area, LAS engaged across its COI, and facilitated a relationship between AEP and the Army Research Lab (ARL), who volunteered to champion the AEP sponsored research initiative. In addition to furthering LAS's understanding of IoT in industrial settings, this project has also established linkages between DHS and ARL that previously did not exist. This expanded collaboration was one of the goals of this effort to promote and enhance knowledge and sharing within the IoT community. Increased collaboration throughout the federal sector has broadened the dialogue between those offices and other NSA research elements, laying the groundwork for collaboration on future research into software-defined networks.

An unexpected benefit of LAS's outreach was the opportunity to promote IoT-focused cybersecurity research within academia. Working through the LAS Principal Investigator, an NC State professor, the government team was able to establish an independent study for Justin Sherman, a Duke University student double-majoring in computer science and political science. He is the third author of this chapter and as a result of the collaboration and relationships he developed with the LAS, he produced a journal paper and a number of articles on IoT privacy and security policies. Further expanding the relationship with LAS, he used government expertise to inform his student-taught cyber strategy course for Duke University ("Cyber and Global Security") and partnered with another student to form Duke's Cyber Team, a competitive group that prepares for "war room"–like competitions. He offers his perspective in Section 3 of this case. Although these initiatives were independent of LAS, he was nonetheless able to leverage his relationship with LAS to obtain subject-matter expertise to inform his own research and course curriculum. Two LAS staff members currently serve as advisors to the Duke Cyber Club and Cyber Team, which promote much needed interest in cyber disciplines to help fill a growing workforce shortage in and out of government.

Section 3: A Collaborator's Perspective

Justin first learned of LAS at Duke University's 2018 Winter Forum, an immersive war room exercise focused on conflict and instability in the South China Sea. By that point, he had conducted numerous technical research projects with Duke's Computer Science Department around cybersecurity and data privacy and was interested in further pursuing the policy dimensions of cyber issues. Collaboration with LAS quickly became an intensive research experience that exposed him to the structure of the US Intelligence Community and the mechanisms by which national security policies are designed and implemented. Within the first several weeks, Justin was communicating with numerous experts and officials across academia, private industry, the intelligence community, and the federal government at large, as well as presenting his research ideas before a large network of collaborators. Settling on the topic of federal IoT policy, Deb and Justin produced their first paper—"Gaps in United States Federal Government IoT Security and Privacy Policies," published in *Journal of Cyber Policy* several months later.

This relationship also yielded articles Justin authored in *Defense One*, *Nextgov*, and *The State of Security*, propelling a number of online and offline conversations about how the US federal government should best address the cybersecurity and data privacy threats presented through the IoT. This was also a segue into additional work on risk-based cybersecurity frameworks and their application to the IIOT. This involved a similarly intensive assessment of existing policies and frameworks for approaching IIOT cybersecurity, including collaboration with NIST and attending a symposium on IoT threat mitigation along with the other two authors. Justin and Deb's policy work on this topic is thus of great importance, as discussed in their most recent article in *War on the Rocks* on better securing connected infrastructure.

Justin's work with LAS provided him an invaluable amount of experience; not only was he able to extensively research and publish on cutting-edge national security issues, but the process of collaboration with LAS also exposed him to the intricate network of analysis and decision-making that is the US IC. Collaborating across numerous agencies during the course of his research, Justin was able to engage with senior officials in the development of our research and policy outcomes. Never before was this possible for him. And outside of LAS, this experience has proved enormously valuable as well—not only has he referred other students to the Intelligence Community through his growing network, but the author's experience researching and advising policy through LAS has helped to more effectively demonstrate his capabilities to other prospective collaborators and employers as well.

Section 4: Lessons Learned

1. Spend more time planning.

President Eisenhower once stated that "the plan is useless, but planning is essential." The LAS team found this to be true as it built its IoT program. One of the major observations from this effort was the criticality of planning. The formatted process used allowed the team to document its understanding of tasks, share that understanding with LAS leadership, and gain agreement to expand the program beyond the initial charter. Additionally, up-front planning made it easier to adjust goals, objectives, and outcomes as circumstances, funding, and the environment changed. Planning also laid the foundation for articulating mission objectives to potential partners.

2. Collaboration is a goal, not simply a byproduct.

Saying you will collaborate, as the team signaled at the inception of this effort, is simple. Finding ways to build in and reinforce collaboration is not. Use of formal and informal communication—as well as a variety of modes and channels—is critical to attracting partners, keeping collaborators, and expanding the body of research. Use of specific mechanisms to support collaboration, such as focused discovery activities (described in Chapter Five), shared websites, video teleconferences, and regular meetings was also important to cultivate a sense of shared ownership in the project, its development, and its ultimate outcome. Collaboration, as with any relationship, requires care, feeding, and trust. Technology can assist with communication, but this is fundamentally a human-to-human function.

3. Be prepared—and be prepared to be awkward.

First, knowing the goals and outcomes the project hopes to achieve and being able to articulate that vision to others is essential. Before engaging with potential partners, it proved to be extremely helpful to research and understand their interests. That research allowed the LAS team to shape the conversation and point out how others would benefit from a partnership with LAS. For example, discussing policy with a technical development organization was not useful. Additionally, asking ourselves what other organizations might be interested in the project often led to new leads and partners.

Sometimes, the first few conversations with a prospective collaborator were awkward. It's best to acknowledge that and move forward. Many people are cautious about trusting someone they have never met and/or worked with before, which means the first few conversations are likely to be stilted and transactional. Be fine with that, and remain open and collaborative. Who you are and what you represent will usually overcome this resistance.

4. Be open to different ideas, because things will not go exactly as you envision.

Often, people have preconceived notions or a mental map of what they think should occur. When something happens that is contrary to that map, some might instinctively react in a visibly negative way (e.g., body language, expressions). Nonverbal cues can hamper collaboration, shut down lines of communication, and stifle open exchanges. Thus, it is often helpful to approach meetings with nothing more than a broad outline of what you want to achieve. Often, it is not the path but the objective that matters; therefore, be willing to take a leap of faith when someone comes up with a novel idea or approach.

For example, as the IoT plan was initially being developed, the LAS government team volunteered to mentor students at a Duke University–wide tabletop exercise. Although this activity did not have a direct correlation to the LAS research, attending the exercise and serving as advisors to the exercise's signals intelligence team and cyber-mission element resulted in our meeting the third author. Within two weeks, he was a member of the LAS research team.

5. Celebrate one another.

Finally, one of the most important things team members can do is celebrate one another's achievements. The small act of acknowledgement will help build and grow trust. This in turn strengthens community and, therefore, communication and collaboration. It is also helpful to acknowledge and formally and informally praise other collaborators who have contributed to a mission and its success.

Section 5: Conclusion

Using the military planning process to establish the LAS 2018 IoT research helped us identify goals, understand the landscape, and develop and implement an approach to achieve organizational goals. When initial outreach did not work as the government team had expected, they were able to regroup and develop an approach that yielded results by using the same planning approach to identify, attract, and cultivate new partners. Similarly, the ability to apply discipline and rigor to the collaboration process while remaining flexible was also the key to expanding participation, increasing the value of the project to the LAS and its partners, and increasing the body of research and knowledge of the IoT.

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12

THE ANALYTIC RIGOR TEAM: TEAM CHARTERS AND COLLABORATION

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[The team charter] approach has been found to promote clarity of purpose, encourage collaboration, increase accountability, and improve communication, as it allows team members, at the onset, to decide their own goals, roles and responsibilities, and deliverables to be produced.

–*Environmental Protection Agency, 2012*

CHAPTER 12

KEY TERMS

- **Analytic Standards**: Standards created to ensure that the judgments and insights of intelligence analysts across the IC were applied against the same standards by all Intelligence Agencies despite their different areas of focus.
- **Analytic Rigor**: Evaluation of analytic integrity of LAS products to ensure they are aligned with the National Security Agency's Analytic Integrity Standards.
- **Team Charter**: A team-negotiated agreement that incudes individual and team goals and objectives and boundary conditions, and necessary pre-work. (EPA, 2012)

KEY POINTS

Program: Program leaders need to be aware that collaboration takes more time if the teams are cross-sector and interdisciplinary than if they are not, but their efforts are more likely to result in radical innovation than would teams of more homogeneous membership. Expectations should be managed accordingly.

Cross-sector interdisciplinary collaborations that produce tools should develop tests of their output and consider revisions and adaptations before delivering the final product.

Team: Personalities, language differences, and sectoral norms matter, but cross-sector interdisciplinary teams can find unique ways to address potential conflict.

Multidisciplinary collaborations focused equally on project deliverables and establishing common language across different areas of expertise pays high dividends in rapid research progress.

Dividing working meetings into technical meetings and full group meetings productively optimizes the team's meeting time.

Individual: Individual team members such as modelers and content specialists see the utility of using ABMs based on their field's methodological training, Fruitful discussions about these differences opened their eyes to new ways to use ABMs while giving us a clearer picture for how they wanted to answer their research questions.

The Motivation for the Analytic Rigor Research Project

The horrific events of September 11, 2001, required a complete and in-depth examination of every aspect of our National Security. Central to the 911 Commission investigations was coming to terms with an intelligence failure that led to an attack of proportions never before seen on American soil. The 911 Commission's report highlighted failures in sharing and collaboration and evidenced the need to ensure rigor across every aspect of the analysis cycle (2004; The Commission on Intelligence Capabilities 2005). In their report, the 911 Commission notes that "the biggest impediment to a greater likelihood of 'connecting the dots' was the resistance to information sharing, and [they] recommended a new, government-wide approach to information sharing" (2004, 416, 417). In support of this idea, the Commission highlighted a series of independent efforts by law enforcement and intelligence agencies that underscored a lack of collaboration among agencies and a failure of appreciation for the role of analysis (2004). In its "Reform of the Intelligence Community," The Intelligence Reform and Terrorism Prevention Act of 2004 put into law recommendations that changed the way the Intelligence Community (IC) carries out its responsibilities to include IC analysis management. This Congressional Act further provided the legal underpinning for the creation of Intelligence Community Directive 203 (IC 203), Analytic Standards. These Standards were created to ensure that the judgments and insights of intelligence analysts across the IC were applied against the same standards by all Intelligence Agencies despite their different areas of focus. Furthermore, the Standards allowed each IC element to develop their own set of discipline-specific standards aligned with their intelligence focus. Regardless of the collection method, all 17 IC Agencies (See Table 9.1) are required to evaluate their analytic processes using the same standards. Specifically, and with regard to Analytic Integrity, The Intelligence Reform and Terrorism Prevention Act of 2004, Section 1019, 118 STAT 3671-3672, required the following:

> *Not later than 180 days after the date of the enactment of this Act, the DNI[1] shall assign an individual or entity to be responsible for ensuring that finished intelligence products produced by any element or elements of the intelligence community are timely, objective, independent of political considerations, based upon all sources of available intelligence, and employ the standards of proper analytic tradecraft.*

[1] Director of National Intelligence.

In this chapter, we report the process used by the Analytic Rigor Team (ART) to enhance the analytic rigor and analytic integrity of the projects conducted at the Laboratory for Analytic Sciences (LAS). We also share some of the challenges experienced by the interdisciplinary, cross-sector team as they worked together to accomplish this objective. As we describe below, the team determined there was a need to expand the scope of the application of ICD 203, Analytic Standards, and the National Security Agency's Analytic Integrity Standards beyond government analysts. During this process, we recognized that the definitions of concepts used by IC analysts do not "resonate" with academics and industry participants. In the spirit of "Never Forget," government analysts sought to ensure that all research and development conducted at LAS by cross-sector teams was subjected to the same rigor expected in the production of analytic products across the IC. Through cooperation, collaboration, elaboration, and flexibility, the LAS ART built a methodology and tool that enables LAS academic researchers, industry developers, and government analysts to assess their products' application to the Analytic Standards. In conjunction with this methodology and tool, the LAS ART additionally developed a short set of questions that practitioners should ask of their work. Lastly, we evaluated an on-going LAS project and engaged with individuals outside of the ART to ensure that our methodology and approach aligned with our processes and expectations.

The Organic Coming Together of the Team

At LAS, government analysts, industry developers, and academic researchers come together to develop research-driven solutions in support of IC requirements. While the cross-sector, interdisciplinary nature of projects conducted at LAS requires information sharing and collaboration to accomplish team objectives, historically there has been no specified requirement that projects meet the rigor requirements assigned to intelligence analysis by the Analytic Standards contained in Intelligence Community Directive 203 (IC 203). The Analytic Rigor Team (ART), in response to Delivery Order 6, officially worked as a team from January 1 to December 31, 2016. The ART sought to challenge the premise that only intelligence products and the information and sources associated with them should be required to demonstrate analytic rigor consistent with IC 203. The objective of ART was to leverage the knowledge of government analysts, academic researchers, and government and industry developers to devise a standardized process in alignment with the Analytic Standards. It is important to bear in mind that this goal reflects a desire to extend the scope and application of the standards beyond the government context.

In late 2015, LAS collaborators from government, academia, and industry selected what projects best aligned with their skills and interests. This organic self-selection process implied, by its very nature, interest in the projects selected. There were no interviews, previous knowledge, or minimum qualifications required. The ART was initially composed of three government researchers and two academics. Informally, it would later also include three government and industry developers who would become especially critical in the validation phase of the project. The team formed a composition of “friendly strangers,” in which team members might have known most members but had not worked with all of them. Team members described their interest for joining the team in terms of learning opportunities. For at least one member, they wanted to better understand the world of analysis. Another member joined because they were interested in working with one of the government collaborators. The developers were not bona-fide team members but functioned as reliable advisors and consultants as the team’s work matured.

Team Goals and Expectations

The LAS ART was formed with the intentional and formally stated goal of improving and expanding the understanding and application of the IC 203 analytic rigor standards beyond intelligence analysis reports or products to include all LAS projects and products. The diverse workforce at LAS created an opportunity to leverage the co-located government analysts and developers, academic researchers, and industry developers to demonstrate that analytic rigor could and should be present in every aspect of the analysis cycle and embedded into the research and development of systems, tactics, or processes developed for or in support of intelligence analysts.

Because the LAS is a partnership between NSA and NC State University, the NSA Analytic Integrity Standards (AIS) provide the foundational base for adherence of product reporting in accordance with Intelligence Community Directive (ICD) 203, Analytic Standards. Since its inception, LAS has chosen to annually assess the analytic integrity of all its projects, which pre-positions the AIS well before an intelligence product is generated. That said, the process was not standardized and had not been evaluated. Since LAS does not produce traditional intelligence reports, the introduction, development, and implementation of such measures required a new and novel approach to achieve compliance within the Standards and apply them to fields not originally intended as relevant, such as academic research and tool development by academics and industry partners.

To improve collaboration, in January 2016 the LAS leadership introduced "charters" to the project teams' research and deliverables process (see Chapter 5). This approach has been found to promote clarity of purpose, encourage collaboration, increase accountability, and improve communication; as it allows team members, at the onset, to decide their own goals, roles and responsibilities, and deliverables to be produced (Environmental Protection Agency 2012). The charter framework was also believed to help establish collective and individual commitment to the project and deliverables. Specifically, the team charter guidelines provided to LAS participants indicated that a team charter establishes the "rules of the road" for the team and helps everyone know where they stand (Tabrizi 2015). It is an agreement among members about how the team will work in partnership to make decisions that will effectively and efficiently lead to quality deliverables (Mathieu and Rapp 2009, 92). Setting goals and being aware of potential obstacles to their achievement help optimize team outcomes, as does taking an active approach to problem identification and problem solving.

The ART dutifully assigned all required tasks to team members as designated in the team charter. Team members collectively identified their group and individual contributions, defined the team's mission, objectives and goals, and stated the proposed deliverables. The mission of the ART was to "produce global, utilitarian definitions of analytic rigor and assess LAS research activities' progress towards infusing analytic rigor concepts within project deliverables" (LAS Analytic Rigor Team Charter 2016, 2). Initially, the ART identified three objectives and two deliverables, but in the end actively worked on two objectives while modifying the third.

Objective 1: Determine to what extent all LAS research activities could satisfy requirements for analytic rigor as expressed in the Nine Analytic Tradecraft Standards included in Intelligence Community Directive (ICD) 203.

Objective 2: Survey data generated in various research activities via secondary data analysis to determine degrees of analytic rigor.

Objective 3 (Modified): Study the processes of an in-house analytical tool to determine degrees of analytic rigor against the Nine Analytic Tradecraft Standards included in ICD203.

As we pledged our full commitment to the charter, some members realized that their schedules and other circumstances prevented them from meeting their original commitments and thus were, from the team's perspective, "relieved" from their obligation to the ART. That said, some of these members would later be called to participate in an ad-hoc manner as "consultants," a role that proved critical in the ART testing phase.

As our work progressed over the twelve-month funding period toward the creation of a "tool" that would accurately measure the Analytic Integrity Standards, team collaboration and elaboration grew stronger with every meeting. We were, additionally, fortunate that one of our academics was given funding for a graduate student who later joined the team. As a team, we fostered a culture of open communication and our willingness to suspend judgment allowed us to hear each other. It was in those moments of active listening—when we were able to gain a deeper understanding of the experience and perspective of team members from different sectors and disciplines—that the ART worked best. The team was not muddled by cancelled or constantly rescheduled meetings, constant revision of team goals, or other external factors that often afflicted other teams. Most of all, the ART members seemed committed to learning from each other. The team's original goal was to examine the definition of Analytic Rigor as it pertained to work performed at the LAS, but the team arrived at a much more complex and rich outcome that propelled team members' razor-sharp focus to deliver a tool that would, by its very nature, push the limits of the IC treatment of the Analytic Integrity Standards (AIS). The ART developed a tool by which to assess not only the intelligence analysis process under the Standards, but also academic research and development efforts by industry and government developers. After all, if research leads to the development of a tool or tactic that removes the analyst from a process, wouldn't we want to be sure that the tool or process also adheres to the same standards?

Building a Tool, Testing the Team

The ART developed their first Word version of the proposed survey (to eventually populate the tool) in February 2016. However, following discussions among the team and with users, the team determined that LAS academic partners and industry developers could not identify with the terminology used in the Analytic Rigor Standards and that in some cases even the questions regarding rigor needed to be modified to clarify understanding. Once the team decided to make these changes, the ART went to a variety of potential users to determine what questions should be asked and how they should be worded. Thus, In May-June the team decided that the survey should be constructed with three different sets of questions based on the LAS participants' classification (government analyst, academic researcher, or government and industry developer). The ART agreed that this application of the Analytic Integrity Standards fit the broader definition and that if we asked two questions of all LAS analysts, researchers, and developers, we would be able to assess AIS alignment in a new and novel way by asking two questions:

- Which of the nine Analytic Integrity Standards is addressed by your research?
- How would your research inform or assist analysts in adhering to the nine Analytic Standards of Analytic Tradecraft?

It is important to clarify that from our first meeting the ART focused on the evaluation of the "products" developed or delivered by the analysts, researchers, and developers. The performers would not measure their adherence to the Standards; they would measure their outputs' or products' adherence. For all intents and purposes, we were "done." The team thought that arriving at these questions and the application of these questions to LAS research projects marked our way to delivery completion. Team members met with academic researchers and government and industry developers working on other projects at the LAS and presented the team's game plan, our assumption, and the questions we had developed for them. Whatever resistance was initially expressed to the ART's argument for expanding the scope of the Analytic Standards dissipated relatively quickly. And while the ART did not test its position broadly, the team assessed that it had met with enough researchers and developers to satisfy a baseline that affirmed that going forward with this premise was the way to proceed.

At this point, the ART decided to proceed using Qualtrics[2], a survey-enabled tool that would allow government analysts, academic researchers, and government and industry developers to evaluate their work using the same tool. Fortunately, the PhD student working with us was very familiar with Qualtrics and his work behind the scenes enabled us to continue working without needing to consider other vehicles. Qualtrics was also easily modifiable, which allowed the team to build an evaluation method that would contain the same theoretical concepts, yet could be worded in a way that was easily understood by the three different audiences (analysts, researchers, developers).

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[2] The survey mentioned in this paper was generated using Qualtrics software. Copyright © 2016 Qualtrics. Qualtrics and all other Qualtrics product or service names are registered trademarks or trademarks of Qualtrics, Provo, UT, USA.

The team began its work building the tool, which included defining each section, setting up the layout, and creating drop-down list boxes, among other tasks. As the ART developed questions that addressed each of the Standards, team members challenged each other. The question often asked was: Are we stating what we want to state the way we should be stating it? The answer was never a simple yes or no. While the process was not cumbersome, to a certain degree it simply felt natural, it was nonetheless slow, with multiple iterations hanging on to the smallest sentence fragments until, as a team, we agreed we had reached the optimal description. The team's collaboration, elaboration, and willingness to listen and learn supported the team's cohesiveness. When the team's cohesiveness failed, it was because we failed to suspend judgment or failed to listen to each other.

As our work progressed, one of our collaborators noted the difficulty that they had understanding the language in the Standards as it pertained to them as a researcher. As a researcher, they posited, the Standards, which were developed by analysts for analysts, could potentially be interpreted by a researcher differently than by an analyst. What seemed completely obvious to the analysts in the team was not necessarily obvious to the researchers. The team's analysts initially thought it was just a matter of finding better explanations for the usage of one term versus another, but as the team analysts explained what was meant by each Standard, it became obvious that a reset was needed. It was then that the ART arrived at the critical realization that for academic researchers to understand the Standards, we needed to change gears and would instead have to build a parallel survey for researchers. This survey would be rooted on the original one, but with language and expressions that would resonate with researchers. Otherwise, we would have done away with rigor, and the ART would not have been able to evaluate responses, as academic researchers would interpret Standards differently than would government analysts. Soon after, the team also realized that the language used in the developers' survey would also have to be modified. After finishing the first set of questions for analysts, the ART went back to the drawing board with one substantial difference: this time, the team's academic researchers were driving the tool development and the "translation" of the Integrity Standards with researchers in mind.

As Senior Leaders in the government, the team's analysts took for granted their role as drivers of this research effort. Ironically, most challenges to terminology or interpretation developed more readily among the academic researchers themselves, which created some separation. For their part, the analysts offered points of clarification that sometimes were of value to the researchers' discussion. One of the researchers decided to provide feedback to the analysts separately, so as not to foment increased separation. The analysts would then embed those suggestions into the conversation with other team members. Whatever separation developed was circumvented through what seemed to be an unorthodox process that, despite its nuance, seems to have worked. With the researchers' version finished, the ART moved on to the developers' version. As the core ART didn't have a dedicated developer involved, the team's analysts thus reached out to government and industry developers for their feedback. The ART reached out to three developers who hesitantly agreed to meet with team members. Once we explained how the Analytic Integrity Standards were different from standards already in place for software developers, the developers were fully on board. The three developers worked independently, "translating" the foundational standards for analysts to language that would resonate with developers. The ART found itself leveraging three different translations to arrive at what non-developers agreed was the best translation of the Standards. Some of the questions were easier to assess, while others were more challenging. Here we were—five government analysts and academic researchers—refining developers' translations, examining every word, every possible nuance, before moving on to the next statement or question. When we finished the last question, there was a palpable sense of relief.

All the variant questions to be asked of the three classifications were completed during October-November, and the final Survey, named the Directed Analytic Rigor Tool (DART), was finalized in December 2016. The need to have variant questions for the three classifications (government, academic, industry) in the construction of the DART was a surprising outcome, particularly for the government analyst team members. However, all ART members acknowledged that this innovative and creative solution was strong evidence of the success of the ART's collaborative efforts and related learning. Furthermore, the DART afforded LAS the flexibility to include the Standards, definitions, and other supporting documentation for users when more detail was desired, but these extra details could be bypassed if a user understood the questions and their relevance to the Standards.

Once the DART was complete and we all parted ways, the analysts then shared the final product with academic and industry partners not familiar with our research. These evaluators were students, researchers from a National Lab, developers, and LAS researchers. The feedback was overwhelmingly positive. Most issues encountered by the evaluators had to do with the tool itself, not the content. As for the objectives, we accomplished Objectives 1 and 2, as stated in our goals. Objective 3 was also completed, but it had to be modified for reasons outside the team's control.

Objective 1: Determine to what extent all LAS research activities could satisfy requirements for analytic rigor, as expressed in the Nine Analytic Tradecraft Standards included in Intelligence Community Directive (ICD) 203.

Results: The development of the DART and the results accumulated by this tool enables government analysts, academic researchers, and government and industry developers to assess their projects' alignment with the Analytic Tradecraft Standards from the beginning to the end of their efforts.

Objective 2: Survey data generated in various research activities via secondary data analysis to determine degrees of analytic rigor.

Results: The ART assessed all 66 projects generated in 2016 at the LAS. These research activities mapped to the Analytic Integrity Standards as follows:

- 31 activities map to quality and credibility of underlying sources, data, and methodologies
- 22 activities map to uncertainties associated with major analytic judgments
- 19 activities map to distinguishing between underlying intelligence information and analyst assumptions and judgments
- 35 activities map to analysis of alternatives
- 26 activities map to demonstrating customer relevance and addressing implications
- 21 activities map to clear and logical argumentation
- 21 activities map to change or consistency of analytic judgments
- 40 activities map to accurate judgments and assessments
- 28 activities map to effective visual information

Objective 3 (Modified): Study the processes of an in-house analytical tool to determine degrees of analytic rigor against the Nine Analytic Tradecraft Standards included in ICD203.

Results: A modification was needed, as the tool was undergoing an overhaul to enhance features. The ART decided to move ahead with the assessment but would conduct a second assessment once the new operational features were in place. The study of the tool was conducted by the same analyst both times. During the first assessment, it was determined that the tool supported six of the nine

Analytic Tradecraft Standards. Six months later, the tool aligned with eight of the nine Standards.

Final Thoughts

The outcome of the ART's work and the manner in which the team worked together stand as examples of the innovation and learning opportunities gained through cross-sector, interdisciplinary collaboration, best practices in communication, and the utilization of standardized team charters that specify goals, role responsibilities, and deliverables. It is not possible to assess whether the ART would have successfully met its goals using a different team composition or program structure, but without a doubt, the development of a team charter supported a process that facilitated team cohesion and cross-sector interdisciplinary collaboration. While the "voluntary" nature of self-selecting research projects/areas of interest could serve as a common thread for team unification, mutual interests alone would not have survived the ups and downs of team dynamics. If the ART were to select one area that would account for its collaborative success, it would be team members' willingness to learn from each other, engage in open communication, and suspend judgment. As it happened, when any of these failed, the team found a way to circumvent roadblocks and move forward.

As for the future of the DART, while proprietary considerations have prevented the LAS from sharing the DART with the broader IC, the LAS continues to work with counterparts on a resolution.

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13

TECHNICAL MATURITY FRAMEWORK

CHRIS KAMPE and MATT SCHMIDT

The tenets of "socially responsive design" encourage designers to first learn a community's needs (from community members) and then gradually build tools with that community, allowing that community to drive the development and, ultimately, take control of these tools.

–from Barab et al, 2005

CHAPTER 13

KEY TERMS

- **Mission Relevance:** describes the extent to which an approach or technology is capable of assisting an intelligence analyst in the course of their duties. The assistance so described exists along a continuum, ranging from speculative (i.e. analysts could potentially find benefit) to validated (i.e. analysts report concrete benefits from use).
- **Technical Readiness Levels:** (1-9) describe the relative maturity of a technology. A low level technology exists only as a set of principles, mid-level technologies have been prototyped and validated in laboratories, high level technologies have been field tested and proved effective/reliable. The methodology was developed by NASA in the 1974, and has since been appropriated by a number of agencies.
- **Activity Theory:** is used to describe human activity in socio-technical systems, such that the activity system becomes the center of analysis rather than the human practitioners. As an analytic framework AT delineates an activity system in terms of: objects produced, actors engaged, social context, tools used, divisions of labor, established rules.
- **Expansion:** Rooted in activity theory, the term Expansion describes a “horizontal dimension of learning” whereby the practitioner of one activity system discovers techniques and/or technologies that are being used different activity system and then integrates these features into her own work. This integration, if it is taken up by other practitioners of her activity system, will cause the system to evolve or expand.

KEY POINTS

Program: As an organization, it's essential that each team has a firm grasp of what will be expected of them, and what steps they should be taking in order to develop successful projects. When developing an evaluative framework, leverage prior art and qualitative analysis. Look to the projects that have succeeded and failed, describe the conditions that led to success/failure, and integrate those conditions into your evaluative matrix. View the matrix as organic; let it evolve as needed.

Team: As a multidisciplinary team, keep an audio record of your meetings. Everyone will raise slightly different concerns and/or perceive slightly different solutions. It is impossible to recognize these subtle differences in real time, especially when you're an active participant. You won't need to review all of these recordings, 80% of the material in them will not be useful, but 20% will be profoundly insightful.

Individual: As an individual working in a multidisciplinary team, remain conscious of your bias. It's too easy to hear only the parts of a conversation that you understand, and to push the conversation in that direction. Be honest about what you don't follow.

The Laboratory for Analytic Sciences (LAS) is a "mission-oriented, translational research laboratory" working to develop "new analytic tradecraft, techniques, and technology" designed to "help intelligence analysts better perform complex, integrated analysis" (LAS website, "About"). Consequently, LAS must investigate unexplored technologies and determine whether they have mission-specific application. In some cases, these technologies were developed externally, then brought into LAS so that their mission relevance could be investigated. In other cases, prototypes were developed by LAS collaborators from various disciplines over the course of one or more years. This chapter focuses on the efforts to evaluate the prototypes developed by LAS and, by extension, our efforts to guide the development of prototypes at LAS to facilitate their translation to the intelligence community (IC).

The goal of LAS is not to fully develop new technologies, but rather to develop prototypes mature enough to be transitioned to another stakeholder capable of producing scalable and fully operational products. As a prototype is developed, it is exposed to analysts, who can provide a degree of feedback about its relevance to the work they are performing at LAS. In some cases, the idea behind a prototype might seem acutely relevant to an analyst's work, but a specific prototype (as it is realized) might be fundamentally incompatible with their working environment (i.e., professional practices, current tools, etc.). Alternatively, analysts might dislike using the new tool to the extent that they resist using it (because it is tedious, disruptive, etc.) In these respects, when we refer to the "technical maturity" of an application, we are not simply describing the sophistication of the application in a vacuum, but rather, the extent to which it has been able to "mature with" potential users (i.e., by becoming reconciled with the needs and constraints of their work). In this regard, LAS is concerned with both the "development" and professional "socialization" of prototypes: allowing potential end users (e.g., intelligence analysts) to interact with the prototype throughout its development so that their concerns and insights can be integrated into its design.

Our group's goal was to develop a matrix that could be used to describe the relative maturity of a prototype, respecting the aspects and requirements discussed above. Its purpose is twofold: to establish generic progress goals for all prototypes, which in turn provide standards by which we can assess where a project is, its progress towards technical maturity and, by extension, its readiness for transitioning beyond LAS. Toward the production of this matrix, we leveraged the framework set up by various "Technical Readiness Models" (Dion-Schwartz 2010; U.S. Department of Energy 2011). However, we found these models to be inadequate for describing the stages of socialization that an LAS prototype would need to progress through in order to find adoption. Here, we drew on Activity Theory, which articulates the various human/technical dimensions involved in productive action; in particular, we leveraged concepts of activity *expansion* (i.e., when the tools and practices of an activity evolve) and the specialized learning that accompanies it. Activity Theory provides a descriptive framework for understanding professional work as a techno-social system of interactions. It asks us to consider work as a recurrent process which is itself constituted by interactions between: subjects (i.e., the ones doing the labor), objects (i.e., the thing being produced), communities, tools, rules, and divisions of labor. These systems don't develop in a vacuum; rather, they inherently draw on the resources of other activity systems (i.e., tools, practices, etc.). As one Activity System changes, we draw from the resources of another system and modify them to address the particular problems of the native system, a process we call (activity) *expansion* (Engeström 2001). A more concrete example of expansion at LAS is as follows. In 2016, Chris (the first author) interviewed a number of analysts about a prototype: the "Journaling" application, designed to curate the documents/websites into a hierarchy of goals and actions, so as to keep records of useful resources and help in the generation of personal activity reports. When asked about the steps one should take when bringing a new technology into a work environment, the analyst responded:

> *[If the new technology] is replacing a tool … it needs to have the functionality of the old tool. But if it's [an entirely] new tool, that's different. … [Nobody's used Journaling before, so this becomes] a question of educating people on how to use it … getting thought leaders … well respected analysts on board … to say here's how it helped me. … Other analysts will look up to them and say … if so and so is going to be using it, then it offers [potential users] some real life cases as to why it would be [advantageous for me] to be able to use the tool.*

Thus, to bring a different/novel technology into an existing activity system (e.g., intelligence analysis), the development team would need to take steps to socialize the application with working intelligence analysts, document cases in which respected analysts used it effectively, and ultimately identify thought leaders who might advocate for the technology.

In the natural, changing context of work, we can expect a regular expansion of these activities as contexts surrounding the activity shift and practitioners begin to integrate new technological approaches into their day-to-day work (Beighton, 2016). This expansion can occur after practitioners encounter contradictions (e.g., ill-fitting tools, counter-productive procedures). As these contradictions aggregate, practitioners begin to "question and deviate from [the] established norms. In some cases this escalates into collaborative envisioning and deliberate collective change efforts" (Engeström 2001, 136). New tools are taken in wholly or in part from other activity systems and then purposefully integrated into the native system. This integration requires translation: of not only the modification of the tool, but also the development of practices that reconcile the new affordances of the tool—such that these practices are now tailored to the needs of the native activity. Furthermore, these tools must be socialized: practitioners need to become aware of them and learn how to use them. In more formal terms, the tools must also meet certain standards for legal usage (Beighton 2016). Put in the language of Activity Theory, a goal of LAS is both reflective (i.e., identifying contradictions/ difficulties in current practice) and expansive (i.e., discovering technological solutions and identifying approaches to practically integrate them into ongoing work).

Initial Efforts at Evaluation (Problems Encountered)

This problem of technical maturity was not fully understood from the outset; rather, it was a concept that emerged after numerous efforts to evaluate new LAS technologies. Some of these technologies were prototyped from the ground up by LAS collaborators, others existed in a (semi-)stable form before coming to LAS, and others were pre-existing commercial products that we investigated for mission relevance. In this chapter, we focus on prototypes developed by LAS collaborators.

Our first efforts at evaluation (2015-2016) were largely descriptive: qualitative researchers were put in contact with development teams and asked to evaluate each prototype in terms of "Mission Effectiveness" and "Usability," with the understanding that an LAS staff member would evaluate each prototype in terms of "Integration" (i.e., the ability to work in the right environment and accept appropriate data) and "Security/Privacy." For each prototype, a report was generated according to these general guidelines and whatever useful information the evaluators could provide. These efforts were fraught with complication in part because of how we approached the problem. We wanted to test the applications: to determine how they supported various mission goals, then evaluate the extent to which they could (in a flexible testing environment) be demonstrated to support these goals. We came at the problem expecting to perform basic usability tests and user-experience case studies, but we found that many of the technologies had not reached a stable-enough state to accommodate such testing. Whatever features they could demonstrate were partial, referring to other components in development (sometimes by other teams)—and from these partial demonstrations, we could hint at possible mission relevance, but we could make no concrete statements about whether or not the "core" of these prototypes would be of use to intelligence analysts in the field. The development teams recognized this problem as well, albeit from a different angle. To paraphrase Matt Schmidt (second author, speaking at the 2015 LAS symposium): "It's painful to work on a project where everyone you talk to says 'yeah, that sounds great.' Then you finish that project and show it to those same people, only to be met with 'deafening silence.'"

There can be a "small infinity" between a prototype that would seem useful and one that professionals actually want to use. As our perspective on the matter matured, we recognized that, in so far as evaluation testing would be concerned, actual user endorsement would be an acid test. The proof that an application was ready to be transitioned out of LAS would come in the form of intelligence analysts, in some formal capacity, saying: "I was able to use this prototype on this problem, and it helped me in these ways; furthermore, I believe the benefits it afforded me outweighed any disruption it had on my workflow." Reviewing numerous prototypes, we found that the priorities (for development) being set by the teams very often failed to confront barriers to adoption—in most cases, because these barriers were not recognized; in many cases, because too much of the development was occurring in isolation from the intended users.

From a developer's perspective, an incredible amount of work must be done in isolation: features must be built, tested, and proven compatible with each other without being confounded by other environmental factors (Callon 2009). However, this sort of work is at inherent odds with more naturalistic (work) settings in which users work on various problems within numerous constraints and conventions. In these sites of exposure (in which actual users try to work with novel products), designers have the opportunity to better understand the constraints their artifacts face in the real world and work to accommodate them (Schön 1987). Furthermore, the tenets of "socially responsive design" encourage designers to first learn a community's needs (from community members), and then gradually build tools with that community, allowing it to drive the development and, ultimately, take control of these tools. (Barab et al. 2005).

Establishing a New Framework

In 2017, chapter authors Matt Schmidt (Director of Programs at LAS) and Chris Kampe (PhD Candidate, Communication Rhetoric & Digital Media) collaborated on the development of a new technical maturity framework. Before becoming the Director of Programs, Matt worked with the Integration to Implementation (I2I) Team at LAS, which was responsible for: determining the extent to which prototypes satisfied mission needs, assessing the feasibility of a team's development timeline, and integrating prototypes into classified environments. Chris had participated in earlier evaluation efforts (see Chapter Twelve), worked with the LAS collaboration group (see Chapter Three), and had performed qualitative research supporting the development of several prototypes (see Chapter Six). In 2017, Matt (and several LAS collaborators) designed a preliminary framework for determining the technical maturity of an application, which described maturity in three dimensions (mission benefit, tradecraft/workflows, and technical capabilities) capable of progression through four levels of maturation. Connected to each level were a series of material deliverables (e.g., storyboards, source code, documentation), which LAS would expect to see produced in the course of development.

Leveraging the extensive catalog work of LAS Primary Investigator (PI) Alyson Wilson, we reviewed every non-classified prototype developed at LAS. We developed a comprehensive list of the prototypes, their degree of completion, points of contact, links to source code, and so on. In reviewing these prototypes, we identified the ways in which projects had developed at LAS: what end states had been achieved, what strategies groups employed, and where they encountered difficulties that stifled or outright halted maturation. In the course of doing so, we found distinctions between "productive failures," in which teams were able to invalidate approaches and establish new directions, and "wasted energies," in which excessive time was spent refining prototypes that suffered from more fundamental flaws. For this process, Chris drew on previously collected qualitative data (interviews pertinent to prototype data), evaluation reports on prior prototypes, and summary reports developed by project leads at the end of delivery orders. He also interviewed points of contact for every prototype we had on record (though it was not always possible to interview project leads).

For several months, Chris and Matt worked together to develop the technical maturity framework described below. Our process was highly iterative. Using prior evaluation documents in conjunction with the new themes that had emerged from reviewing reports and interview data, we developed a more expansive framework. Our goal was to create a framework that could be used to both describe the current maturity level of a prototype and—if deployed longitudinally—to monitor a prototype's maturation over time. Throughout this development process, we kept the principle of activity expansion in mind, taking stock of non-abstract steps that could be taken toward prototype socialization and reconciliation with extant technologies. Eventually, we settled on five dimensions of development, each of which could be divided into five stages. As we articulated each of these stages, in an effort to minimize ambiguity, we associated each of them with non-abstract deliverables whose existence could serve as (partial) proof that a stage of maturity had been achieved. From these efforts, the framework illustrated in Table 13.1 emerged:

Task Relevance	Progress made to tailor the prototype solution, so that it serves a knowable, analytic task while enhancing an analyst's performance during said task.
Completeness	Extent to which the core and peripheral features of the prototype have been developed and behave in a stable, predictable manner.
Support	Degree to which documentation sufficiently describes the prototype solution, provides instruction for its use, and formally demonstrates its efficacy.
Adoptability	Progress made to insure the potential solution will be adopted by its intended users: general usability, fitting into established workflows, reasonable input and processing, etc.
Integrability	Progress made to insure the potential solution can be integrated into an operational environment: taking available inputs, providing required outputs, and interoperating with existing, specialized services.

Table 13.1: Maturity Dimensions.

Maturity Scale Progression

Each dimension can be described in terms of its relative maturity, which can be represented on a scale of 0 to 4, with "0" denoting inadequacy/absence of the property associated with a dimension, and "4," a state of the property that would well support further development efforts to transition the prototype to an operational environment. The results are shown in Figure 13.1. Though each dimension measures development over a distinct spectrum, it would be impossible to reach higher levels of maturity in some dimensions without previously advancing in others. For instance, lower levels of task relevance cannot be determined without first producing storyboards/demos that can then be evaluated by users; in the same respect, adoptability cannot be considered until more exact behaviors of the prototype are defined.

To determine the maturity of a given dimension, we can rely on a combination of internal reporting, external evaluation, examination of reports, and shared/submitted documentation. In the earlier stages, a prototype's maturity can be determined by team-produced products; however, later stages cannot be determined without external review (shown shaded in Figure 13.1). Although development may vary from project to project, we can make certain assumptions about how (over a given period) we might expect to see progress across each of the dimensions. If we observe lopsided progress (e.g., a score of "3" in completeness but "1" in relevance), it may serve as an indicator of future problems and/or the need for additional team guidance.

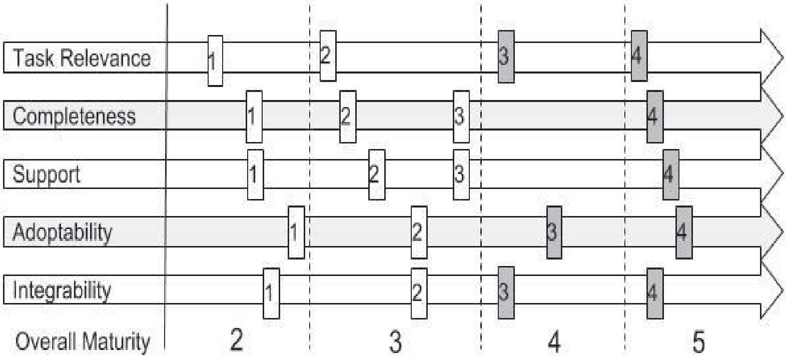

Figure 13.1: Example of Maturity Scale ratings that demonstrate progression through stages of maturity.

When communicating our assessment of a prototype's maturity, it is often useful to project these five dimensions onto an overall maturity level (analogous to a traditional Technical Readiness Level) that considers a prototype's progression across all dimensions (as opposed to an average of the values for each). Thus, the solution matures as milestones are reached across all dimensions. This is meant to encourage coordinated progression across all dimensions of maturity—intended to dissuade teams from focusing on refinement of a prototype prior to rigorous determination of the tool as suitable for analytic workflows. A breakdown of each dimension by stage is shown in Table 13.2.

0	Relevance remains speculative and non-specific.
1	*Speculative Use Case and Benefit.* The team has identified potential end-users who could benefit from the possible solution and is in the process of gathering qualitative data from said users about the specific activities in which they would make use of the application. Using this data, the team will develop a storyboard, demo, and/or guided mockup that describes the behavior of the potential solution and the activities in which it may be situated.
2	*Validated but Hypothetical Use Case and Benefit.* The team shared their storyboard (or guided mockup) with potential end users; from this, they have developed preliminary feedback about what behaviors the prototype should demonstrate to be useful. Said storyboard/mockup has been positively received by potential end users (possibly requiring iteration). The team is in the process of determining specific analytic activities (or types of activity) that could benefit from this application.
3	*Validated Use Case, Hypothetical Benefit.* The prototype solution has undergone authentic use-case testing. From testing, the evaluating team has determined that users believe a future version of the prototype could assist them in their job (via novel insight, increased efficiency, etc.). However, the current version of the prototype cannot demonstrate concrete benefits. As a consequence of these trial runs, the team has developed a specific list of modifications that they will develop to better accommodate the task for which it is being developed.
4	*Validated Use Case and Benefit.* Following authentic use-case testing, the evaluative team has determined that the prototype was able to help an analyst perform a mission-relevant task "better" (i.e., without significant disruption to workflow). As a result of testing, we have a concrete record of what the benefit was and how it was measured/described.

Completeness

0	No sophisticated mock-up or articulation of the potential solution exists.
1	*Basic Diagrams, Storyboards, and/or Mockups* Conceptual articulation of potential solution (i.e., no running program or experimental proof of success), including a mock-up of what the solution could look like, a description of its critical components, and an accounting of the theory upon which it is based.
2	*Prototype in Development: Usable Components* Low fidelity prototype capable of demonstrating the basic, core functions of the potential solution. Put another way, the majority of the core components have been developed and tested; however, they have not yet been integrated into a unified prototype. At this stage, the full prototype solution cannot be used; rather, its intended purpose is still largely conveyed through the use of mock-ups.
3	*Early Alpha: Running but Incomplete* An early alpha version of the prototype has been developed (i.e., the majority of the core components have been integrated and are interoperable). At this stage, the prototype may still contain "hacks" that limit the end functionality of the prototype or require it to operate upon artificially limited datasets. The prototype is of a state in which it can now be externally evaluated.
4	*Early Beta* All core features of the potential solution have been developed. Core use cases can be demonstrated without hacks or workarounds.

Support

0	No documentation for the solution or prototype exists.
1	*Concept Description*

	Adequate concept-level documentation to enable analysts and evaluators to understand what the potential solution is intended to do.
2	*Concrete, Technical Description* Adequate development-level support documentation: description of prototype as a whole and a clear articulation of its individual components, their behaviors, input needs, and expected output.
3	*User and Technical Documentation* User-level documentation is sufficient to support individual (unguided) use of the prototype. Technical documentation is sufficient to support general management of the prototype and navigation of its architecture.
4	*Report: Mission Beneficial Use Cases, Guidelines for Integration* User-level documentation (potentially extending into dedicated forums) includes strategies for applied use (i.e., tradecraft) and recorded cases in which prototype use resulted in mission benefit.

Adoptability

0	The proposed solution is in a state of vagueness; the team can only get feedback about the general idea of the potential solution rather than a specific implementation.
1	*Users Express Conceptual Interest* Conceptual evaluations of adoptability: potential users have reviewed storyboards and given feedback on the proposed solution, the scenarios it might be used in, and the features it would require to provide user benefit in said scenarios.
2	*Proxy/End Users Advise Design, Preliminary Testing* The team is currently performing informal usability tests on the prototype. Initially, these tests may focus on components of the prototype and may be conducted by the developers themselves.

	Later tests should involve non-team participants who interact with the "complete" application. Finally, the team is in the process of identifying potential users willing to test this application for them, and refining the application to "work" for said users.
3	*User Tests* Actual or high-fidelity users were able to successfully use the prototype. However, external evaluation reports that users would be unwilling to use the current version of the prototype solution because it has performance issues (e.g., demands too much hand-holding, disrupts workflow).
4	*User Endorsement* High-fidelity or actual users were able to successfully use the prototype and indicated that it is ready for more general use "as is." Users may indicate customization features they would desire, but external review suggests the prototype is free from obstructive performance issues that would serve as serious barriers to user adoption.

Integrability

0	No operational environment has been considered in the development of the prototype.
1	*Integration Interfaces Identified* Services that the potential solution would be dependent upon the operational environment to provide have been identified.

2	*Concept of Integration Specified* People familiar with an operational environment have analyzed the potential solution and identified any components that are redundant, incompatible, or noncompliant with that environment. These components have been modularized and isolated from the rest of the system, with the objective of enabling easier replacement with different components for the operational environment.
3	*Integration with Simulated/Test Environment* Simulated, proxy, or historical inputs (i.e., data) can be provided to the prototype to enable use-case exploration in a sandbox/non-operational environment.
4	*Integration with Demonstration Environment* All interfaces with the operational environment necessary to demonstrate the validated use case have been implemented. All applicable compliance requirements arising from the demonstration of the validated use case have also been satisfied.

Table 13.2: Task Relevance.

Conclusion

The maturity levels described here make a number of assumptions (which have not been robustly validated) about the requisite steps that lead to the production of successful applications. We do not assert that deviation will inherently lead to failure; nonetheless, we believe lopsided development (i.e., larger value discrepancies among dimensions) may serve as in indicator for future problems, some of which may prove intractable to research transition efforts. If, upon application of this scale, these problems prove general, then we may be able to develop successful intervention strategies to prevent or address them.

Here, we present a few hypothetical scenarios to illustrate how one might use maturity level assessments to diagnose and address potential long-term issues with the project's progression. Consider the following hypothetical scenarios:

I. *Completeness: 3; Task Relevance: 1; Adoptability: 1*
This could serve as an indication that the team is "on path" to develop a prototype solution that will function but ultimately serve no one. In this instance, leadership could ask the project to prioritize discovery (i.e., research, interview, demo feedback) before further developing the application.

II. *Completeness: 2; Task Relevance: 2; Adoptability: 2*
(With scores unchanged for two review periods). This may indicate that, although the concept shows promise, the current team may not have the capacity to develop the prototype and capitalize upon that promise. In such an instance, either the idea would need to be scaled back or the development team expanded/reorganized.

III. *Completeness: 4; Task Relevance: 3; Adoptability: 3*
These scores (belonging to a mature prototype) could indicate that we've reached the limits of a given approach, or could indicate that the development team is spending time polishing the prototype without addressing essential, underlying issues. Likewise, this could be an indicator that the project should be retired.

IV. *Completeness: 4; Task Relevance: 4; Adoptability: 3*
These scores could indicate that the prototype shows promise, but that the team has not been able to realize that promise, given the constraints of an actual work environment. This could be an indicator that the team needs assistance redesigning the interface or needs to radically reconsider what it demands of its users—in either case, potentially benefiting from design support.

As of summer 2018, we are exposing LAS teams to this framework and using it as standard means to describe their progress on individual prototypes. It remains to be seen whether or not this framework will clarify goals and direct them toward more successful outcomes.

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CONCLUDING THOUGHTS

KATHLEEN M. VOGEL,
JESSICA KATZ JAMESON,
and BEVERLY B. TYLER

The challenges here are so broad that the idea that one sector or one individual organization is going to solve this, I just don't think is realistic. It is going to take a true partnership between the private sector, the government and academia to address the challenges we have.

–Admiral Mike Rogers, Former NSA Director

The above quote is an illustration of the kind of “immersive collaboration” that has been developed and realized at LAS—a multi-year effort of government employees collaborating closely with faculty and industry partners. The relationships formed by government staff with experts outside the NSA/IC are now part of their network and available for future academia-intelligence-industry engagement when government personnel return to their next assignment. This unique, collaborative creation has brought new ways of thinking into the intelligence community (IC) and has led to knowledge outputs that are beyond what any individual government, academic, or industry member could accomplish on their own. This model of collaboration is also a tangible realization of the more than ten years’ effort—started via Intelligence Community Directive 205 (ODNI 2008a), and then Vision 2015 (ODNI 2008b)—aimed at better integrating expertise, technology, and work practices inside and outside of the IC to decrease bias and groupthink and optimize intelligence.

LAS is a hybrid organization that has made great strides in breaking down the social, cultural, and organizational walls that can exist between academia, industry, and intelligence. It has revealed that such collaborative spaces are rich places for testing new ideas and early prototypes for the intelligence community because these spaces provide a range of expertise, methodologies, and motivations to inform tradecraft and technology development. In spite of the distinctive history, organization, and character of LAS, there are several lessons that have emerged from the lived experiences there that contribute to a useful model for collaborative approaches to intelligence engagement. We have learned from our study of LAS that collaborations don’t just happen; rather, leadership, structures, and practices are all important to facilitating collaborations that accomplish a specific project deliverable. Thus, we include this final chapter to summarize some of the key program, team, and individual level themes that emerged across the chapters and case studies included in this book. The cumulative findings reported for each of these organizational levels are consistent with scholarly research in diverse disciplines and the practitioner literature on collaboration (Pherson and McIntyre 2009; Anderson-Cook et al.; Hackman 2011). We encourage current and future cross-sectoral interdisciplinary academia-industry-intelligence partnerships to consider the lessons learned at LAS.

Program-Level Insights

Program leaders need to be risk takers and understand that it will take time and persistence to develop collaborative work. They need to articulate a clear vision and mission, and communicate the expectation of inter- or transdisciplinary work from the very beginning; they also need to be able to create incentives, structured opportunities and mechanisms, and collective "rules of engagement" to make this happen. These practices will help individual team members negotiate and construct a common understanding of project goals to support task and goal interdependence. Program leaders also need to work to accurately identify the amount and types of diverse knowledge required to accomplish project team goals, create activities or rituals that bind team members together, and create an environment that allows for failure and promotes learning. Program leaders also need to provide ongoing feedback on expectations they have for the teams and what successful output looks like. Finally, leaders need to celebrate team successes and milestones reached. Leaders that follow these principles will assist in the development of effective and efficient team processes, encourage knowledge fusion among team members, empower teams, assist team members in addressing conflict productively, and encourage the development of trust and enthusiasm for collaboration among team members motivated to achieve truly interdisciplinary, collaborative, and innovative end goals and products.

Team-Level Insights

Teams in cross-sector, interdisciplinary programs must socially construct a commonly accepted goal that all members find mutually beneficial and intellectually interesting. Teams need to work with their members, through a formal, interactive planning process, to create clear goals and ensure that individual members understand how their knowledge, skills, and expertise will support these goals, while also helping individual members achieve their own personal goals. For example, government members need to achieve operational success, academics need to produce publications, and industry partners are interested in creating a customer base for their work or a tool they can market. Teams need to discuss and decide how the project work will create value in all three of these currencies. Furthermore, teams need effective leaders experienced in facilitating communication, managing conflict, and supervising interdisciplinary work. Team leaders must foster member empowerment and build trust among team members, as well as hold team members accountable for engaging and contributing to team goals and deliverables. In addition, teams who are concerned with translating their products back to the intelligence community should involve external IC members in the conversation early and often, and be specific about how the project contributes to mission objectives.

Teams should be sure that the collaborators within a team have the right mix of expertise, work and communication styles, and personalities—and, most importantly, have an interest in the problem. Teams should be confident every team member can contribute to their team's goals and recognize that the expertise and perspectives of all the collaborators are necessary for success. Just throwing people together on a team is not enough; successful collaborations involve identifying a problem or question that binds the collective together. Finally, teams need to create the opportunity for members to develop good personal relationships and an atmosphere in which team members know that their contributions are valued—this is especially true at the start of any collaboration.

Individual-level Insights

Individual members of cross-sector collaborations must commit time and effort to collaborative work, realize they are responsible for effective communication—which includes engaging in discussions, asking questions, and admitting when they don't understand something—know how their knowledge and expertise contribute to team goals, and recognize the need to build relationships and manage conflict effectively. Individuals should be available to talk or meet; actively participate in team decision making; be open to learning new information; consider issues and challenges from multiple points of view; and be conscious of their biases. Individuals need to actively participate in regular collaborative conversations (meeting face-to-face or virtually, as needed), even when they believe their work can be completed independently, so that they can begin to jointly establish a common and agreed-upon understanding of team tasks, goals, and outcomes. Participants in cross-sector, interdisciplinary research must learn to become comfortable with speaking freely—and living with some level of ambiguity and awkwardness—as the team-based interdisciplinary work and process of discovery develops and unfolds. All individuals need to engage in continuous reflection of their work and processes, be flexible and open, be responsive to feedback, and maintain a sense of humor—especially when things are not working our as expected or problems arise.

Program Interventions and Initiatives

The chapters included in this book report a number of program interventions leaders can use to foster the right program-, team-, and individual-level outcomes. Perhaps one of the most important takeaways for program leaders is the need to experiment with different interventions to see what works for their particular context and incorporate this feedback into an ongoing, evolving collaborative process. For example, a number of different programmatic strategies were introduced at LAS—and then discarded or maintained—over time to help improve collaboration. As described in Chapter Five, LAS management created cross-cutting teams in 2015 to facilitate LAS participant networking, ensure cross-sector communication, and collaboratively develop the tactical aspects of their work by sharing information, plans, and ideas, and obtaining feedback from multiple perspectives within the teams. Although participants initially did not see the value of this teaming structure, within a year, teams were more focused; subsequently, the intervention was no longer necessary.

Other LAS initiatives are more events-focused, such as the Annual Kick-Offs, Collaborators' Day, and Annual LAS Symposium, which provide dedicated day-long events for academia, industry, and government participants to meet, listen to presentations, attend poster sessions, and explore possible future collaborations. Other initiatives include weekly research meetings that allow LAS-affiliated researchers to present works-in-progress to the LAS community or activities such as FDAs, hack-a-thons, design courses, and workshops that immerse the LAS research community in a more narrowly defined interdisciplinary problem. There are also more "nuts and bolts" interventions at the team level, such as the creation of team charters, which spelled out member roles and responsibilities on the project, and on-boarding activities. The development of on-boarding materials and processes helped new team members get up to speed on the expectations of the program and the steps they should take to engage in collaboration. It also acquainted them with the LAS team.

Conclusion

In concluding this chapter and book, we provide a few words of caution, explicitly recognizing the dynamic nature of cross-sector, interdisciplinary programs established by IC agencies, and advising care in partner selection. IC agencies and programs should not expect that the processes, interventions, and initiatives that worked for LAS will necessarily work for other programs or teams in different contexts. Yet the ideas, processes, interventions, and initiatives presented in this volume create a toolkit IC agency and program leaders might want to institute and maintain as part of any complex, cross-sector, interdisciplinary, team-based effort. Furthermore, these kinds of partnerships need to be malleable and adaptive as needs, circumstances, funding, and environmental conditions change—one of LAS' strengths has been its ability to make necessary personnel, structural, and practice changes from year to year as they have evaluated and understood both what is working and what is not. In addition, our experience with LAS reveals the importance of careful partner selection between academia, industry, and intelligence. Institutions vary in their histories, competencies, cultural values, visions, and leadership. Thus, if intelligence leadership is interested in developing future collaborative engagements like LAS, they will need to assess the strengths and weaknesses of all potential partner institutions and make a final decision based on a multi-dimensional matrix of considerations. The stakes are high for these kinds of immersive collaborations—however, the cases described in this book demonstrate that the payoff is potentially huge for developing new technologies, tradecraft, and tools to transform the future of intelligence collection and analysis.

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GLOSSARY OF TERMS

Activity Theory (AT): used to describe human activity in socio-technical systems, such that the activity system becomes the center of analysis rather than the human practitioners. As an analytic framework, AT delineates an activity system in terms of: objects produced, actors engaged, social context, tools used, divisions of labor, established rules.
Affinity Diagramming: a tool that gathers large amounts of language data (ideas, opinions, issues) and organizes them into groupings based on their natural relationships. The affinity process is often used to group ideas generated by brainstorming.
Agent-based models: a computational model for simulating interactions of multiple autonomous agents within a predefined environment to generate or predict complex relationships.
Agent: individual or collective entities taken to be the smallest autonomous unit of interest in an agent-based modeling simulation.
Analytic Component System: a new computational architecture that includes a variety of analytic components, such as automated algorithms, interactive tools, or manual techniques. These components are modular, which means that the performance of each component is relatively independent of the others, allowing new workflows to be composed by exchanging or adding components in the workflow.
Analytic rigor: evaluation of analytic integrity of LAS products to ensure they are aligned with the National Security Agency's Analytic Integrity Standards.
Analytic standards: standards created to ensure that the judgments and insights of intelligence analysts across the IC were applied against the same standards by all Intelligence Agencies despite their different areas of focus.

Analytic Workflow: the process the analyst uses to derive or discover intelligence from available data sources.
Anticipatory thinking (AT): the intentionally divergent exploration and analysis of relevant futures to help avoid surprise by identifying leading indicators and causal dependencies of future scenarios**.**
Application Programming Interface (API): a system of tools and resources to facilitate software development.
Artificial Intelligence (AI): the science of enabling computers to perform tasks that requires reasoning a human would typically identify as intelligent.
AT Day: a full-day, collaborative, research workshop that includes Anticipatory Thinking performers.
Backstage: side or private conversations among a subset of team members not intended for the entire group.
Big data: the use and management of information at an extremely large scale.
Black box: in science, computing, and engineering, a black box is a device, system or object which can be viewed in terms of its inputs and outputs without any knowledge of its internal workings. Social scientists often use this term to refer to conversations for which researchers cannot predict what communicators will say, how they will say it, or what the result will be.
Collaboration champion: the individual within business who has both the passion for, and the authority to implement collaboration solutions for their workforce.
Collaboration engineer: someone who can work with users of the collaborative technologies to integrate them into the existing work practices or to modify the existing work practices to better integrate the technology.

Collaboration Group (CG): a project team created by LAS to facilitate, study, and improve its collaboration process.
Collaboration: communication and activities among interdependent parties that includes the sharing of information, resources, and ideas.
Collective identity: the emotional significance that group members in a given group attach to their membership in that group.
Cross-cutting teams (CCTs): teams created to bring LAS participants together to share and integrate diverse ideas and perspectives on the same theme or content area.
Crowdsourcing: the practice of eliciting knowledge from a large distributed group of people.
Delivery Order: also referred to as DO, literally an order by LAS funders to deliver products within a set time frame. DOs are mostly annual, but several can run at the same time. Only academic and industry performers complete deliverables under DOs; however, LAS-G staff align their efforts with DOs to support immersive collaboration efforts. Throughout this book when we refer to a DO#, we are referencing the goals of or deliverables completed for that delivery order.
Dialectical tensions: coming from Relational Dialectics Theory, dialectical tensions are described as opposing needs experienced in human relationships at the dyadic, group, and organizational levels. The three most commonly described are needs for both connection and autonomy, certainty and uncertainty, and openness and closedness.
Discovery: new ideas or insights for problem solving that emerge from interdisciplinary team interaction.
Diversity: the distribution of differences among the members of a unit with respect to a common attribute, X, such as tenure, ethnicity, conscientiousness, task attitude, or pay.

Dwell times: the length of time that a user spends on a page.

Emergent states: dynamic processes that emerge as team members work together over time.

Entity extraction: identifying terms in natural language text into predefined categories such as persons, places, organizations, and money.

Expansion: rooted in activity theory, this term describes a "horizontal dimension of learning" whereby the practitioner of one activity system discovers techniques and/or technologies being used in a different activity system and then integrates these features into his/her own work. This integration, if taken up by other practitioners of her/his activity system, will cause the system to evolve or expand.

Facilitation teams: sub-teams within the CG that included a facilitator, an observer, and a designer. Each collaboration facilitation team worked with two groups for one year.

Focused Discovery Activity (FDA): a collaborative session in which a group comes together for a period of two hours to two weeks to focus on a specific problem and come up with a solution.

Future States Processing (FSP): a set of LAS projects focused on developing the "Science of Projectors."

Geospatial intelligence (GEOINT): Intelligence derived from the exploitation of imagery and geospatial information to describe, assess, and visually depict physical features and geographically referenced activities on the earth.

Hackathon: a series of day-long efforts organized periodically to rapidly develop tradecraft around a particular problem and/or technique.

Illicit networks: any collection of individuals coordinating to produce illicit or illegal goods or services.
Immersive collaboration: a process through which cross-sectoral members share their disciplinary perspectives, cultures, methods, and insights to create a shared, transdisciplinary approach to problem finding and definition, project planning, and solution development.
Integrative collaboration: participants work together by sharing information and exchanging ideas throughout the task.
Intelligence Advanced Research Projects Activity (IARPA): an IC element that sponsors leading-edge research relevant to intelligence challenges.
Intelligence Community (IC): a community of people working on various intelligence activities for the US Government.
Intelligence: the result of processing data into more actionable knowledge.
Interdisciplinary: a mode of research that integrates concepts or theories, tools or techniques, information or data from different bodies of knowledge.
Internet of Things (IOT): a global system that enables advanced services by interconnecting physical and virtual things through information and communication technologies.
Inverse reinforcement learning: a set of techniques for deducing the rules governing an agent's behavior over a sequence of choices.
Journaling Application ("Journaling"): a collective effort across private, public, and/or nonprofit sectors.

Kick-Off Events: held at the beginning of each new project year to bring together all LAS participants working on a common or related content area or exemplar.
Low-power, wide-area networks (LPWAN): a wireless telecommunication network designed to allow long-range communications at low bit rates among connected objects, such as sensors.
LoRaWAN: a low-power, wide-area (LPWA) networking protocol designed to wirelessly connect battery-operated "things" to the Internet in regional, national, or global networks, targeting key IoT requirements, such as bidirectional communication, end-to-end security, mobility, and localization services.
Mapping exercises: a general method of concept mapping that can be used to help any individual/group to describe ideas on a given topic in pictorial form.
Microsoft Kinect Sensors: a line of motion sensing input devices that was produced by Microsoft for Xbox 360 and Xbox One video game consoles and Microsoft Windows PCs.
Mission relevance: describes the extent to which an approach or technology is capable of assisting an intelligence analyst in the course of their duties. The assistance so described exists along a continuum, ranging from speculative (i.e., analysts could potentially find benefit) to validated (i.e., analysts report concrete benefits from use).
National Intelligence Strategy (NIS): a document produced by high ranking members of the IC that outlines the requirements for the near term future.
Offboarding: the reverse of onboarding, it involves separating an employee from a team or organization. It often includes a process for sharing knowledge with other group members and retaining institutional memory.

Onboarding: Formal and informal practices, programs and policies enacted or engaged in by an organization or its agents to facilitate newcomer adjustments.
Open-source intelligence: Intelligence produced from publicly available information that is collected, exploited, and disseminated in a timely manner to an appropriate audience for the purpose of addressing a specific intelligence requirement.
Operational processes: (noun) a series of actions or operations conducing to an end; (verb) to subject to or handle through an established usually routine set of procedures. In this book, we use “processes” to refer to patterns that develop to achieve a goal that may become routinized, either at the individual, team, or program level.
Physical structure: something arranged in a definite pattern of organization. Here, we use the term to refer to organizational features that apply to LAS as a whole.
Platform: a foundational system on which a large number of capabilities can be developed.
Publicly available information: Information that has been published or broadcast for public consumption, is available on request to the public, is accessible on-line or otherwise to the public, is available to the public by subscription or purchase, could be seen or heard by any casual observer, is made available at a meeting open to the public, or is obtained by visiting any place or attending any event that is open to the public.
Scenario Explorer: a software platform that provides imagination support for anticipatory thinking.
Securing Critical Infrastructure at LAS (SCILAS): a set of LAS projects focused on developing solutions to challenges of protecting key national services.

Signals Intelligence (SIGINT): Intelligence derived from signals intercepts comprising, individually or in combination, all communication intelligence, electronic intelligence, and/or foreign instrumentation signals.

Smart cities: local municipal infrastructure that embeds computers to control and monitor its processes with some level of autonomy.

Smart city: a municipality that uses information and communication technologies to increase operational efficiency, share information with the public, and improve both the quality of government services and citizen welfare.

Smart power grid: an electrical grid which includes a variety of operational and energy measures including smart meters, smart appliances, renewable energy resources, and energy efficient resources.

Social network analysis: the study of social structures and interactions between people, groups, or organizations to identify patterns of relationships between them. The primary components in a network analysis are nodes, such as individual team members and technical team leads, and ties, or the connections among the nodes.

Software-defined radio (SDR): a radio communication system in which components traditionally implemented in hardware (e.g., mixers, filters, amplifiers, modulators/demodulators, detectors) are instead software-based applications that run on a personal computer or embedded system.

Sprint: a two-hour working group that used design theory methods and techniques to explore a current analytic process.

Structured Analytic Techniques (SATs): well-defined procedures and tools that aid analysts in performing their tasks and avoiding common cognitive pitfalls.

Team centrality: how connected a team is to the whole network.

Team Charter: a team-negotiated agreement that includes individual and team goals, objectives and boundary conditions, and necessary pre-work.
Team complexity: the number of sectors represented in a team (drawn from government, academia, and industry). Greater representation results in greater complexity.
Team cooperation: teammates' behavioral decisions about whether to act in promoting the objectives of the team.
Team knowledge diversity: the dissimilar experience and education of team members required for the team to meet its goals.
Team knowledge meshing: an interdisciplinary team's ability to pool and interlace their knowledge to blaze new scientific pathways to discovery and subsequent translation into practice.
Team leader centrality: how connected the team's leader is to the rest of the network.
Technical readiness levels: describe the relative maturity of a technology on a scale of 1 to 9. A low-level technology exists only as a set of principles, midlevel technologies have been prototyped and validated in laboratories, high-level technologies have been field tested and proven effective/reliable. The methodology was developed by NASA in 1974 and has since been appropriated by a number of agencies.
Test captures: Pre-deployment activities of hardware and software to ensure that the audio/video capture meets the need of the research objective.
Third place: A place separate from one's home and work spaces where community building occurs.
Tradecraft: specific techniques and methods used to perform intelligence analysis.

Translation: the practical application of newly discovered solutions to a real-world problem.
Translational: LAS efforts to translate basic science and research into practice through the development of methods and prototypes that address mission needs.
U/X "Veracity": A virtual-reality platform and multiplayer, 3D, immersive game that allows users to insert themselves into a completely simulated world—similar to a video game or online environment (e.g., "Second Life").
War room: a room used to host meetings to develop strategies that address/overcome problems.

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Richard Tait spent the last 35 years committed to excellence in language and intelligence analysis as a technical leader of Korean issues for the Department of Defense. He has worked as the first Senior Multi-disciplined Korean Language Analyst at the Laboratory for Analytic Sciences (LAS) on the campus of North Carolina State University (NCSU), where he has led mission-inspired, language-related research activities involving the government, industry, and academia.

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Kathleen M. Vogel, PhD, is an associate professor in the School of Public Policy, University of Maryland at College Park. Her research focuses on studying the social and technical dimensions shaping the production of knowledge and big data in intelligence assessments. Her work has kept close engagement between academia, intelligence, and policy.

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