Investigation of Learning by Proximity Using An Agent-based Model and Simulation

by

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Abstract

This thesis investigates individual and organizational learning, focusing on the impacts of knowledge acquisition and transfer due to cognitive, social, and organizational proximity. A literature review on individual, team, and organizational learning identified how knowledge is acquired and transferred. Knowledge can be broken down into two main categories, explicit and tacit. Tacit knowledge is difficult to articulate and transmit but can frequently occur through collaboration. Simulation analyses using an agent-based model was utilized to explore collaboration as a mechanism for knowledge transfer. Large cognitive distances showed significant increases in collaboration times and a decrease in overall organizational performance. Agents with no prior experience will acquire more knowledge when placed on mixed skilled teams than similarly skilled teams but at the cost of more senior agents' ability to complete their work demands. With more data readily available, organizations should be more intentional about talent management regarding the development of new skills to penetrate an organization.

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I want to thank my employer, who allowed me to take an educational leave of absence to retool my skill set. Their dedication to my learning and development has been on full display, and I hope to bring back these new skills to help accelerate change upon returning to the workforce.

No one can get through an experience like this on their own. I want to thank my cohort for their endless support and optimism, which was needed due to this process being entirely virtual. I specifically would like to thank Christian Dowell for reviewing draft versions and providing constructive, critical feedback.

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Chapter 1

Introduction

Even the most casual observer of the world would have noticed how much everyday life has changed in the past few years. Several significant events and movements have reshaped the way we live and work. The global pandemic caused by a novel virus, the continued digital transformation, and the emergence of people analytics are a few examples with substantial impact. No single sector is immune from the changes that will propagate out of these events, including the energy industry. Energy companies may need to adapt quickly to the new operating conditions and spread knowledge across their organizations to survive this rapidly changing environment.

1.1 Global Pandemic

On March 11th, 2020, the World Health Organization indicated that the novel virus circumnavigating the globe had reached a point to qualify as a pandemic (WHO, 2020). The world plunged into turmoil as the pandemic began shutting down offices, leading to one of the most significant global disruptions in history. As the number of cases continued to rise, individuals, organizations, and governments had to process the available information and develop new strategies.

Figure 1-1 shows one such strategy implemented by governments worldwide that placed a significant portion of the population into lockdown in an attempt to minimize the spread (IEA, 2020). The lockdown decisions had a considerable impact on the energy sector for a couple of reasons. First, companies had to learn how to conduct business in a remote setting which involved employees conducting virtual meetings, utilizing new collaboration tools, and balancing home and work demands. Working from home also increased the complexity of keeping confidential information safe as employees connected to company networks remotely. While this transition was not easy, many organizations have discovered how to utilize distant work methodologies better and intend on integrating these practices after the pandemic (Kaushik, 2020).

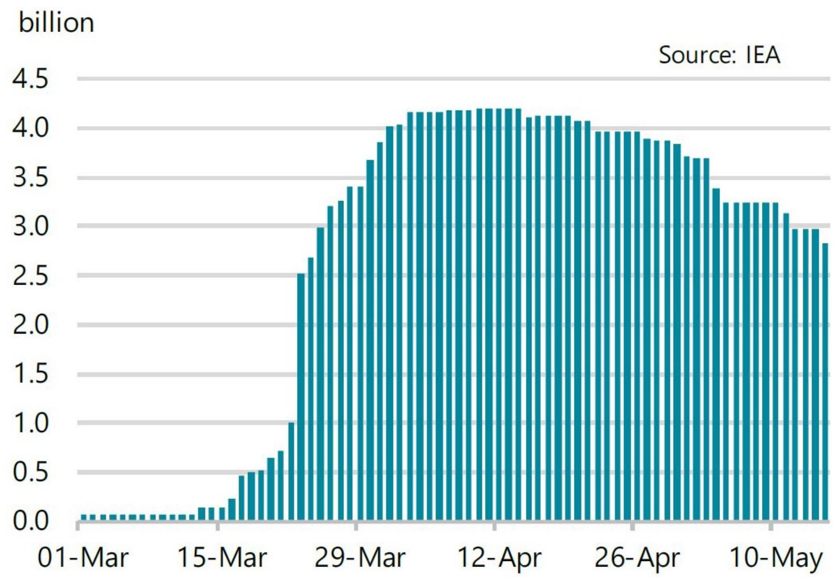

Figure 1-1: World Population Under Lockdown (IEA, 2020)

Second, due to the aforementioned lockdown restrictions, demand for finished petroleum products plummeted up to 25 million barrels per day as, shown in Figure 1-2 (IEA, 2020). The markets responded as crude oil pushed storage units to capacity, with the WTI crude futures contract posting the first-ever negative price of -$37.63 (Saefong, 2021). Negative pricing means that exploration and production companies, those that extract raw oil and gas, pay purchasers to buy their products. In response to these prices, new analytic models were developed to triage their assets and shut-in crude production for economic reasons, a fundamental shift in production optimization thinking. Crude oil tankers were also utilized as floating storage, a move traditionally seen in trading to capture arbitrage opportunities as land-based storage reach capacity. Refinery configurations were altered to respond to the new market conditions to avoid containment issues as demand fell.

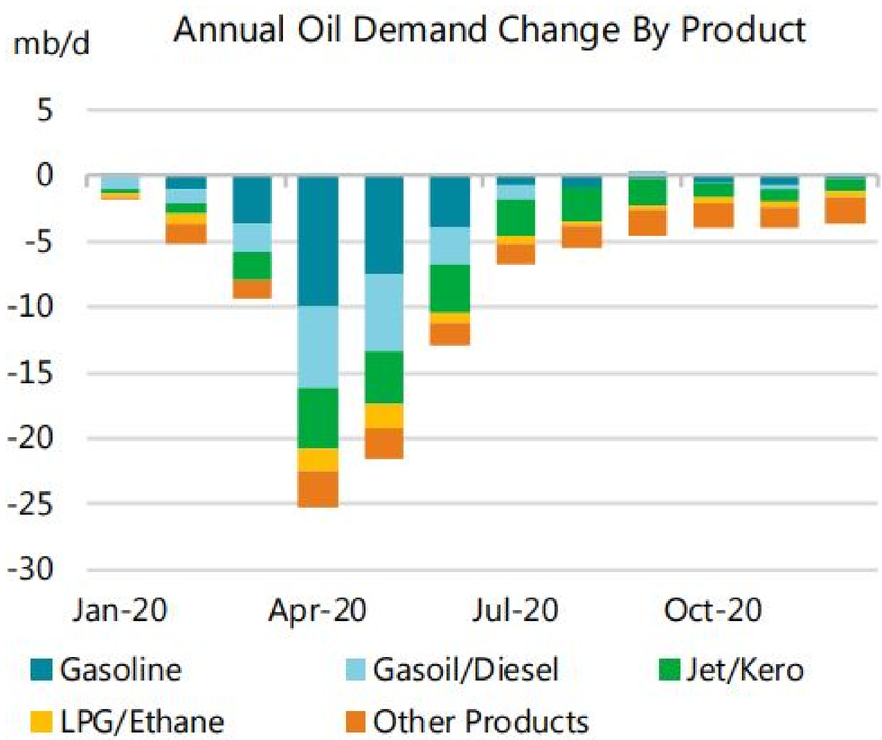

Figure 1-2: Global Demand Change (IEA, 2020)

Both individuals and organizations were required to learn at record speeds to endure the pandemic. Energy companies, in particular, were hit especially hard with ExxonMobile, Chevron, and British Petroleum each having negative annual earnings shown in Table 1.1 (*ExxonMobile, 2020 Annual Report*, 2021; *Chevron, 2020 Annual Report*, 2021; *BP, 2020 Annual Report*, 2021).

Company	**2019 Earnings**	**2020 Earnings**
Exxon	$5.7	-$22.4
Chevron	$2.9	-$5.5
BP	$10.0	-$5.7

Table 1.1: Energy Companies Annual Earnings in Billions

These companies may have to rethink how to operate in the new lower-priced environment as the impacts from the pandemic are expected to last for some time.

1.2 Digital Transformation

Before the pandemic overtook daily life, another revolution was already underway, known as the digital transformation. Digital transformation involves the utilization of new technologies to reimagine business processes and products. Business problems have been solved since the 1930's using computational power but have moved from simple experimentation to exploitation and now business integration (Ritter & Pedersen, 2020). As more data becomes digitized and computational capabilities increase, the opportunity for complex analysis increases, including the use of drones and robots, IoT connected devices, blockchain, and artificial intelligence (Ebert & Duarte, 2018). Every corporation is affected, resulting in 90% of leaders recognizing and taking action to evolve their businesses to make better, faster, data-driven decisions (Hess et al., 2016). Many different applications are currently being explored in the energy sector, including predictive safety analytics, improving drilling performance, and crude price forecasting using deep learning (Tarrahi & Shadravan, 2016; Yin et al., 2018; Chen et al., 2017).

For organizations to succeed in this environment, comprehensive digital strategies will need to be developed that cross traditional corporate strategies, as shown in Figure 1-3 (Matt et al., 2015).

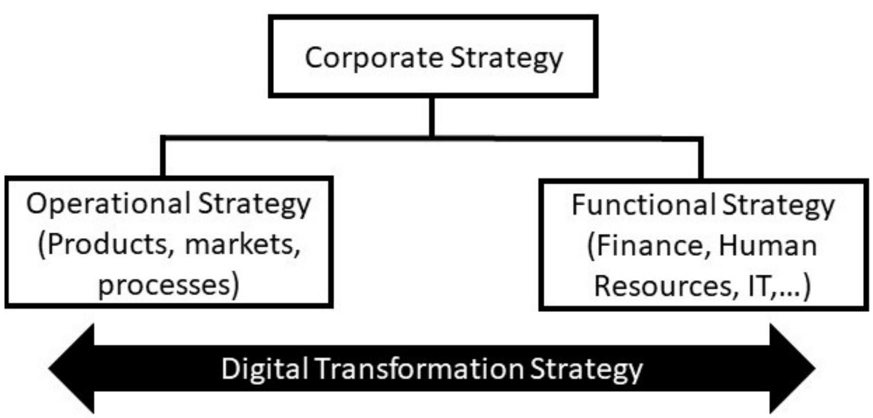

Figure 1-3: Relationship Between Digital and Corporate Strategies (adapted from (Matt et al., 2015))

To successfully transform requires acquiring new skills to assist the change, and these capabilities will need to be sustained to maintain operations after initial development (Matt et al., 2015). One of the issues that will inhibit companies from achieving their goals is focusing on the technology itself instead of the people (Frankiewicz & Chamorro-Premuzic, 2020).

1.3 People Analytics

Digital transformation is commonly associated with the information technology function becoming an increasingly important business partner. However, human resources (HR) is also being elevated through the emergence of people or talent analytics. The term has gained popularity since the early 2000s and is correlated with HR management to make better people decisions (Tursunbayeva et al., 2018). HR began with managing payroll and benefits but is now shifting to other parts of the employee experience (Rihan, 1998).

Data is necessary to develop people analytics tools. Research has shown that organizations that have robust knowledge management systems in place will lead to more organizational innovation (Liao & Wu, 2010). Collecting data can be done directly through surveys or indirectly by collecting employees' digital exhaust, making it possible to start generating insights into what drives performance in an organization (Leonardi & Contractor, 2018). New tools networking a workforce can be utilized to ensure the right skills are available for different business opportunities (Berman, 2012).

1.4 Thesis Motivation and Outline

As seen from the pandemic, operating environments can change rapidly, requiring individuals and organizations to learn new knowledge to meet changing business demands. The energy industry is in the middle of the digital transformation, but many of the data science skills needed are not already institutionalized; thus, knowledge creation and transfer are necessary.

This thesis seeks to understand how personal knowledge can translate to organizational learning. In particular, to explore how proximity to others impacts knowledge transfer and an organization's ability to meet future work demands.

In Chapter 2, a literature review shows past work relating to learning and knowledge transfer. In Chapter 3, research questions are formulated to explore cognitive and organizational proximity. Chapter 4 covers the research methodology focusing on agent-based modeling. The agent-based model is defined, and validations are displayed in Chapter 5. The analysis results are then discussed in Chapter 6. Finally, conclusions and recommendations for future work are summarized in the final chapter.

Chapter 2

Literature Review

The objective of the academic literature review is to explore the learning phenomena, in particular, how knowledge is gained and transferred. This chapter will explore learning curves, tacit and explicit knowledge, and knowledge transfer mechanisms. Proximity is defined, and a historical view of talent management is explored.

2.1 Learning

2.1.1 Learning Curves

The first mention of the learning curve phenomena was in the 1930's in relation to airplane manufacturers' ability to reduce cost as production volumes increased. These curves were based on empirical evidence and refined over time resulting in a logarithmic formula relating cost and quantity. By doubling the number of airplanes manufactured, an 80% cost reduction in assembled operations was observed (Wright, 1936). Wright's formula is defined as follows:

$$Y = aX^b \tag{2.1}$$

where:

$$Y = \text{Average time (or labor cost) per unit}$$

$$a = \text{Time (or labor cost) per unit}$$

$$X = \text{Cumulative production volume}$$

$$b = \frac{log_{10}(\text{Learning Rate})}{log_{10}(2)}$$

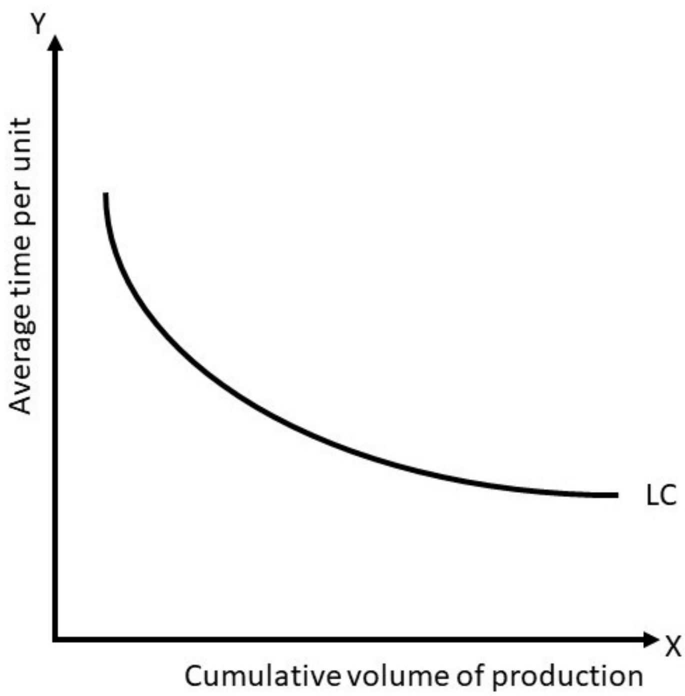

Figure 2-1: Wright's Learning Curve (adapated from (Wright, 1936))

A comprehensive assessment of learning curves and their industrial applications was completed during the 1970's. Up until that point in time, there were five applications commonly used (Yelle, 1979):

1. Various shapes of learning curves

2. Parameter estimation

3. Industrial engineering applications such as setting time standards and incentives

4. Classical cost control

5. Purchase and bidding functions

Further research showed that there was no one size fits all approach to the direct application of Wright's phenomena, resulting in various learning curve equations and use cases. Learning curves soon began being used for predicting the development of new products, but an analysis showed trying to fit past performance to predict future performance was not the best idea due to errors in labor requirements (Alchian, 1963). Comparisons for skilled practitioners versus new unskilled showed the time to complete tasks decrease for new products with similarities to previous experience (Jong, 1957). An important note is that the learning curves described show organizational learning, not necessarily the learning curves of individuals.

2.1.2 Organizational Learning

Organizational learning is an increasingly important aspect of creating and maintaining a competitive advantage for an ever-changing environment (Marquardt, 1996) and has been shown to be positively correlated with both innovation and performance (Jiménez-Jiménez & Sanz-Valle, 2011; Bolaji Bello & Adeoye, 2018). However, defining organizational learning can be difficult because there has been a lack of cumulative work (George P. Huber, 1991). One definition is that organizations' knowledge is the culmination of individuals' knowledge distributed through shared mental models (Kim, 1993). Others argue teams are the fundamental building blocks of learning (Senge, 1990). Lately, there has been a trend toward multilevel, indicating learning is multidirectional between individuals, teams, and organizations (Wiewiora et al., 2019).

One of the most noteworthy works received the Academy of Management Reviews decade award for it's multilevel organizational framework shown in Table 2.1 (Crossan et al., 1999).

Level	Process	Inputs / Outcomes
Individual	Intuiting	Experiences Images Metaphors
Group	Interpreting	Language Cognitive Map Conversation / Dialogue
	Integrating	Shared Understandings Mutual Adjustment Interactive Systems
Organization	Institutionalizing	Routines Diagnostic Systems Rules and Procedures

Table 2.1: Learning/Renewal in Organizations: Four Processes Through Three Levels (adapted from (Crossan et al., 1999))

The learning process begins with intuiting, which happens at the individual level. Past experiences enable pattern recognition to inform actions effortlessly by experts. A distinction is made between expert and entrepreneurial intuiting. Entrepreneurs can identify new connections that have not been previously identified through past experiences. Interpreting is also local to the individual, involving synthesizing information through the context in which it is presented. The integrating process moves from the individual to the group level by achieving a collective understanding. Shared understandings are gained through the use of language familiar to the individuals. From there, organizations can institutionalize learning through the structures, strategies, and routines established. Figure 2-2 shows the dynamic learning process according to Crossan.

2.1.3 Individual Learning

Learning theories go back to the early 1900's beginning with John Watson's behaviorism theory stating learning is a conditioned reflex (Watson, 1913). Rewards or punishments would influence behavior, and people would adjust their actions based on the outcome. Behaviorism was later deemed insufficient because it was based on how children learn but does not translate to adults. Andragogy sought to replace

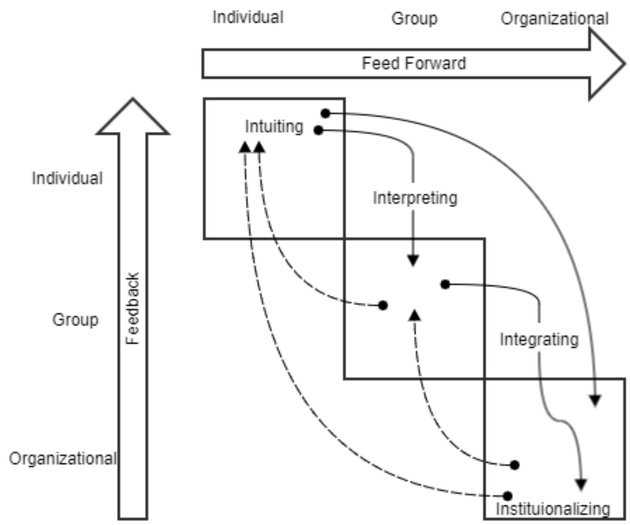

Figure 2-2: Organizational Learning As a Dynamic Process (adapted from (Crossan et al., 1999))

this method focusing on adult learning and was based initially on four major assumptions, with the fifth being added several years later (M. Knowles, 1973; M. S. Knowles, 1984):

1. Self-concept

2. Experience

3. Readiness to learn

4. Orientation to learning

5. Motivation to learn

The argument is centered around as people mature, they begin to develop specific characteristics that impact learning. Self-concept is the idea that adults are self-directed and desire to know what they will learn and why it is important. By drawing on their experiences that accumulate over time, individuals are ready to learn to assume new roles in society. The learning then becomes more problem-centered from subject-centered, with motivation being internal to the individual.

Transformation learning is another concept focusing on a learner's frame of reference (Mezirow, 1997). The theory concentrates on habits of mind and points of view. By critically assessing previously held assumptions through a reflection process, a transformation of one's frame of reference can be achieved. Experience learning theory describes four processes contributing to learning: experience, observation, conceptualization, and experimentation (Kolb, 2014). A literature review showed a surplus of psychological, adult educational, and management learning theories (Tusting & Barton, 2003).

2.1.4 Collaborative Learning

Experts are not aligned on a formal definition of collaborative learning but can generally agree that it involves two or more individuals who intend on learning together (Dillenbourg, 1999). Collaboration does not happen just because people share proximity, but a sustained effort must be applied to share knowledge (Roschelle & Teasley, 1995). Early research showed that learning in pairs resulted in better outcomes than those who learned by themselves (Light et al., 1994).

Zones of proximal development highlight the gap between what an individual can learn independently versus their capability with the assistance of a more knowledgeable person or collaboration with a peer (Vygotskiĭ & Cole, 1978). Learning can be reinforced through collaboration simply because people must articulate their thinking, forcing them to elaborate on their thoughts (van Boxtel et al., 2000). Collaboration can also lead to conflict, mainly when clear roles and responsibilities are not defined (Jones, 2006). Psychological safety plays a prominent role in overcoming these conflicts allowing people to speak up without fear of punishment (Edmondson, 1999). Overall, collaboration increases individuals' knowledge as long as any conflict is mitigated.

2.2 Knowledge Creation and Transfer

2.2.1 Tacit versus Explicit Knowledge

Knowledge creation is considered a chaotic process, with knowledge being described as either tacit or explicit (Nonaka & Takeuchi, 1995). Tacit knowledge is the information that is ingrained in an individual after years of experience and is often difficult to express. Explicit knowledge, on the contrary, can be easily transmitted since it can be stored and processed. Nonaka and Takeuchi proposed three characteristics of knowledge creation.

- Metaphor and analogy
- Personal to organizational knowledge
- Ambiguity and redundancy

Tacit knowledge heavily relies upon interpersonal communications where spatial proximity plays a significant role (Morgan, 2004). Communities of practice can assist in overcoming spatial constraints (Gertler, 2003). Since tacit knowledge is difficult to describe, metaphors can be utilized to communicate complex ideas in a way that others can understand. Organizations can then leverage the individuals knowledge through discussion, observation, and experience sharing (Nonaka & Takeuchi, 1995). Ambiguity and redundancy seem counter-intuitive to productivity, but the lack of clarity can allow multiple interpretations of an organization's mission, sparking dialogue between individuals enabling innovation.

2.2.2 Depth of Knowledge

The literature shows that knowledge requires learning and that prior knowledge allows for the acquisition of new knowledge (Cohen & Levinthal, 1990). A framework proposed laid out four levels of knowledge shown in Figure 2-3 (Webb, 1999).

Recall and reproduction is the lowest level depth of knowledge and involves the simple recollection of facts or following simple procedures. Skills and concepts is

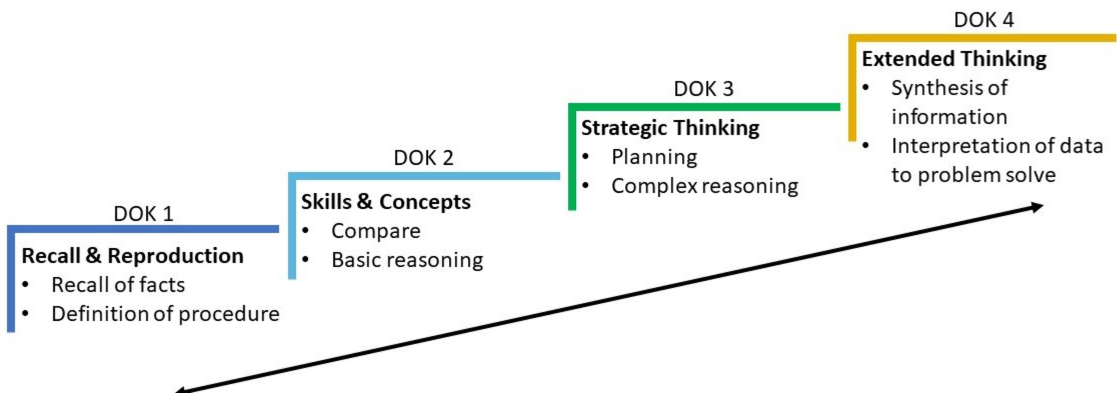

Figure 2-3: Webb's Depth of Knowledge (adapted from (Webb, 1999))

level two requiring individuals to organize, predict, or estimate while completing tasks. Strategic thinking is a higher level of complexity that often involves reasoning skills. Individuals must be able to think critically as often there is more than one possible solution. The final level is extended thinking by synthesizing information from multiple sources. Level four can be time consuming as tasks are not routine, often pulling knowledge from one domain and applying it in another.

2.2.3 Knowledge Transfer Mechanisms

Knowledge transfer can be challenging to achieve, but there is potential for significant increases in performance by successfully transferring knowledge from one group to another (Argote, 1999). One positive outcome for organizations skilled at the diffusion of knowledge is an increase in the probability of organizational survival (Argote et al., 1990). Organizations can learn from their own experiences and those external to them (Levitt & March, 1988). Various mechanisms have been researched demonstrating knowledge transfer, including personnel movement, training, communication, technology transfer, and inter-organizational relationships (Argote et al., 2000).

2.2.4 Proximity and Knowledge

There are several dimensions of proximity that include cognitive, organizational, social, institutional, and geographical (Boschma, 2005). Cognitive proximity is the concept that a minimum level of knowledge is required for agents to absorb new information. The greater the cognitive distance, the less likely new knowledge will be acquired. On the contrary, individuals with similar knowledge bases will be able to collaborate more effectively, enabling learning. Organizational proximity relates to structure and control. Centralized organizations can better integrate knowledge into an organizations workflow processes versus decentralized. However, decentralized allows for companies to pivot faster to a changing operating environment.

Social proximity involves the relationships between individual agents, which is strongly correlated with organizational and geographical proximity. As individuals work together, trust is formed, allowing tacit knowledge to be communicated more easily. Small social distance can stifle innovation as people become comfortable with the status quo, which can harm organizations in a dynamic environment. In- institutional proximity relates to the habits and routines established that influence an organization's interactions. Finally, geographical proximity is the spatial distance between agents. A long history of research shows that knowledge is generally geographically constrained, and those organizations close to knowledge centers benefit. Table 2.2 below shows a summary of the five forms of proximity from Boschma.

	Key dimension	Too little proximity	Too much proximity	Possible solutions
1. Cognitive	Knowledge gap	Misunderstanding	Lack of sources of novelty	Common knowledge base with diverse but complementary capabilities
2. Organizational	Control	Opportunism	Bureaucracy	Loosely coupled system
3. Social	Trust (based on social relations)	Opportunism	No economic rationale	Mixture of embedded and market relations
4. Institutional	Trust (based on common institutions)	Opportunism	Lock-in and inertia	Institutional checks and balances
5. Geographical	Distance	No spatial externalities	Lack of geographical openness	Mix of local "buzz" and extra-local linkages

Table 2.2: Five Forms of Proximity (adapted from (Boschma, 2005))

2.3 Talent Management

Similar to learning, talent management also has multiple interpretations of what it is. The majority of research has historically focused on talent management practices and activities which fall into three categories (Thunnissen et al., 2013).

1. Recruitment, staffing, and succession planning
2. Training and development
3. Retention management

There are inclusive and exclusive approaches to training and development (Powell et al., 2012). An exclusive tactic generally focuses on developing high potential employees, typically considered the top 10-20% of employees. The inclusive approach argues all employees have talent and can be developed to reach a higher level of performance. One argument shows that an exclusive approach predetermines performance outcomes by stating those not listed as high performers will receive less development opportunities, thus solidifying their status as non-high performers (Pfeffer, 2001). Scholars are split on categorizing the workforce into different buckets, especially since talent is subjective (Thunnissen et al., 2013). Even though there is a material amount of information in this space, talent management has minimal empirical research (Collings & Mellahi, 2009).

Chapter 3

Research Questions

This chapter covers the research objectives for this thesis, focusing on knowledge transfer through proximity and how the research intends to contribute to the academic community.

3.1 Motivation and Academic Contribution

Motivation for this thesis is based on observations on how fast the world is changing, especially in the energy industry experiencing digital transformation and energy transition. Research indicates companies will need to develop a capacity to change while maintaining current capabilities and institutionalizing change processes (Meyer & Stensaker, 2006). Therefore, understanding how knowledge is transferred through an organization may enable organizational transformations.

3.1.1 Research Questions

This thesis aims to answer the following:

1. What are the implications to organizational learning due to varying cognitive distances?

2. What impact does social proximity have on knowledge transfer?

3. How do changing work demands influence knowledge creation and diffusion?

A variety of different methods will be considered, including observational, experimental, and computational, to explore knowledge transfer through cognitive, social, and organizational proximity. This thesis intends to contribute to the body of knowledge on the merger of talent management systems and the dynamic process of organizational learning.

Chapter 4

Research Methodology

In this chapter, several methods are examined for suitability to explore the research questions outlined in Chapter 3, with agent-based modeling ultimately selected to run simulations.

4.1 Method Goals

There are several requirements this researcher hopes to accomplish with this thesis, the primary being to understand how individual knowledge transfers through an organization. The analysis needs to be forward-looking with predictions that indicate a range of possible outcomes. There is also a desire for research to be transferable to business applications, particularly for organizations managing multidisciplinary teams to solve complex problems. The method also needs to have the ability to be adaptive to changing operating environments.

Several methods are available to explore organizational learning through cognitive and organizational proximity, including observational, experimental, and simulations. Each of these methods has strengths and weaknesses that can influence research insights. Much of the early research studying learning was completed through observational and experimental techniques. However, simulation analysis is the best option available for the method goals listed above. According to the National Research Council, there is an incredible amount of uncertainty when dealing with human behavior, and simulation models have the ability to show many plausible outcomes (National Research Council, 2008). Several simulation methods are available, including system dynamics and agent-based modeling. System dynamics ignores the individual and focuses on higher-level aggregated properties of a system. On the other hand, agent-based modeling zooms in on individual decisions that can impact overall system performance. An agent-based is best suited for this analysis based on the research questions focusing on cognitive proximity, which is based on individuals.

4.2 Agent-based Modeling

Agent-based modeling (ABM) was developed in the 1960's with one of the first examples being Conway's Game of Life (Gardner, 1970). Autonomous agents could interact by defining straightforward rules, with their aggregate behavior showing emergent outcomes (Macal & North, 2010). A simple spatial model simulated how two groups naturally segregated based on simple preferences (Schelling, 1971). ABMs have been used to study various complex problems, including energy technology adoption, energy networks, and climate-energy policy (Castro et al., 2020; Farmer et al., 2015; Rai & Robinson, 2015). An ABM will usually have three main elements (Macal & North, 2010):

1. A set of agents, their attributes and behaviors
2. A set of agent relationships and methods of interaction
3. The agents' environment

According to Macal and North, there are several critical attributes and other valuable characteristics of an agent, which are summarized in Table 4.1. Once the agent attributes are determined, the way agents interact must be modeled. Two main concerns must be addressed, including how the agents are connected and the dynamics of the interaction. The interactions can be static or dynamic, forever linking agents or allowing agents to make new connections according to the rules programmed. Some examples of the different types of interaction networks are shown in Figure **??**.

	Attribute	Definition
Critical	Self-contained	Uniquely identifiable individually and modular
	Autonomous	Self-directed and can function independently of environment and in its interactions with other agents
	State	Varies over time, agents behaviors conditioned to current state
	Social	Interactions with other agents influence behavior
Valuable	Adaptive	Ability to learn and adjust behaviors as experience is gained
	Goal-directed	Compares outcomes of behaviors and adjusts responses in future interactions
	Heterogeneous	Characteristics and behaviors vary between agents

Table 4.1: Agent Attributes and Behaviors (adapated from (Macal & North, 2010))

Finally, an environment must be created where agents can interact with each other or directly with the environment. The environment can be as simple as a spatial model, which shows where agents are located, or it can be complex with specific characteristics based on the location, for example, climate.

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Chapter 5

Model Implementation

This chapter will develop an agent-based model for simulation experiments to seek answers to the research questions from Chapter 3. The definition of an agent will be presented along with its interactions with other agents and the environment in which it operates.

5.1 Model Setup

In order to address the research questions, simulations will be conducted based on the learning theories and mechanisms for knowledge transfer presented in Chapter 2. Development of the ABM will be based on a framework proposed by Macal and North (Macal & North, 2010).

5.1.1 Specific Problem To Be Solved By ABM

The primary goal of this research is to explore how cognitive and organizational proximity will shape organizational capabilities. Tacit knowledge has been demonstrated to be best transferred through collaboration. Several managerial levers will be toggled, including organizational structure and work demands. Finally, the model will be critically assessed on the appropriateness of integrating into an existing organization to simulate organizational capabilities at a future state.

5.1.2 Design of Agents Attributes

Agents will have several static and dynamic attributes that will influence their behavior. When dealing with large organizations, a heterogeneous population would be preferred over a homogeneous one as workforce populations are diverse. For modeling simplicity, agents' dynamic properties will be considered homogeneous. For example, all agents will have the same learning curve when completing tasks of similar complexity. Table 5.1 lists the different agent features in this model.

Agent Attribute	Status	Definition
Age	Static	Age of individual agents
Gender	Static	Gender of individual agents
Skill Categories	Static	List of skills
Knowledge Level	Dynamic	Webb's depth of knowledge levels
Team	Dynamic	Based on organizational structure
Capacity	Static	Working hours per year

Table 5.1: Agent Attributes

Age

Age distribution will be based on the industry breakdown, according to the US Bureau of Labor Statistics in Table 5.2 (of Labor, 2020).

Age	16 - 19	20-24	25-34	35-44	45-54	55-64	65+
Oil and Gas Extraction	0	3	23	29	23	13	7

Table 5.2: Oil and Gas Industry Age Breakdown

Gender

Gender distribution will be based on the industry breakdown, according to the Catalyst in Table 5.3 (Catalyst, 2019).

Gender	Male	Female
Percent	78	22

Table 5.3: Oil and Gas Gender Breakdown

Skills

A variety of different technical skills are required to bring an oil and gas well online. Several general skill buckets will be utilized for this analysis as shown in Table 5.4

Technical Skills
Engineering
Operations
Commercial
Financial
Data Science

Table 5.4: Technical Skills

Knowledge Level

Knowledge levels will be adapted from Webb's depth of knowledge to reflect common language in the industry in Table 5.5. The timing to move from one category to another will be based on the author's experience and literature. Expert status can be achieved after approximately ten years and over 10000 hours of considerable effort in technical domains (Prietula & Simon, 1989).

Webb's Knowledge Level	Industry Term	Hours of Effort
	No Exposure	0
Recall and Reproduction	Awareness	1 - 40
Skills and Concepts	Fundamental	41 - 3200
Strategic Thinking	Skilled	3200 - 10000
Extended Thinking	Expert	10000+

Table 5.5: Knowledge Levels Breakdown

Teams

Individual agents will be placed on teams which will determine the agent's social proximity to knowledge. Team sizes will range utilizing best practices of seven plus or minus two (Miller, 1994).

Capacity

A typical work year comprises approximately 2080 working hours. In many industries, vacation time is correlated to time of service, so individual agents' working capacity will be adjusted by age bracket. After vacation time is removed, an assumption is made that only 75% of working hours will be productive due to other administrative tasks shown in Table 5.6. Only focused working hours will be available for agents to complete work tasks.

Age	**Vacation Hours**	**Total Working Hours**	**Focused Working Hours**
20-24	80	2000	1500
25-34	120	1960	1470
35-44	160	1920	1440
44-54	200	1880	1410
55+	240	1840	1380

Table 5.6: Agent Working Capacity

5.1.3 Design of Environment

Demands, or work tasks, will be generated and loaded into the environment. The demands will have the following attributes, as shown in Table 5.7. Agents will be placed into the environment with the ability to collaborate with other agents on their team to complete work tasks.

Task	**Engineering**	**Skill Level**	Operations	**Skill Level**	Commercial	**Skill Level**	**Data Science**	**Skill Level**	**Financial**	**Skill Level**
1	50	Fundamental	0	No Exposure	0	No Exposure	0	No Exposure	0	No Exposure
2	0	No Exposure	0	Fundamental	45	No Exposure	0	No Exposure	5	Awareness
3	0	No Exposure	50	Skilled	0	No Exposure	0	No Exposure	0	No Exposure
4	0	No Exposure	0	No Exposure	0	No Exposure	25	Fundamental	25	Fundamental
5	30	Expert	10	Awareness	0	No Exposure	10	Fundamental	0	No Exposure

Table 5.7: Sample of Environmental Demands

5.1.4 Design of Agent's Behaviors

Since the work tasks will be loaded into the environment, the agents will query the demands and select work based on Knowles' argument that individuals are self-directed (M. Knowles, 1973). As demands are completed, an agent will learn, enabling them to finish similar tasks more quickly, first documented by Wright (Wright, 1936). On the contrary, skills can also degrade for procedural tasks, so an agent's skills will erode over time if not utilized (Bailey, 1989). At any point in time during the task, an agent can send a signal indicating a desire to collaborate.

5.1.5 Design of Agent's Mutual Interactions

In the event that the agent does not have the necessary skills required to complete the task or wishes to collaborate, agents can send a signal to collaborate within their team. Receiving agents can decide based on their workload if they have the capacity to assist. Collaboration will have multiple implications in that it will be time spent not completing work tasks. However, the communication between two agents allows the transfer of tacit knowledge enabling agents to complete tasks they may not have been able to otherwise. An object process diagram shown in Figure 5-1 summarizes the model.

5.2 Validations

Model validations are critical to any agent-based model to ensure agents rules are functioning as expected. Several validations were developed and tested.

5.2.1 Age and Gender Distributions

This unit tests aims to ensure the proper age and gender distribution are accurately represented in the model. Vacation time is a function directly related to age, impacting agents' time to complete tasks and learn new skills. Gender does not influence the model, but is an area of potential future work as identified in Chapter 7.

Age and Gender Distributions Expectations and Unit Test Results

The breakdown of gender and age distributions expected are the same as mentioned in Chapter 5. Fifty-three agents will be loaded into the model to test if distribution

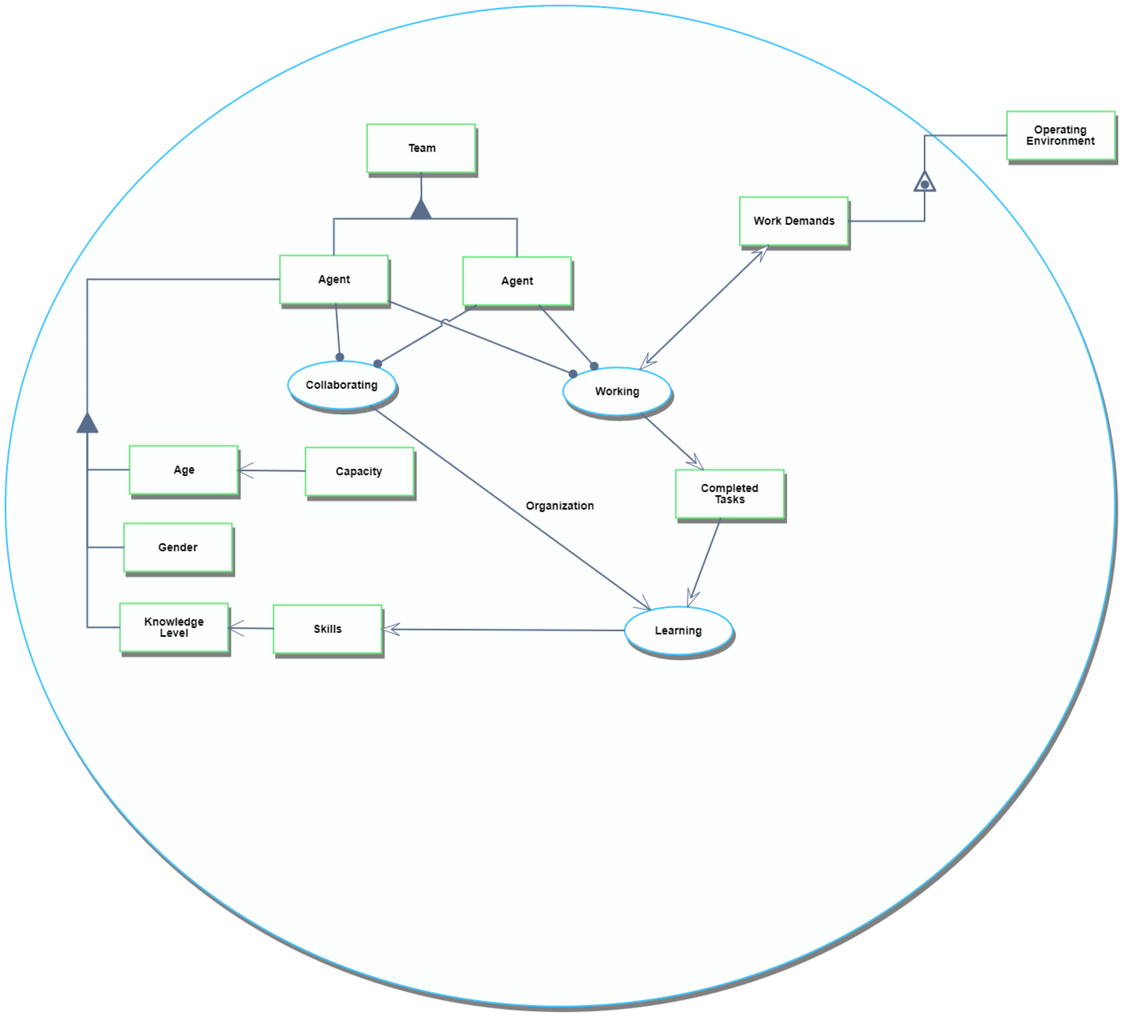

Figure 5-1: Object Process Diagram of Agent-based Model

functions coded give results close to expected. For gender, an acceptable difference will be considered within +/- 5% of actual. Age distribution due to the smaller sample size may vary up to 10% in any category.

Analysis of Age and Gender Results

Unit tests conducted showed positive results with gender and age distributions meeting expectations. The age distribution doesn't quite match expected, but most likely due to the smaller sample size influencing the outcome. One potential implication for this single scenario is that an older than expected population could reduce the

Gender	Count	Expected	Actual
Women	12	22%	22.6%
Men	41	78%	77.4%

Table 5.8: Gender Distribution Unit Test

Age	Count	Expected	Actual
20-24	1	3%	1.9%
25-34	9	23%	17%
35-44	17	29%	32.1%
44-54	13	23%	24.5%
55-64	6	13%	11.3%
65+	7	7%	13.2%

Table 5.9: Worker Distribution Unit Test

number of collaborators available due to the increase in vacation time, thus reducing knowledge transfer.

5.2.2 Work Schedule

This unit test will utilize the same fifty-three agents as the prior but will focus on agent state transitions based on typical working hours. The agent-based modeling application used has a built-in schedule function, allowing for a calendar to be built. The logic for the schedule is Monday - Friday with hours of work from 8AM - 2PM. The shortened workday is a workaround to remove 2 hours for administrative tasks. Figure 5-2 displays the application interface for setting a work schedule. Messages are sent to agents at the given time intervals impacting their actions.

Work Schedule Expectation and Unit Test Results

The expected number of workday transitions should be approximately equal to the number of workdays per year minus vacation days. A snapshot of a thirty-three year old agent is shown in Figure 5-3, with the value expected being 1280, twelve more than witnessed in the unit test. A more important metric is actual working time relative to anticipated, as shown in Table 5.10.

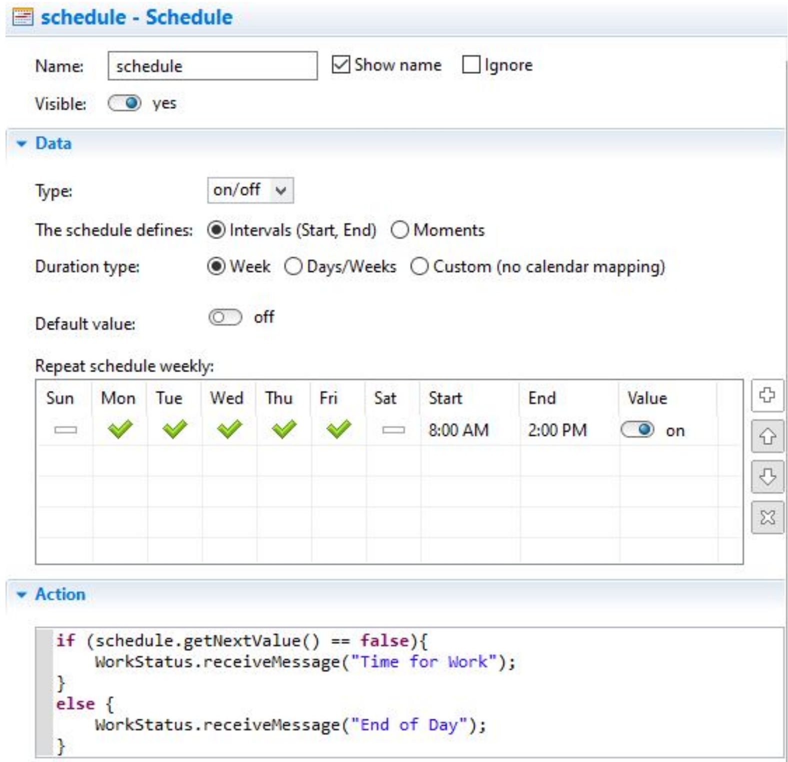

Figure 5-2: Work Schedule

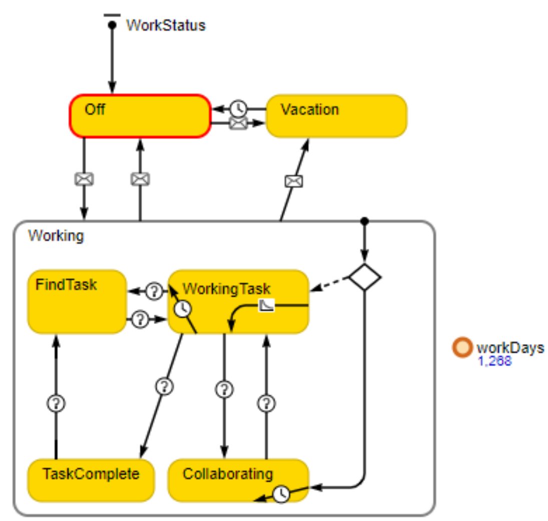

Figure 5-3: Work Schedule Unit Test

Work Schedule Analysis of Results

The individual snapshot displays the potential for deviations on an individual basis due to vacations being scheduled events based on rates. A thirty-three year old

Age	Expected Working	Actual Working	Difference Working
20-24	1500	1462	2.6%
25-34	1470	1500	2.1%
35-44	1440	1419	1.5%
44-54	1410	1416	.4%
55-64	1380	1392	.8%
65+	1380	1426	3.3%

Table 5.10: Hours Worked Averaged Over Five Years Unit Test

agent will receive a message for vacation at a rate of four times per year, but the actual number can vary. The high-level overview shows agents working within 4% of expected values, which is considered acceptable because that amount is equivalent to one week of work per year and aligns closer to reality.

5.2.3 Task Selection and Knowledge Levels

This unit test focuses on an agent's ability to select skill-appropriate tasks for three months. A collection of demands is generated on model initiation, with thousands of demands created. The agent will then remove the first demand on the list and check the demands knowledge level requirements against its own level. If the agent selected a task that does not match its skill, the demand would be returned to the collection, and another task will be selected. After choosing a skill-appropriate task, the agent will work the task for the duration of the demand. Upon completion, the agent will bank those hours, and if hours in that particular domain exceed the minimum required to be promoted to the next level, the agent will transition states to the new knowledge level.

Task Selection and Knowledge Level Expectations and Unit Test Results

The agent will start with no experience in state No Exposure and select a task in the Awareness category. Upon completing tasks equating to forty hours of effort, the agent will move into the Fundamental category and begin selecting tasks with that knowledge level. Several snapshots will be provided showing the agent's knowledge level state and the amount of experience in the engineering function.

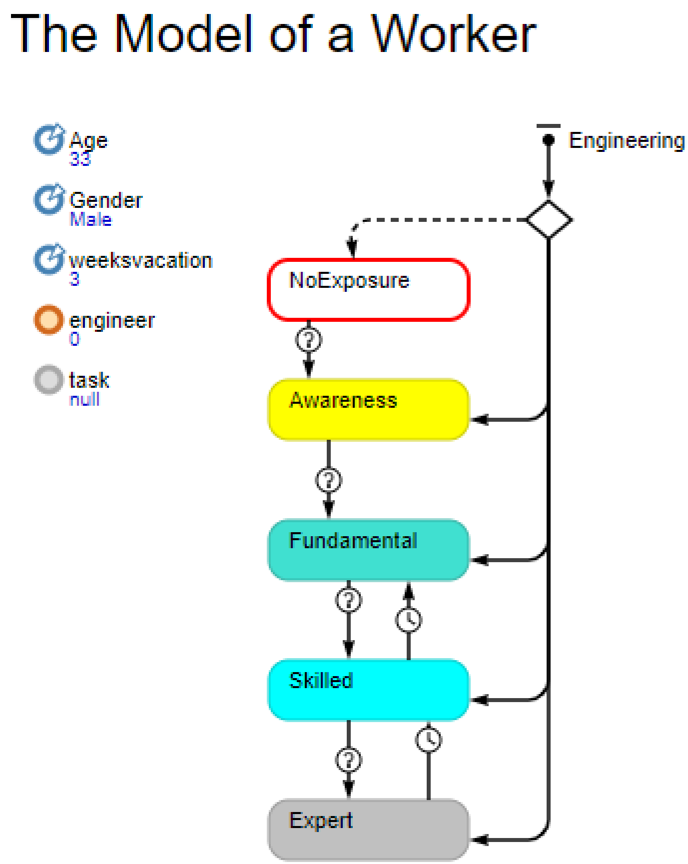

Figure 5-4: Worker Statechart at Time 0

Figure 5-5: First Task Selected

Task Selection and Knowledge Level Analysis of Results

The function called is a recursive function that can lead to a stack overflow error if implemented improperly. The initial unit test failed due to this issue, which was resolved by increasing the number of demands for each knowledge level, ensuring there are adequate tasks available for agents. The agent successfully selected a skill-appropriate task based on its current knowledge level and moved through the different knowledge levels once a minimum amount of effort was achieved.

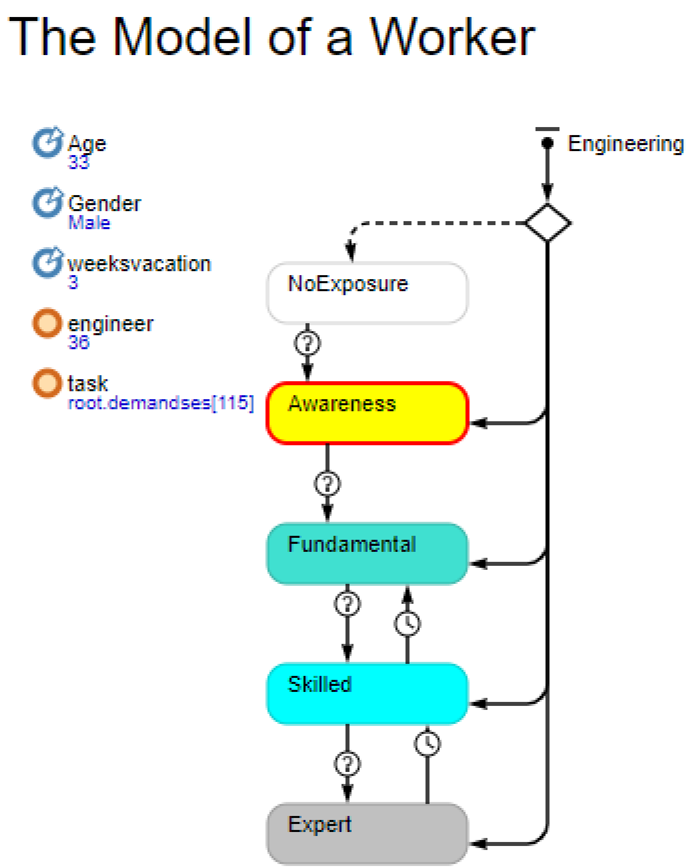

Figure 5-6: Worker Statechart After Task 1 Completed

Figure 5-7: Second Task Selected

5.2.4 Learning Curve

The learning curve implemented and tested will utilize Wright's learning curve equation. For each task completed at a knowledge level, a counter will be incremented by one. When an agent enters a new knowledge level, the counter will be reset to one. A learning curve of 80% will be applied to each task, and all tasks will have a ten-hour duration. Demands will be deemed complete when hours of effort equate to the adjusted task duration after the learning curve is applied. The agent's knowledge bank will increase by ten after the completion of each task.

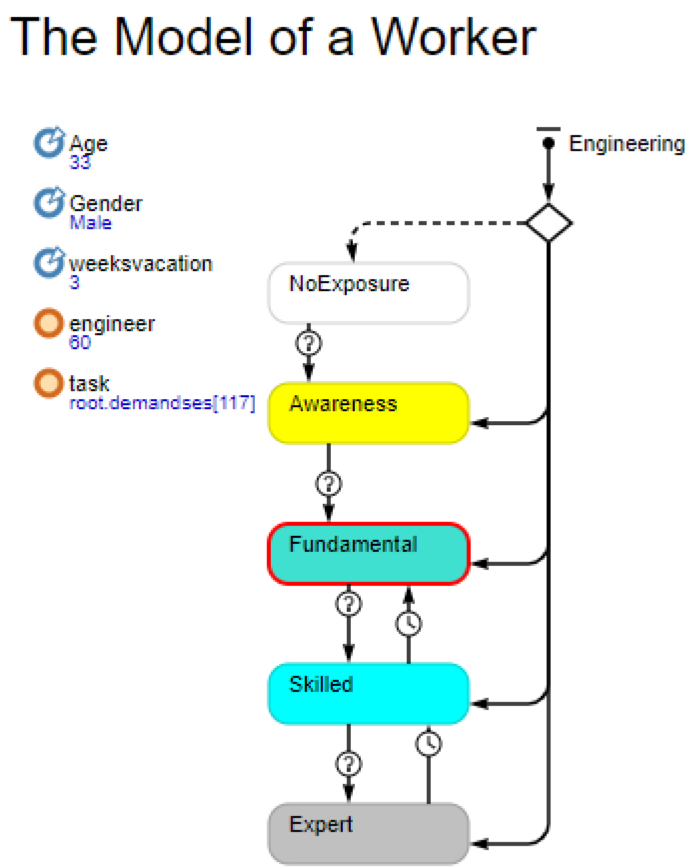

Figure 5-8: Worker Statechart After Task 2 Completed

Figure 5-9: Third Task Selected

Learning Curve Expectation and Unit Test Results

The expectation for this unit test is for the agent to complete five tasks in the Awareness category before moving into Fundamental. The total amount of effort required should be 37.37 hours based on a learning curve of 80%. Upon completing the fifth task, the agent should move into the Fundamental category with the first task requires ten hours of effort due to the reset task completion counter. Several snapshots show the adjusted hours for the selected task, agent knowledge level state, and the knowledge bank. Table 5.11 displays a comparison of expected versus actual results.

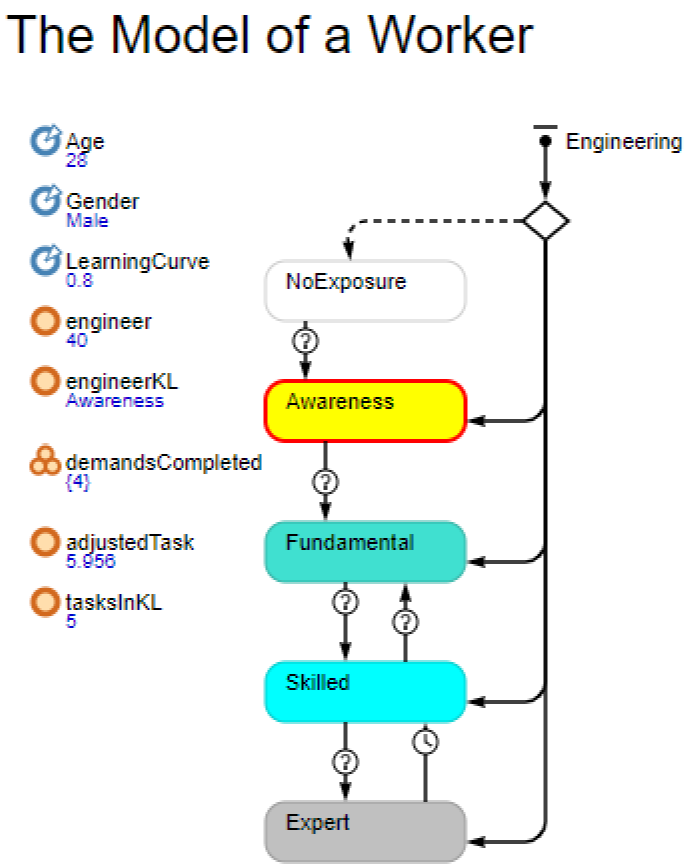

Figure 5-10: Agent State With Task Five Active

Task	Knowledge Level	Knowledge Bank	Expected Hours of Effort	Actual
1	Awareness	10	10	10
2	Awareness	20	8	8
3	Awareness	30	7.02	8
4	Awareness	40	6.4	7
5	Awareness	50	5.96	6
6	Fundamental	60	10	10
7	Fundamental	70	8	8
8	Fundamental	80	7.02	8

Table 5.11: Agent Task Completion Actual versus Expected

Learning Curve Selection Analysis of Results

The unit test fails to deliver the expected level of performance. An hourly check is run to determine task completion by verifying if work hours on a task are greater than the adjusted hours required to complete. Original task lengths are loaded into

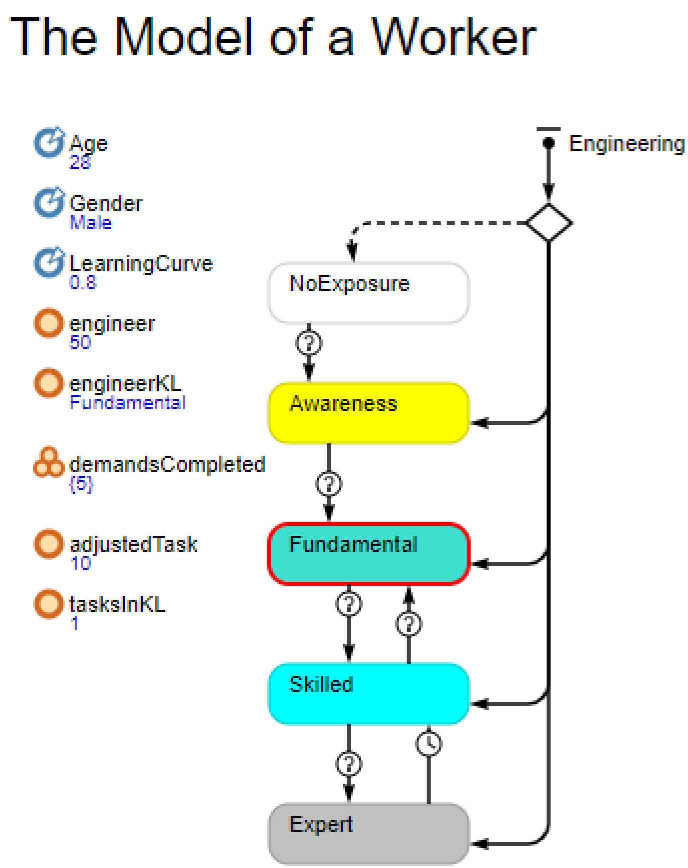

Figure 5-11: Agent State With Task Six Active

the environment in whole numbers, and it is only through the addition of the learning curve that this discrepancy is seen. An increase in the check frequency was also tested but resulted in stack overflow errors due to a significant increase in events created. A workaround was implemented that rolls any extra hours worked into the next task, minimizing the additive time effect witnessed.

Another issue was also noticed during this unit test showing unrealistic experience in the engineer knowledge bank. An unreasonable assumption was originally made to add the task's original hours instead of the adjusted hours. This has been corrected, and after five 10-hour tasks, the engineering bank shows 37.37 hours of effort.

5.2.5 Collaborator Selection

This unit test aims to test the ability of two agents to be linked, allowing for collaboration. Agents will be constrained to only collaborate with other agents on their team determined on model startup. The link will be bi-directional, allowing both agents to connect. In the case of uneven teams, there is a chance for no collaborator to be available. Upon completion of collaboration, the link will be broken, allowing for new pairs to be formed.

Collaborator Selection Expectation and Unit Test Results

The expectation for this unit test is for agents to link with one other agent within the same team. Agents will not be able to connect with agents on other teams. The agent should send the collaboration request to random team members allowing for a diversity of pairings.

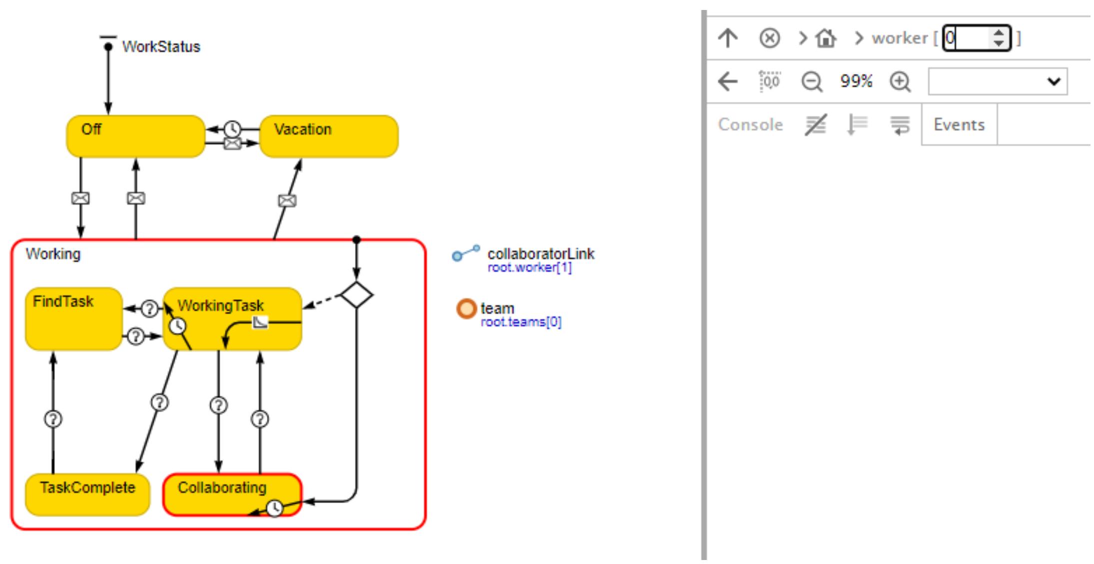

Figure 5-12: Agents Worker [0], [1] On Team [0] Connected

Collaborator Selection Analysis of Results

The unit test passes with expected results being achieved. However, there is room for improvement based on the nature of real-world work demands. In practice, more than one collaborator may be necessary to complete a task as complexity increases,

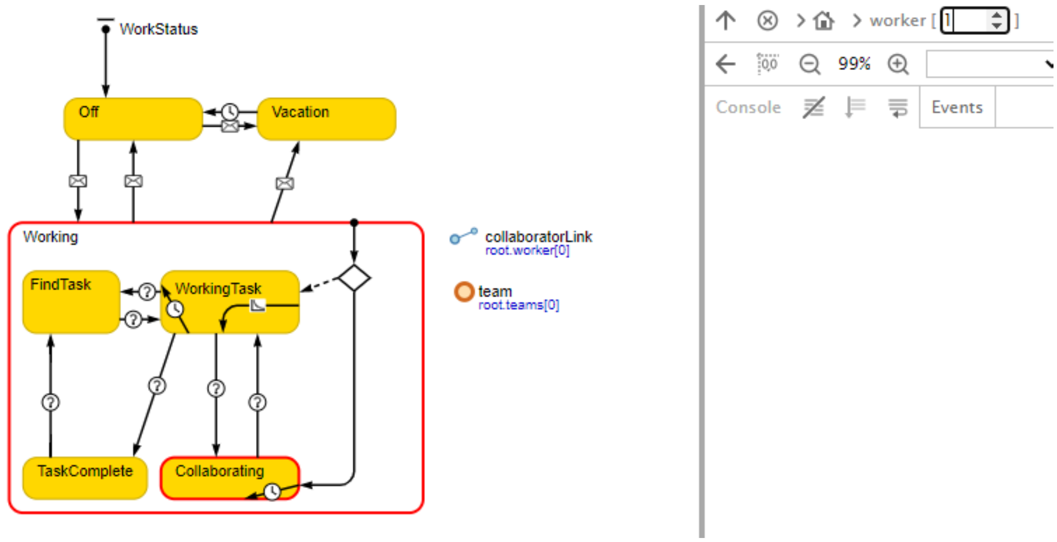

Figure 5-13: Agents Worker [1], [0] On Team [0] Connected

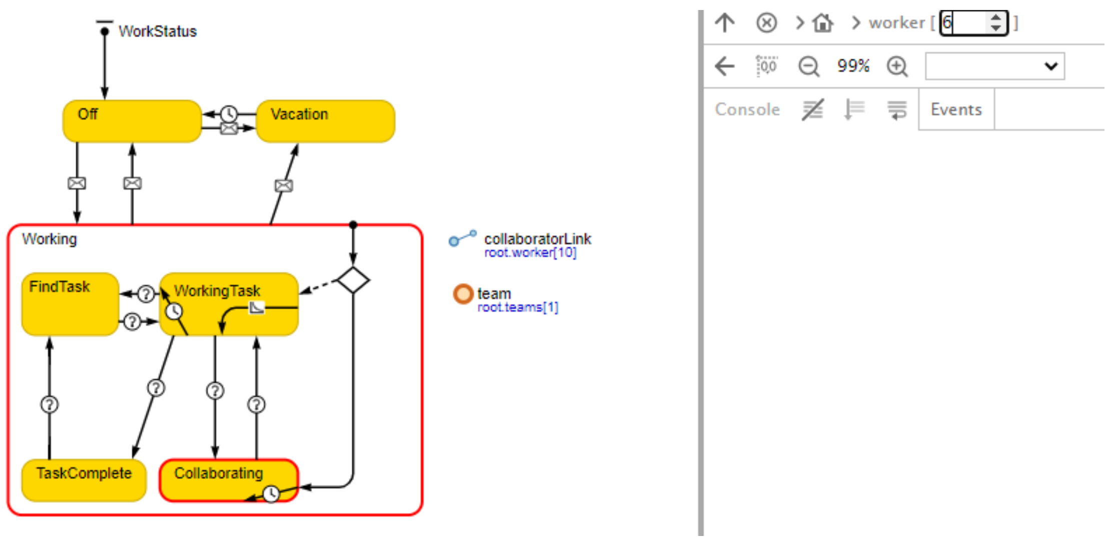

Figure 5-14: Agents Worker [6], [10] On Team [1] Connected

including multiple people collaborating simultaneously. Snapshots provided in Figure 5-12 through 5-16 shows a small sample of results. Figures 5-16 displays a list of collaborators, showing no links created above worker [4], indicating connections only apply to teammates.

5.2.6 Collaborators Knowledge Levels and Cognitive Distances

This unit test is designed to check the knowledge level of collaborators and determine the cognitive distance between the two agents. The agent requesting help will be

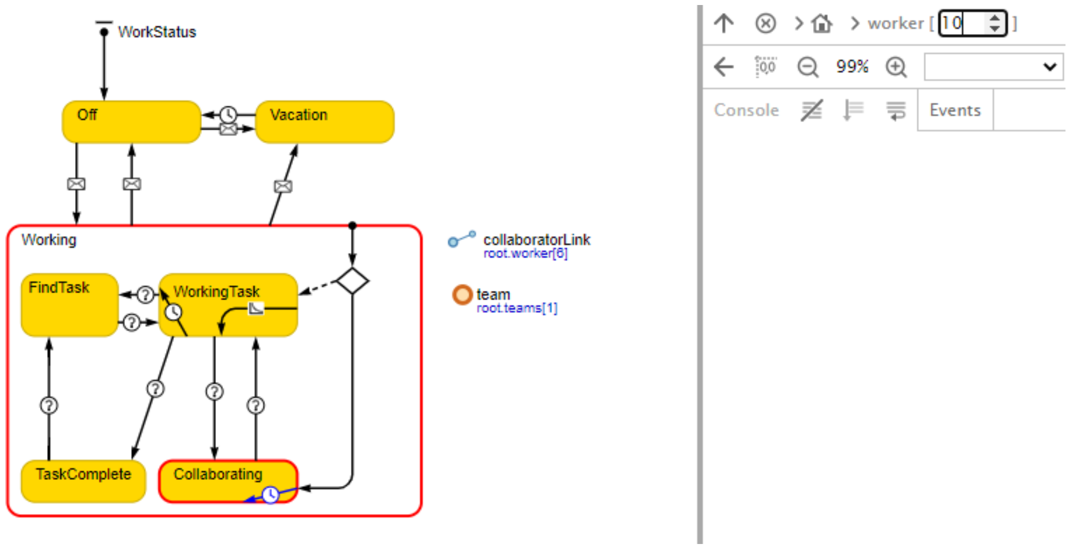

Figure 5-15: Agents Worker [10], [6] On Team [1] Connected

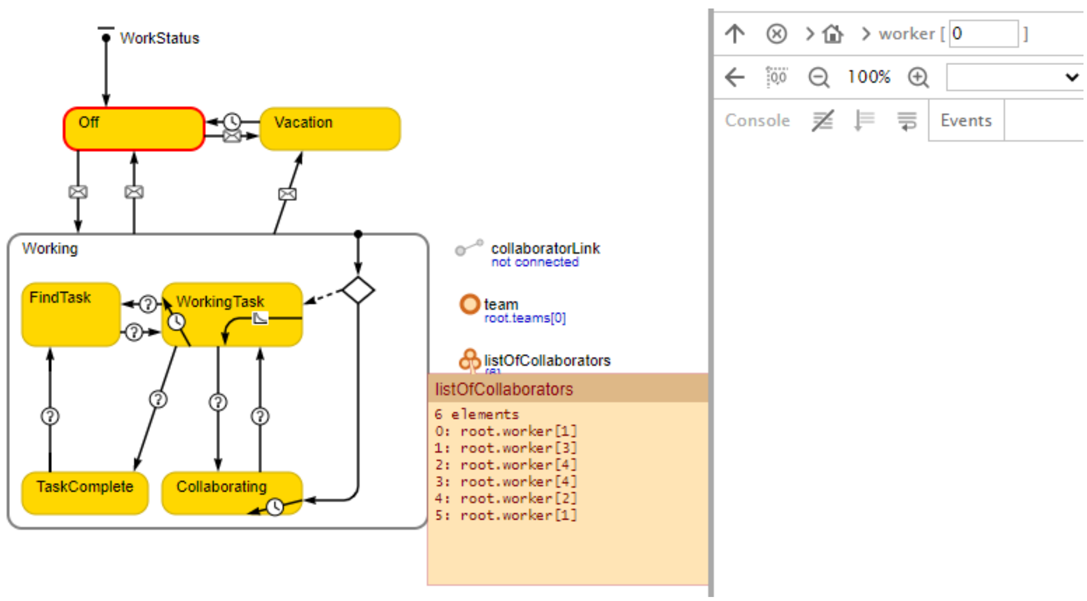

Figure 5-16: Collection of Worker [0] Collaborators on Team [0]

constrained to connecting with other agents of an equal knowledge level or greater. . If they successfully find another agent that fits the criteria, a cognitive distance, as shown in Equation 5.1 will be calculated.

$$D = |log_{10}Agent[i] - log_{10}Agent[j]| \tag{5.1}$$

where:

$$D = \text{Cognitive distance}$$
$$Agent[i] = \text{Agent[i] Hours of Effort Bank}$$
$$Agent[j] = \text{Agent[j] Hours of Effort Bank}$$

The cognitive distance factor will then be utilized to adjust the duration of collaboration time. The larger the distance, the longer the collaboration will be. Collaboration time will default to 20% of the task duration of the requesting agent but will be augmented according to Equation 5.2. A simulation will run between two agents for one year. Agents of equal or lower skill levels will gain experience through collaboration, but agents of superior skill will not.

$$T = H * P * (1 + D) \tag{5.2}$$

where:

$$T = \text{Collaboration time}$$
$$H = \text{Task hours of effort}$$
$$P = \text{20\% Default collaboration time}$$
$$D = \text{Cognitive distance}$$

Cognitive Distances Expectation and Unit Test Results

The expectation for this unit test is for an agent to connect with the other agent of equal or greater skill. Worker [0] begins with zero experience in knowledge level Awareness, while Worker [1] begins with 3500 hours of experience in knowledge level Skilled. Only Worker [0] should be able to link the two agents together.

Figure 5-21 displays the first time the two agents link together to collaborate on a

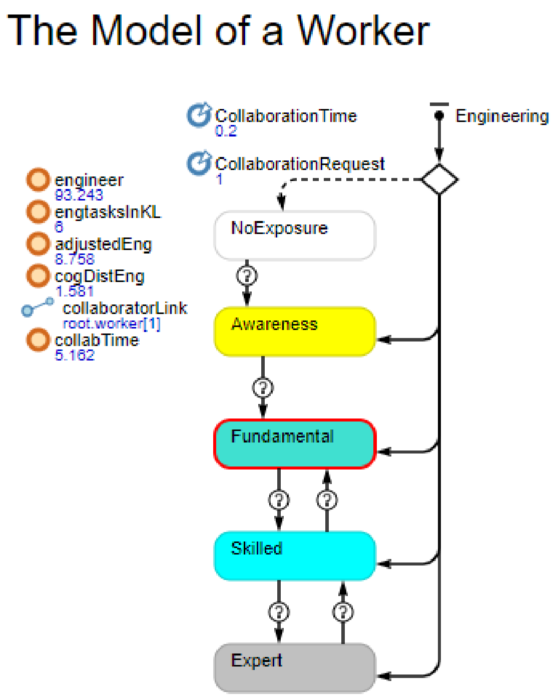

Figure 5-17: Cognitive Distance for Worker[0] and Worker[1]

task. The expected cognitive distance and collaboration time required are calculated in Equations 5.3 and 5.4. At this point in time, the hours of effort for Worker [1] is equal to 3589.

$$D = |log_{10}(93) - log_{10}(3589)| = 1.58 \tag{5.3}$$

$$T = 10 * .2 * (1 + 1.58) = 5.16 \tag{5.4}$$

Cognitive Distances Analysis of Results

The unit test passes with results meeting expectations. As shown in the figures, Worker [0] was able to gain more experience than Worker [1] for completing a task of equal duration. In practice, senior-level employees mentor early-career individuals through tasks that can be a one-direction knowledge transfer.

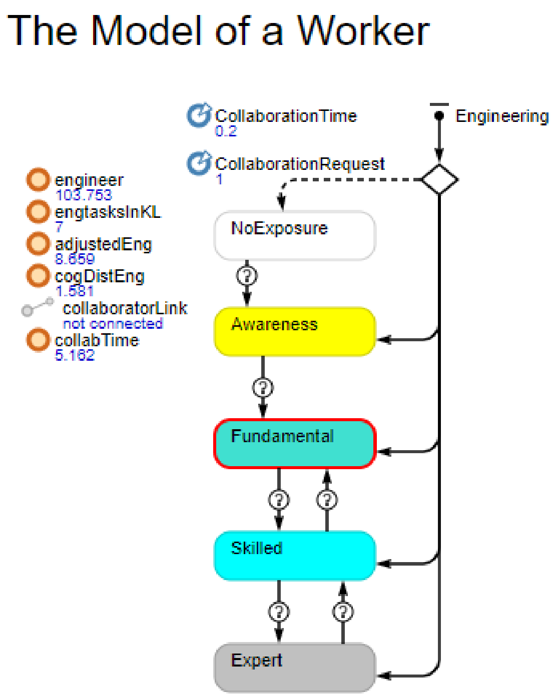

Figure 5-18: Worker[0] After Collaboration and Task Completion

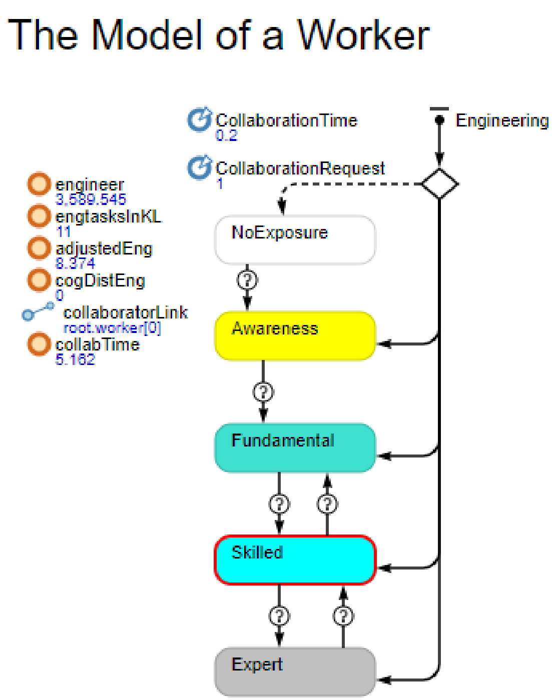

Figure 5-19: Worker[1] Before Collaboration and Task Completion

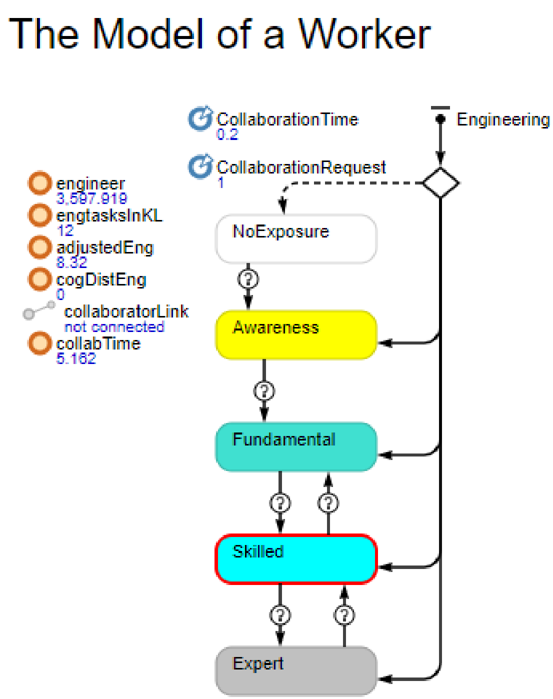

Figure 5-20: Worker[1] After Collaboration and Task Completion

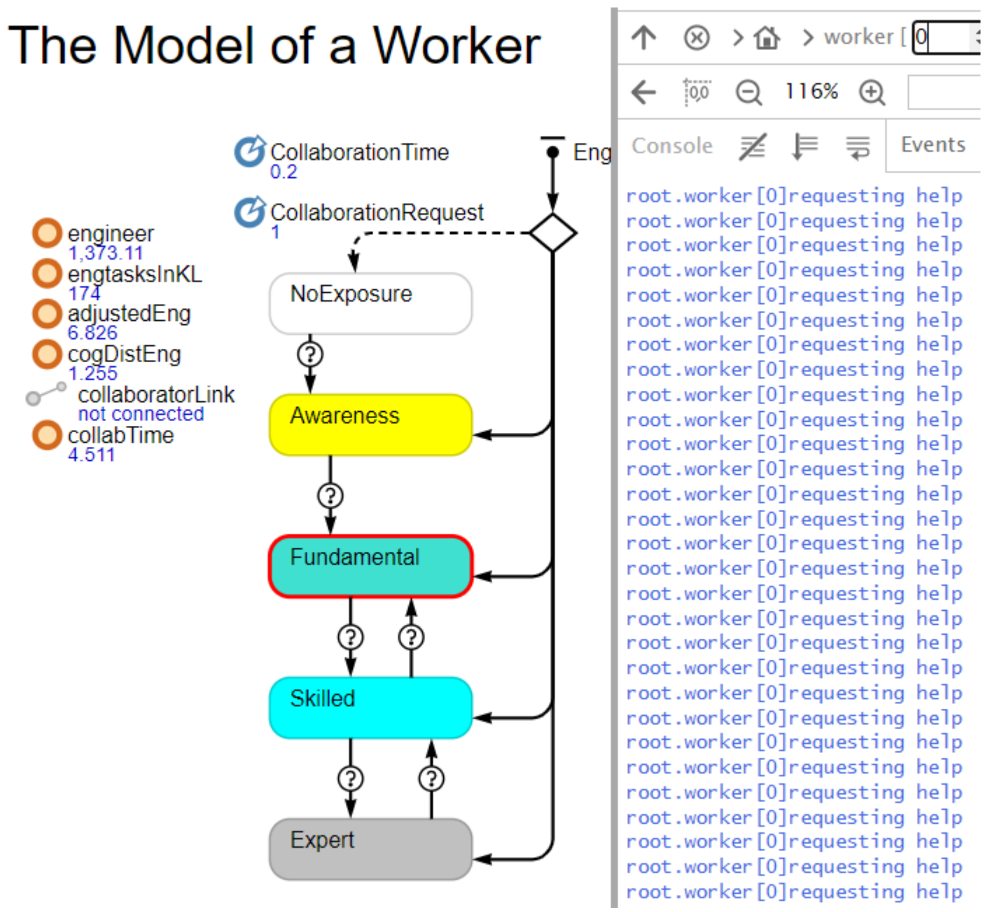

Figure 5-21: Event Log of Collaborations

Chapter 6

Agent-Based Model Experiments

In this chapter, experiments are defined and analyzed to explore cognitive, social, and organizational proximity.

6.1 Experiment 1

The first experiment will involve two teams, each with seven team members with skills in only one functional domain. Demands in the environment will be loaded with tasks that only represent a single skill. The differentiating factor between the teams is the starting point of prior experience. Team A will be comprised of only entry-level employees with skill level No Exposure. Team B will be a mixed team with skill levels ranging from No Exposure to Expert. The model will be run for a duration of five years.

6.1.1 Research Question Addressed and Hypothesis

The purpose of this first experiment is to begin testing research question 1 as noted in section 3.1.1. This researcher anticipates that the entry-level employees on the mixed team will complete more tasks and have more knowledge at the end of the five-year period due to their proximity to others with prior knowledge.

Team	Team Size	Knowledge Level	Domain
Team A	7	No Exposure	Engineering
Team B	7	No Exposure - Expert	Engineering
Parameters			
Model Duration		5 years	
Number of Simulations		15	
Help Request Rate		1 per 24 hours of Working Time	
Demands Hours of Effort		Uniform Distribution (1,50) Hours	
Learning Curve		.85, .90, .95	
Performance Metrics			
Number of Tasks Complete			
Number of Tasks Failed			
Total Experience Gained			
Number of Collaborations			
Total Collaboration Time			

Table 6.1: Experiment 1 Parameters and Performance Metrics

6.2 Experiment 2

The second experiment will involve three teams, with each group starting with no experience. Demands in the environment will be loaded with tasks that only represent a single skill. The differentiating factor between the three sets is the number of teammates per team. Set A, B, and C will have 5, 7, and 9 team members, respectively. The model will be run for a duration of five years.

6.2.1 Research Question Addressed and Hypothesis

This experiment is targeted to begin addressing research question 2. Having more or fewer individuals available to collaborate could have the potential to impact knowledge transfer. The hypothesis is that groups of five employees will show lower productivity and knowledge acquisition than the larger groups due to the limited amount of collaborators available.

Team	Team Size	Knowledge Level	Domain
Team A	5	No Exposure	Engineering
Team B	7	No Exposure	Engineering
Team C	9	No Exposure	Engineering
Parameters			
Model Duration		5 years	
Number of Simulations		15	
Help Request Rate		1 per 24 hours of Working Time	
Demands Hours of Effort		Uniform Distribution (1,50) Hours	
Learning Curve		.85, .90, .95	
Performance Metrics			
Number of Tasks Complete			
Number of Tasks Failed			
Total Experience Gained			
Number of Collaborations			
Total Collaboration Time			

Table 6.2: Experiment 2 Parameters and Performance Metrics

6.3 Experiment 3

Experiment three is designed to look at organizational proximity by shifting work demands. A team of six will be specializing in one domain will have another function introduced into their work environment. Demands in the environment will be loaded with tasks that are both function-specific and cross-functional.

6.3.1 Research Question Addressed and Hypothesis

Research question 3 is focused on knowledge acquisition in multiple domains. Organizations have the ability to dictate focal areas impacting what information will be learned. Cross-functional demands will now be able to be addressed as the skill sets in the workforce are diversified. Hypothesis for this research question is knowledge acquisition will be linearly proportional to the demands.

Team Size	Engineering Knowledge Level	Data Science Knowledge Level
6	No Exposure - Expert	No Exposure
Parameters		
Model Duration		1 years
Number of Simulations		25
Help Request Rate		1 per 24 hours of Working Time
Demands Hours of Effort		- Engineering Uniform Distribution (1,50) Hours - Data Science Uniform Distribution (1,15) Hours
Learning Curve		.95
Percentage of Demands Including Data Science Component		1 - 100%
Performance Metrics		
Number of Tasks Complete		
Number of Tasks Failed		
Total Experience Gained		
Number of Collaborations		
Total Collaboration Time		

Table 6.3: Experiment 3 Parameters and Performance Metrics

6.4 Experiment 1 - Cognitive Proximity

In experiment 1, cognitive proximity was investigated. The difference between the two teams was the team makeup, with Team A comprises agents with no prior experience and Team B having a team of mixed knowledge levels. The learning curve, which adjusts the efficiency of tasks completion, was modified from .85 to .95 to observe if learning rates change outcomes.

6.4.1 Results of Cognitive Proximity Experiment

The results from the first experiment showed Team A gaining more experience through the fifteen simulations. Figure 6-1 displays the summation of the seven agents' knowledge acquired for each run. This result matches expectations as agents on Team A would almost always request the help of another agent of equal or greater knowledge level. With agents regularly in the same knowledge level, the collaboration efforts were bi-directional, allowing both agents to gain knowledge through the collaboration. Collaboration times would also be of a smaller duration due to closer cognitive distances, allowing agents more time to complete tasks.

A closer look at the total experienced gain by individual worker shows the range of

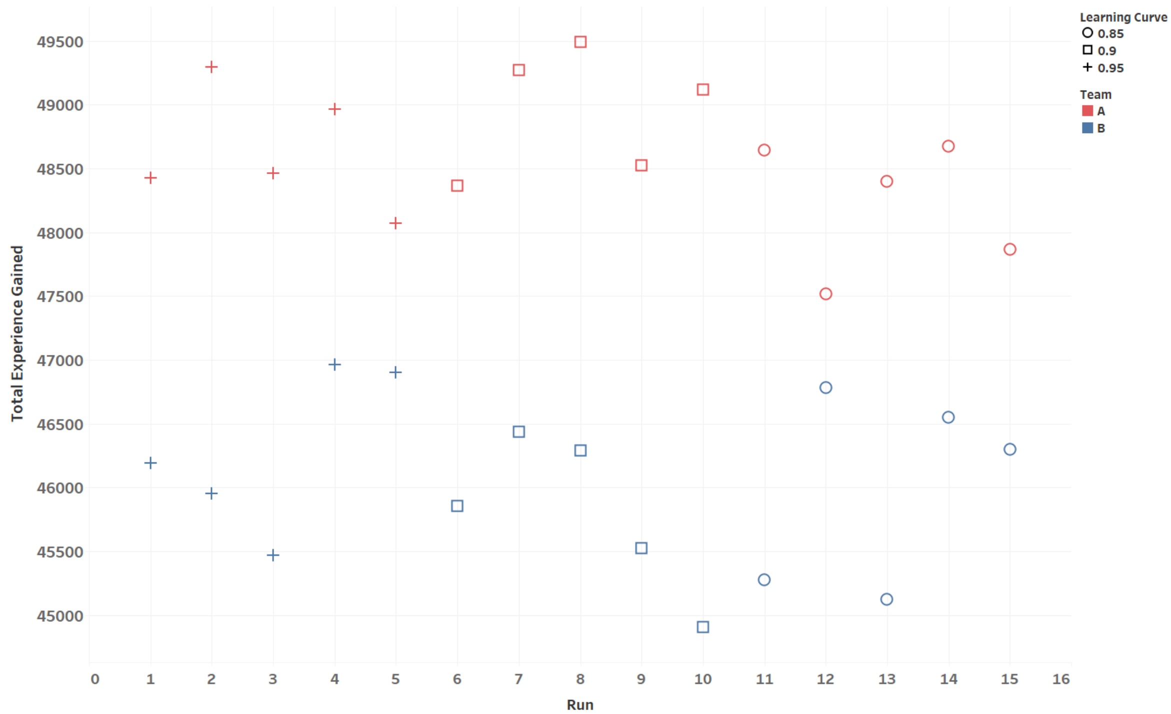

Figure 6-1: Team Experience Gained

outcomes for the agents on the two teams. This result is significant with the average increase of Team A over Team B of 5.8%. Figure 6-2 indicates that those of higher knowledge levels on Team B sacrifice their knowledge acquisition efforts to collaborate with agents of lower skill, allowing them to increase their skills.

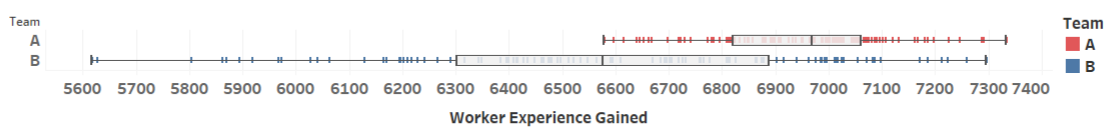

Figure 6-2: Worker Experience Gained

However, the goal of this experiment was to see how agents with no experience would fair in the two groups. Figure 6-3 filters the data to show only those agents with no prior experience. A different story emerges with agents on Team B showing larger knowledge gains from working on mixed experienced teams. Although Team B results appear materially greater, the knowledge gained is only 1.5% greater than those on the Team A.

Figure 6-4 displays the total team collaboration times. Team B consistently col-

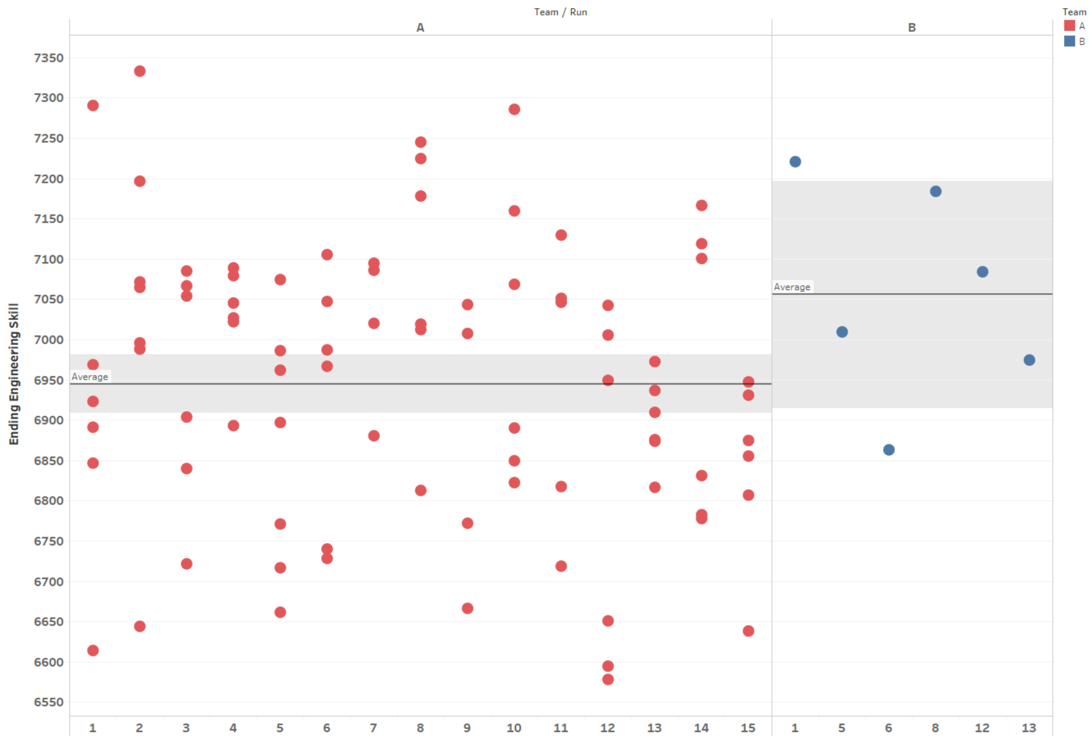

Figure 6-3: No Experience Workers Knowledge Gains

laborates more hours due to greater cognitive distances, matching expectations. The impact of the learning curve creates some surprising results. The faster individual agents learn the more hours they spend collaborating.

Despite the increase in collaboration times for Team B, Figure 6-5 indicates a higher range of tasks completed. Although the agents acquired less knowledge overall, they were able to complete 4.7% more tasks in the five-year timeline. Team B also experienced more failure than Team A by 29.5%, with most failures occurring in the higher knowledge levels due to lack of available collaborators.

The results of the first experiment yielded some expected and unexpected results. Team B overall had lower team learnings, but agents on Team B with no experience benefited the most, with higher skill levels than those on the inexperienced Team A Even with large cognitive distances, agents may learn more by being placed on experienced teams. The experience gained by these agents does come with a cost, a sacrifice of knowledge acquisition for more senior agents.

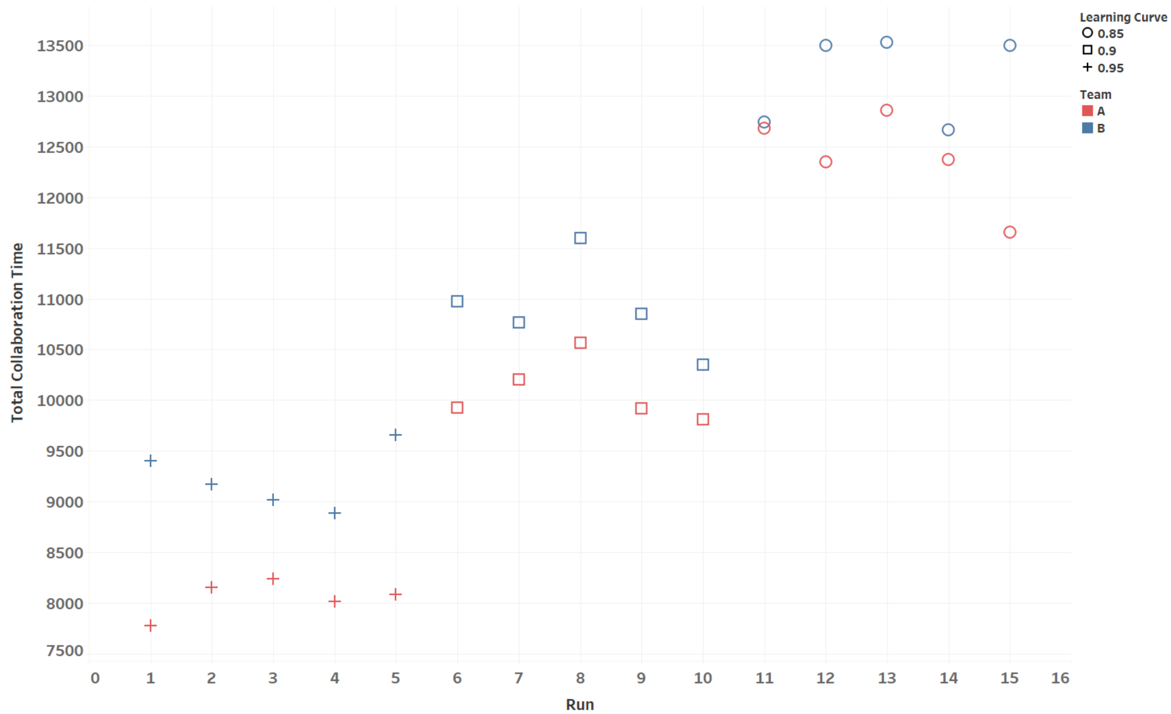

Figure 6-4: Team Collaboration

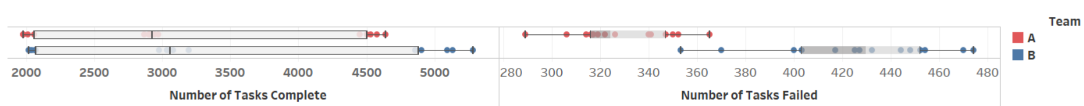

Figure 6-5: Team Tasks Completed versus Failed

6.5 Experiment 2 - Social Proximity

The second experiment was designed to look at social proximity. Team A, B, and C each consisted of five, seven, and nine team members respectively, each with no prior experience.

Figure 6-6 shows the average amount of experience gained per worker for the fifteen simulations. As expected, Team C's range of learning outcomes outperformed both Team A and B. As more team members are available for collaboration, the time searching for an agent to is reduced allowing for more time for knowledge acquisition activities.

Team C also demonstrated the highest collaboration time relative to the other peers shown in Figure 6-7. Due to the logic that collaboration is bi-direction for

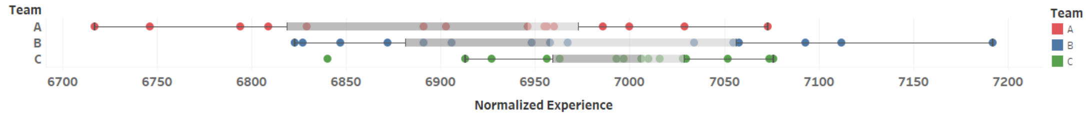

Figure 6-6: Average Worker Experience Gained

agents in the same knowledge level, this allows for more team learning relative to the other teams.

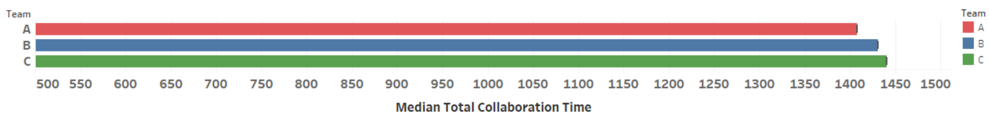

Figure 6-7: Worker Collaboration Time

Tasks completion and failure rates are unexpected. There is no statistical advantage on task completion, as all teams experienced a similar level of performance which goes against expectations. However, the benefit does show up in the quantity of tasks failures, with Team C failing at a lower rate than the other two teams due to more agents being available for assistance.

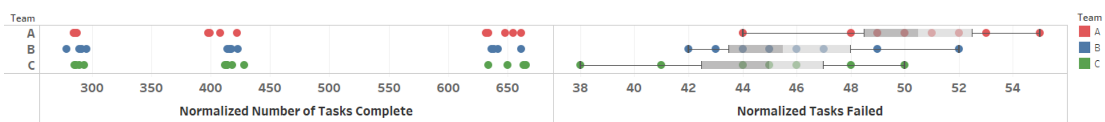

Figure 6-8: Average Worker Tasks Completed versus Failed

6.6 Experiment 3 - Organizational Proximity

Experiment three concentrates on how work demands influence organizational learning. With previous experiments, agents were considered completely self-directed by choosing skill appropriate tasks. Agents maintain decision rights of which tasks they work on, but the tasks available were influenced by a central authority. Figure 6-9 and Figure 6-10 indicate how changing the mix of work demands influence skill acquisition.

Engineering and data science skill acquisitions follow a logarithmic function in relationship to the percentage of tasks with a data science component. The total

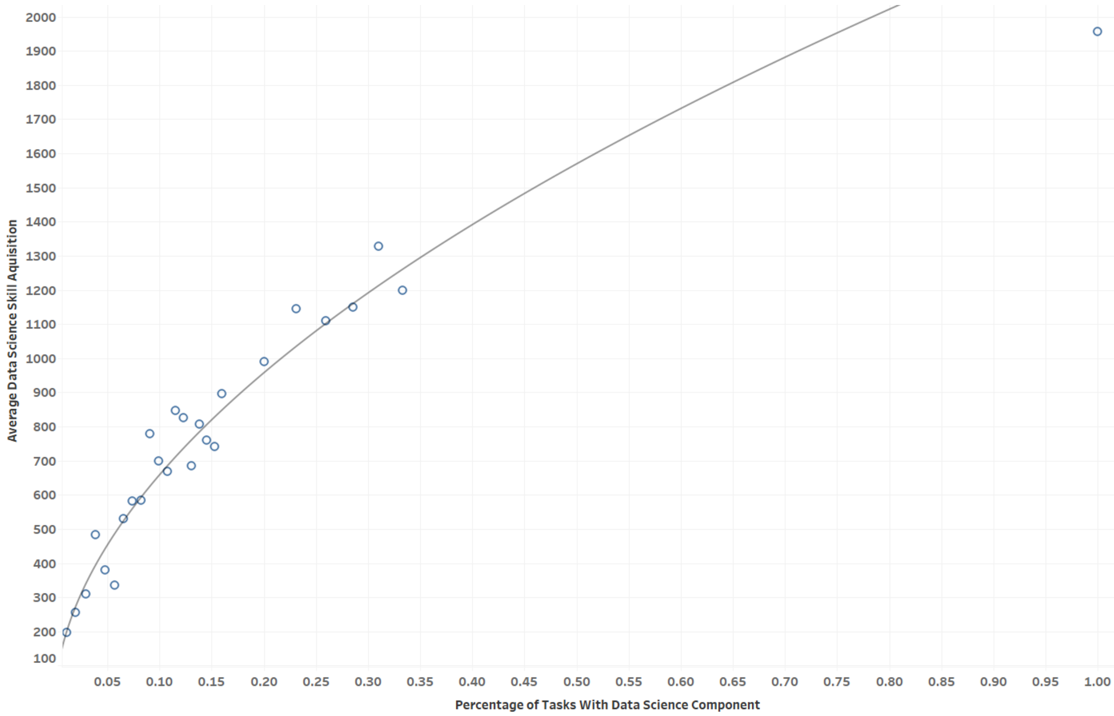

Figure 6-9: Average Data Science Knowledge Acquisition

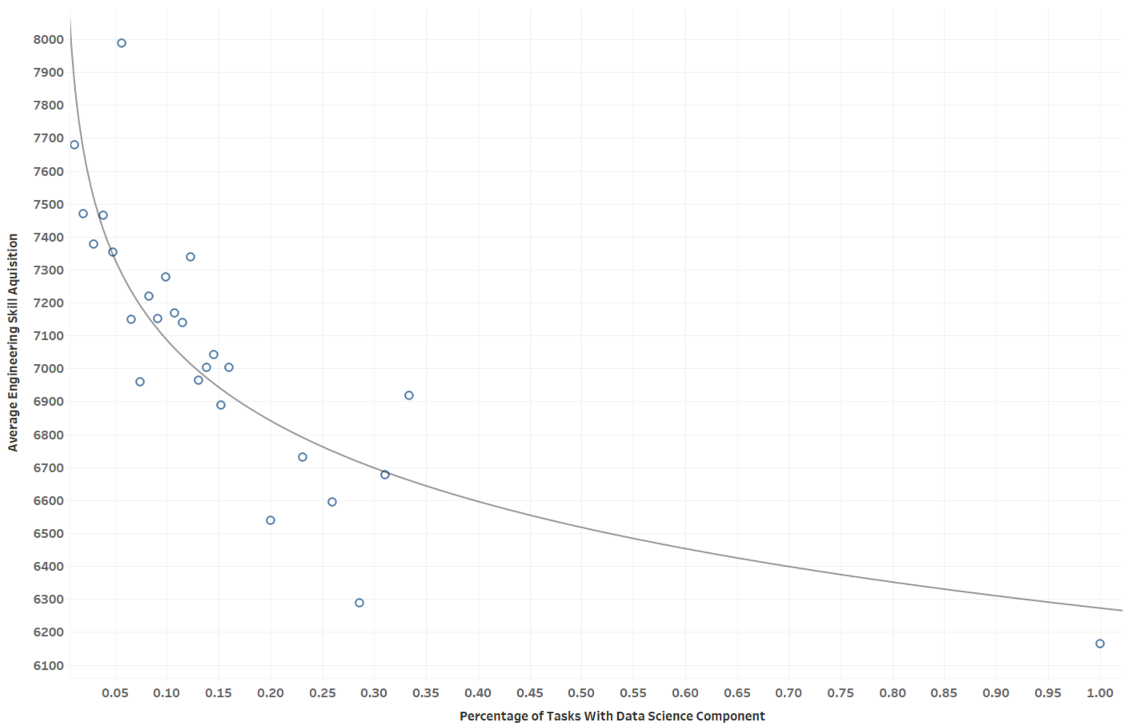

Figure 6-10: Average Engineering Knowledge Acquisition

experience gained during the one year stays relatively constant through all the simulations. When comparing the two functions directly, a linear relationship is shown in Figure 6-11, indicating a trade-off is made when the new skill is added to the work environment.

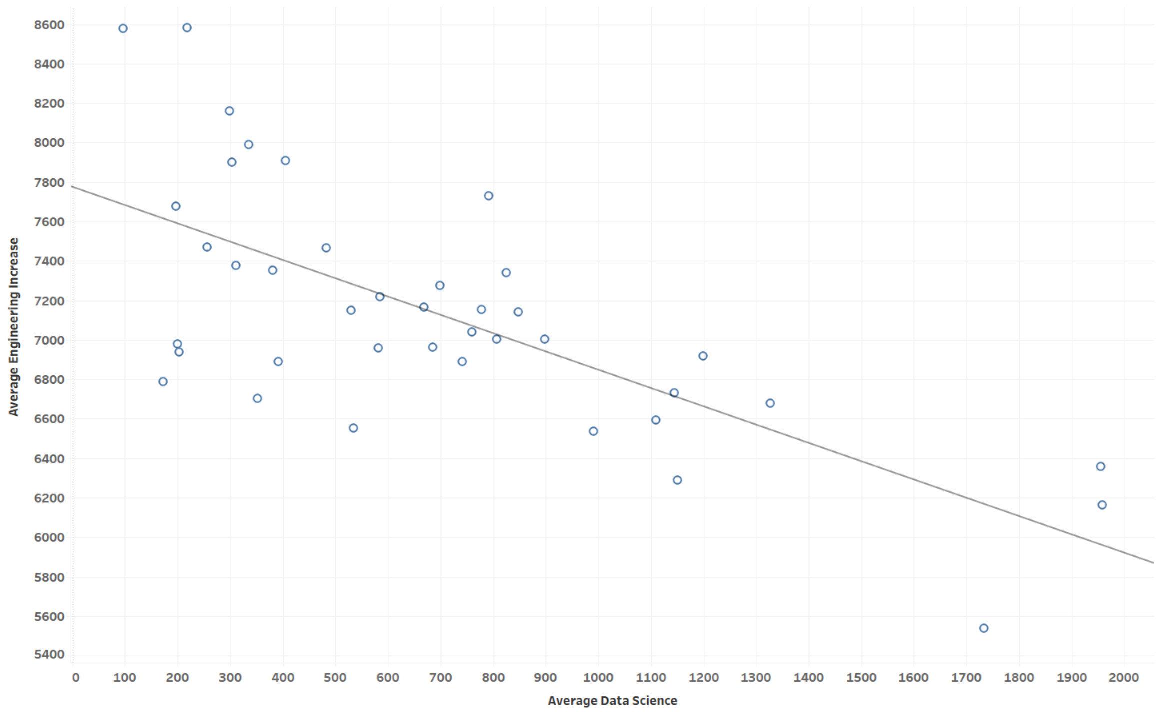

Figure 6-11: Average Engineering Knowledge Acquisition

Chapter 7

Discussion and Conclusions

This chapter concludes this thesis by discussing findings relating to cognitive, social, and organizational proximity. Gaps in the implementation of the method are clearly articulated, and opportunities for potential business applications and future research are proposed.

7.1 Discussion of Findings

Individual, team and organizational learning is a complex field that is covered by many different domains, including psychology, education, and management. There is much debate on the various mechanisms to transfer knowledge between individuals effectively. One proposed mechanism to transfer tacit knowledge is through collaboration. An agent-based model was developed to explore the transfer of knowledge through different types of proximity. The first is cognitive proximity, based on the information individuals have stored away based on past experiences. An argument was made that the greater the cognitive distance, the more difficult it is to communicate and therefore transfer knowledge. This premise was tested in the first experiment, with results being mixed. Analysis of the data indicated that overall organizational learning is minimized where cognitive distances are large. The lower values were due to the longer collaboration times experienced, resulting in more senior personal sacrificing their own time to assist less skilled individuals. The unexpectedly high failure rate of tasks on the mixed experienced teams highlights the need for collaborators of equal or greater skill to be present in an organization and be available. The finding from cognitive proximity ties well with social proximity. In experiment two, team sizes were toggled to test how a varying sizes of collaborator pools would impact overall organizational learning. Results matched expectations with the teams of nine individuals outperforming the teams of five and seven. The final experiment looked into organizational proximity, which involves a central authority influencing the work environment. Demands were varied, with increasing amounts of cross-functional tasks being added to the slate. Results showed a logarithmic decay of the primary skill set with the inverse for the secondary skill.

7.2 Gaps and Opportunities For Future Work

The findings in this thesis mostly align with past research; however, there were many assumptions made that influenced the outcomes of the analysis. The first being was applying a learning curve to individual agents. Although learning curves are well established in the academic community, they are typically applied in manufacturing applications at the organizational level. Using a set learning curve to an entire population of agents may not be appropriate given that learning is individual-specific and non-linear, likely leading to non-reproducible results in practice.

Another potential opportunity for improvement involves collaboration. The implementation assumes that collaboration will be required at a given rate, resulting in a failure to complete a task if no collaborators are available. If another agent were available, the model would automatically link the two together for a duration based on their cognitive distances. Common practice is for individuals to reach out to others for assistance when they need help, but limiting the collaborations to one individual may not be realistic. Oftentimes, more than one collaborator may be necessary to complete a task, especially when working on complex problems.

The most significant opportunity for future research in the modeling approach would be applying skill atrophy or forgetting. The results only show skills increasing over time, but people have the tendency to forget information that isn't actively practiced. An area for improvement would be to implement a forgetting function to account for this phenomenon. Another improvement opportunity is adding and removing agents, considering a company will most likely see significant personnel changes over a five-year time horizon. Organizations are rarely static, so an opportunity to enhance the model would be to incorporate acquisition and attrition rates.

7.3 Conclusion

The energy sector is going through significant changes that force its employees to learn new skills outside their core competencies. This thesis's motivation was to better understand how knowledge is created and transferred to influence business processes and increase knowledge diffusion within an energy company. In particular, an exploration of creating talent management systems that better suits business and individual needs. This system could be beneficial for organizational transformations, especially in areas where much of the data needed is already available. One area that may be well suited for implementing a new talent management system would be the IT function, where many companies use agile project management methods. In agile, tasks are tracked by the owner and hours of effort for completion. Using development operations applications, much of the data needed to analyze individuals' learning and performance over time is already available. This data, coupled with collaboration data, could track how an organization learns and performs over time and develop a talent management system that enables individualized learning. For example, suppose a new hire's tasks completion rates are below a certain threshold. In that case, automated training opportunities could trigger, or a notification could be sent to the manager informing them an intervention may be necessary. Managers could also run simulations to predict future capabilities relative to future demands and take action when there are sizable disconnects by supporting training for current employees or hiring externally.

Another potential application for this type of talent management system is business continuity planning. Many disruptions in everyday life remove an individual from the workforce for a short period of time. Having a talent management system containing each person's skill level and learning rates could minimize corporate exposure to personnel discontinuity. This would come with some complexity as skill sets are not always easily transferable. A prime example in this analysis is the skill bucket of engineering was utilized, but an electrical engineer most likely will not be able to back-fill a petroleum engineer. Specialization has the potential to complicate a talent management system by adding a significant administrative burden ensuring system integrity. Overall, the potential to run simulations on actual-world data appears possible and may enable organizations to understand how they learn and transfer knowledge.

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