

ARE MANAGERS BECOMING OBSOLETE?
THE EMERGING UBIQUITY OF
ARTIFICIAL INTELLIGENCE
IN THE WORKPLACE

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ABSTRACT

The implementation of Artificial Intelligence has become more prevalent in organizations over the last decade. AI will cause a fundamental shift in an organization's operating mode on a variety of dimensions such as: how work gets done, including the design of business and decision-making processes, the nature of interactions within organizations, the skills that employees need to develop, and how managers function, lead and operate in this new era of digitization and automation. Because of the rapid changes that AI will bring to organizations, effective management practices will still be essential and maybe even more necessary than in previous eras of technological change. Thus, there is an opportunity to uncover those specific managerial tasks, capabilities, and mindsets that will lead to AI being a useful tool at a micro-level. Because AI tools are relatively in the early stages of adoption, there is little to no academic research on the role of the manager. Therefore, it is a timely topic, and research can make an early (and potentially unique) contribution to the management literature. The critical question that this study will attempt to answer is the following: *"How Will the Manager's Role Change Due to the Implementation of Artificial Intelligence?"* The study will primarily focus on managers who oversee administrative functions or processes and are currently leading teams or organizations implementing AI. This research will be a mixed-methods approach starting with interpretivist case examples of several organizations applying AI along with a quantitative survey that will collect objective data.

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CHAPTER 1

RESEARCH MOTIVATION

From the Gutenberg printing press to the internal combustion engine, or from Henry Ford's car assembly production process to the rise of transistor technology and the introduction of the personal computer, new technologies have altered economies, industries, organizations, and human social relations. The introductions of these major technologies have ushered in dramatic changes ranging from the increase in reading and wholesale dissemination of information (the Gutenberg press); the rapid proliferation of suburbs and urban spread (the car); the growth of major electronic consumer industries (the transistor and computer chips); and the increase in work productivity and information sharing (the personal computer). In the last decade, technology has become an even more ubiquitous part of individuals' personal and professional lives. This includes the proliferation of the cellphone (in which there are more cellphone subscriptions than the global population¹), smart devices like Amazon's Echo, and embedded sensors in industrial machines or household appliances. Most recently, the growth of Artificial Intelligence in concert with several emerging digital technologies, such as Cloud Computing, the Internet of Things, and Robotic Process Automation have begun to transform the personal and professional lives of individuals in organizations. AI has begun to impact how organizations make decisions, structure work, and measure employee effectiveness and engagement (e.g., use of sociometric monitoring badges)².

¹ Source: International Telecommunications Union's Facts and Figures for 2017.

² One of the leading technology and software companies in this space is Humanyze which was founded by Sandy Pentland (from MIT's Media Lab) and some of his students notably Ben Weber. They pioneered a

Most of all, AI has affected what skills are required to operate effectively in the “age of the smart machine.”

One cannot read a newspaper or popular management publication today without seeing authors extolling either the merits or dire consequences of AI. For example:

- A New York Times article titled “A Machine May Not Take Your Job But Could Become Your Boss” discussed how an AI-enabled pop-up provides real-time feedback to customer service employees.
- A Wall Street Journal article titled “When Chatbots Falter, Human Steer the Right Way” discussed “how new jobs are popping up around chatbots as companies realize they need humans to make the AI operate in a useful way.”
- MIT Sloan Management Review’s Summer 2019 Issue was titled “Making Good on the Promise of AI” and featured four articles on AI’s influence on innovation, strategy, operations, and ethics.
- The Harvard Business Review’s July-August 2019 issue article “The AI-Powered Organization: The Main Challenge isn’t Technology: It’s Culture,” written by three McKinsey partners, described the conditions necessary for success as well as organizing for scale.
- In terms of negative press, Apple issued its new Apple digital credit card in conjunction with Goldman Sachs. There were complaints that husbands and wives with similar financial records had received different credit limits for this new card.

wearable device which is worn around one’s neck (think of a small cell phone) that is able to measure the nature of one’s interactions such as who talks to whom; how much they speak; the spatial distance between individuals when they are speaking and the tonality of their voices.

This nascent cottage industry of futurists has begun to predict AI's impact on employees. Managers at all levels will assume a pivotal role in the successful adoption of AI to ensure the workforce is willing and able to maximize these new tools' economic and strategic benefits. But because these tools remain in the early stages of adoption, there has been little academic research³ on the manager's role in AI technology adoption. My research in this area makes an early (and potentially unique) contribution to the management literature in the realm of AI. I want to study a contemporary issue and help build my knowledge base, reputation, and network in this space to be a thought leader at the intersection of technology, strategy, organizational change, and leadership. Although it might be a stretch to attempt this integration, this topic demands a multi-disciplined perspective.

Problem Formulation, Research Question, and Focus Areas

As noted above, managers are a critical fulcrum in creating an engaging work environment, which is not on the path of obsolescence. Moreover, the more effective managers are usually at the forefront of implementing the organizational change or deploying strategic initiatives; hence my research question is: How will the manager's role change due to the implementation of Artificial Intelligence?

To unpack elements in the research question and to understand second-order issues that will eventually guide my research approach, some further thoughts include the following:

³ So far, there are only two articles that have been published neither which are in top tier journals nor publications. One was titled *AI Bias: How Does AI Influence the Executive Function of Business Leaders?* published in Muma Business Review (University of South Florida) in June 2019 which was not research based. The second was published in British Academy of Management proceedings in September 2019, which was titled, *The Evolution of Managerial Skills Towards the Rise of Artificial Intelligence*.

- **“How Will”**: While AI will not disintermediate the manager's role, I aim to understand how it will impact the role. However, my working hypothesis is that the manager’s role will change, and there is an opportunity to understand the depth, breadth, or speed of its transformation.
- **“Manager's Role”**: Ideally, my research will tease out how AI will change the role's various dimensions. For example, my research would include exploring the following:
 - a. How do managers allocate their time?
 - b. What are the specific work and managerial processes that they are involved in?
 - c. What are the set of capabilities (skills, knowledge, attitudes, and behaviors) and mindsets that will be needed to flourish in this new environment?
 - d. What is the degree of decision-making authority?
 - e. How do they coach and train their employees?
 - f. What are the change management levers that they employ to implement AI?
- **“Implementation of Artificial Intelligence”**: Depending on the organization's penchant for technology as a strategic or operational capability, AI implementation will vary. Knowledge-intensive (e.g., pharmaceuticals), data-driven (e.g., Netflix, financial services) organizations, and technology-based companies (e.g., Microsoft) would be the leaders in deploying AI from the front end of their business (e.g., customer/client-facing or revenue-generating) to the

back end (e.g., closing the books; processing expense vouchers; managing vendors, etc.). A report published by MIT and BCG labeled these organizations 'Pioneers', where they undertake projects with higher risk as well as have a broad range of initiatives that drive efficiency and cost savings, drive revenue growth, and create new products and services (Ransbotham, 2019). A Microsoft AI senior leader described the four stages as "Foundational, Approaching, Aspirational and Mature." These companies are characterized as being in the more "mature life cycle" of technology implementation as noted on the far-right hand side of the "Implementation of AI" horizontal line labeled "Full Scale," stated in Figure 1.1 Relationship of AI's Implementation to the Manager's Role.

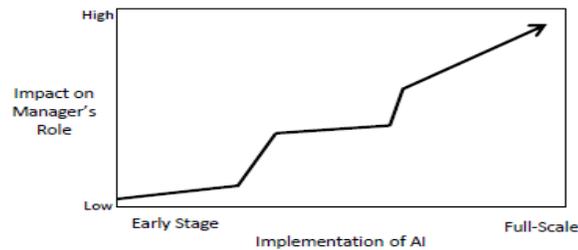


Figure 1.1. Relationship of AI's Implementation to the Manager's Role

One of my working assumptions is as organizations mature (i.e., moving up the adoption curve for AI implementation), the role of the manager will change, possibly in step-function (as seen in the above line).

An extensive body of literature has examined the application of AI in industrial settings. For example, Tesla has implemented their beta software to test driverless cars and autonomous vehicles; and mining giant Rio has deployed self-driving trucks from their mines (Agarwal, 2019). In addition, Rolls Royce changed their business model from

selling engines to managing its uptime for customers, implementing technologies to analyze, predict, and alert customers when engine replacement or maintenance is needed. In contrast, my research proposal focuses on "white collar" settings and administrative processes (e.g., financial reporting, financial monthly closing process, customer call centers, etc.) given the greater accessibility of research sites and the shifting nature of our economy (i.e., more service-oriented than manufacturing-oriented).

Consequently, three focus areas will underlie the research approach.

1. There will be a moderate to significant change to the manager's role (e.g., their tasks, how they allocate their time, and focus) due to the utilization and power of AI.
2. Managers will continue to play an essential role in employee development, engagement, and inspiration because of the potential impact of AI to work design and employee's motivation to embrace AI.
3. Managers at all levels will need to enhance their technical, leadership, interpersonal knowledge, skills, abilities, and personal attributes to thrive in the AI environment.

Importance of The Research Question

This research question is important on several levels. First, even though AI has grown tremendously in the last several years, only a tiny percentage of companies have implemented it on a broad scale; therefore, there has been a lack of research on AI's impact on managers. Second, research will surface some practical insights that will help shorten the learning curve for managers and senior leaders who will implement AI. Finally, this research will sit at the intersection of several academic and practitioner areas

such as technology implementation, people/workforce practices, organizational improvement, and leadership behaviors, potentially adding to the literature in these related but separate disciplines.

CHAPTER 2

LITERATURE REVIEW

AI History and Overview

Artificial Intelligence (AI) in its most basic form is the automation of work traditionally done by humans. Over the last three centuries, the use of automation can be characterized by three distinct eras (Davenport, 2015). “In the first era (19th century), industrial machines were treated as *substitutes* for dangerous and onerous work. This work was mostly in textiles, such as the cotton industry” (Davenport, 2015). The second era occurred in the 20th century when automated interfaces came into being, substituting dull, routine, or service-oriented work. Examples included airline kiosks and ATMs. Now, the 21st century has given rise to a third era. In this AI era, digital devices and technologies are poised to take over a higher degree of human decisions because automated tools can make predictions quicker and more reliable than humans.⁴

Over the last decade, private companies have increasingly adopted AI solutions due to increased computing power, more robust algorithms, and open-source software proliferation, often byproducts of steady investment by corporations. There has also been a dramatic increase in the availability of big data characterized across four dimensions—volume, velocity, variety, and veracity (Guha & Kumar, 2018)—because of the ability to obtain data from various sources, including social media and the "internet of things."⁵

⁴ However, these tools are still fraught with their own set of unintended consequences such as biases, privacy, data security and explainability.

⁵ Additional sources include By-Product of Operations; Web Scraping, Data from Governments, Computer-Generated Data, Hiring Humans to Label Data (e.g., through Mechanical Turk), Sharing Data (e.g., Open Images Data Set), etc. (Varian 2019)

Ginni Rommety (IBM's former CEO) reinforced the importance of data when she said in IBM's annual report: "Data is becoming for the 21st century what steam power was for the 18th, electricity for the 20th. (Varian, 2019)⁶. However, data quality remains greatly important. This quality is reflected across and encompassed by four dimensions: intrinsic (accuracy), contextual (completeness), representational (interpretability), and accessibility (availability or easily and quickly retrievable. (Vial et al. 2021). A critical factor driving the increased availability of data is the capability of public cloud vendors to collect, store and access large amounts of information. Providers also offer various machine-learning services such as voice recognition, image recognition, and translation" (Varian, 2019).

The term "artificial intelligence" was coined in 1955 by Professor John McCarthy at Massachusetts Institute of Technology for a conference he was organizing (Brynjolfsson & McAfee, 2017). The meeting, which was later called the Dartmouth Conference by AI researchers, established AI as a distinct discipline (Shubhendu & Vija, 2013). In the 1960s, researchers and thought leaders were beginning to make the connection between "human thinking as wholly information processing activity" and "digital computers as information processing devices, programmed to carry out any of the information processes thus explicated" (Feigenbaum, 1963) as cited in Meinhart (1986). Herbert Simon and A. Newell are pivotal in this study, as they are associated with management, decision-making, and Artificial Intelligence (Pomerol & Adam, 2006). Simon was an early pioneer, articulating that computers are systems designed for

⁶ There are some fundamental distinctions between oil and data. "If one person consumes oil, there is less available for others therefor oil is 'rival' while "data is nonrival—one person's use of data does not reduce or diminish another person's use" (Varian 2019).

complex information processing and decision making. Initial research in the 1960s focused on simulating cognitive processes, especially general problem solving (GPS) behavior. Simon asserted that "the computer and the new decision-making techniques associated with it bring changes to white-collar, executive and professional work as momentous as those that the introduction of machinery has brought to manual jobs" (Pomeroy & Adam, 2006).

More recently, AI has been described as the most important general-purpose technology of our era (Brynjolfsson & McAfee, 2017). Microsoft CEO Satya Nadella stated, "AI is the 'runtime' that is going to shape all that we do in terms of applications as well as the platform." By runtime, Nadella is referring to the operating environment that will shape the execution of business processes (Iansiti & Lakhani, 2020). Two Harvard academicians are not hyperbolic when they state that AI is becoming the new operational foundation of business—"the core of a company's operating model, defining how the company drives the execution of tasks" and could alter the concept of a firm. (Iansiti & Lakhani, 2020).

The following data points illustrate the explosive growth and rapid proliferation in AI (Perrault, 2019). Globally, investment in AI startups continue its steady ascent from a total of \$1.3B raised in 2010 to over \$40.4B in 2018 (with \$37.4B raised by November 2019); funding has increased at an average annual growth rate of over 48%. 58% of large companies surveyed report adopting AI in at least one function or business unit in 2019, up from 47% in 2018. Between 1998 and 2018, the volume of peer-reviewed AI papers has grown by more than 300%, accounting for 3% of peer-reviewed journal publications and 9% of published conference papers. Before 2012, AI results closely tracked Moore's

Law, with computation power doubling every two years. However, after 2012, compute has been doubling every 3.4 months.

Figure 2.1 demonstrates the explosive growth of AI since 1950. The graph shows AI's rate of adoption, with growth emphasized by the steepness of the AI curve (labeled as #7) as compared to complementary technologies such as Web 2.0, Cloud, Mobile (#4), Big Data, Analytics, and Visualization (#5), IoT and Smart Machines (as #6).⁷ In particular, the convergence of advances in three areas has notably contributed to AI's growth rate: the explosion of data, ever-increasing computing power, and new algorithms, mainly neural networks and deep learning (Malone et al. 2020). For AI to continue on this trajectory, it will require significant preexisting investment in other assets, such as technical expertise, business processes, data, and culture (Rock, 2020).⁸

⁷ One observation about the chart is how the lines are consistent with S shaped innovation theory curves.

⁸ The history of AI has included several “waves” of ideas. The first wave, from the mid-1950s to the 1980s, focused on logic and symbolic hand-encoded representations of knowledge, the foundations of so-called “expert systems”. The second wave, starting in the 1990s, focused on statistics and machine learning, in which, instead of hand-programming rules for behavior, programmers constructed “statistical learning algorithms” that could be trained on large datasets. In the most recent wave, especially in the last decade, research in AI has largely focused on deep (i.e., many-layered) neural networks, which are loosely inspired by the brain and trained by “deep learning” methods (Jenkins, et al (2020)

exactly how to accomplish all the tasks it is given (Brynjolfsson & McAfee, 2017).

There is some expectation that intelligent computer systems will write new programs because learning is incorporated into their abilities (Makridakis, 2017).

- ***Natural Language Processing:*** NLP focuses on identifying and processing natural language texts in written and spoken form using Deep Neural Networks (DNN) or Deep Learning. DNNs can learn patterns in speech, image, and video data faster and more automatically than ever before (Taddy, 2019). Consumer devices like Alexa and Echo are examples of NLP technology.
- ***Intelligent Robotic Process Automation (RPA):*** This is the "autonomous execution of recurring, rule-based process steps or chains," eliminating the need for human intervention and automatically transferring data from one system to another. The application of RPA has been most prevalent in high volume and low complexity, such as routine transactional processes such as loan processing or accounts payable processes. These tools mimic what users typically do, such as transferring structured data from an excel spreadsheet into a mainframe computer. With RPAs, this activity happens automatically. Processes or tasks that are not well suited to RPA include those requiring independent judgment, those for which all contingencies are not predictable in advance, and those involving unpredictable interactions with customers or employees (Davenport, 2019) or where the data is unstructured.

From the perspective of what AI can do, consulting firm Oliver Wyman classified five distinct tasks that AI can undertake. AI can classify (e.g., recognize a data point and assign the correct label), predict (e.g., estimate current or future values using new types of data), cluster (finds structures and patterns in large and complex data sets), create (e.g.,

generate original audio, images, or texts), and learn (e.g., complete goal-oriented tasks through trial and error). Tom Davenport (Davenport, 2019) described eight broad types of AI or cognitive technologies that they can perform such as: Create highly granular prediction and classification models (e.g., optimize pricing, identify fraud); perform structured digital tasks (e.g., automate reports; reconcile records); manipulate information (e.g., extract data from documents); understand speech and text (e.g., online chatbots, education testing); plan and optimize operations (e.g., supply chain forecasting; optimal shipping routes); perceive and recognize images (e.g., facial recognition in technology, classifying online photos); move purposefully and autonomously (e.g., self-driving cars; autonomous drones), and assess human emotions (e.g., social robot companions)

Due to AI's computing and analytical capabilities, as illustrated by the above tasks, AI is expected to improve many facets of business and society dramatically. Physicians will have additional up-to-date information on how to treat diseases at their disposal because of AI tools such as IBM Watson becoming more prevalent in doctor's offices. Self-driving vehicles are projected to reduce accident fatalities once related socio-technical issues are resolved, and drones can be used to deliver disaster relief supplies or just move small packages to consumers. Kleinberg et al. (2018) found that algorithmic predictions can improve the judge's decision-making capability⁹. This heightened set of expectations has been reinforced and amplified by researchers who predict that "AI will outperform writing high school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a best-selling book (by 2049), and working as

⁹ The authors reported that enhanced prediction quality could enable crime reductions up to 24.7 percent with no change in jailing rates or jailing rate reductions up to 41.9 percent with no increase in crime rates. (Agarwal, 2019)

a surgeon (by 2053). These experts believe there is a 50% chance of AI outperforming humans in all tasks in 45 years" (West, 2018).

Cognitive machines are deliberately designed to carry out complex tasks and decision-making on an organizational level, improving overall organizational cognition and improving the enterprise's computational capacity (Nobre, 2009). On a personal consumer level, "AI tools predict the intention of speech (Amazon's Echo), predict command context (Apple's Siri), predict what you want to buy (Amazon's recommendations), and predict which links will connect you to the information you want to find (Google search)" (Agrawal et al., 2018).

Although organizations are in various stages of maturity related to implementing A.I, organizations with the most experience have a set of common characteristics (Iansiti & Lakhani, 2020). They consolidate data to develop a single, sophisticated data platform. Second, they use business intelligence tools and analytical models with sophisticated data platforms. Third, they utilize data and analytics across their value chain of engineering, manufacturing, and operations to understand drivers of operational decisions. Last, they use the internet of things (IoT) technologies with connected sensors that gather telemetry on equipment and product usage. Figure 2.2 Business Impact Based on Companies AI Maturity summarizes the business building impact of AI in different stages of companies' AI journeys. When AI is used for operations efficiency, AI-leading firms have a minor advantage over their laggard counterparts. However, when it comes to customer-facing applications or innovating through the delivery of new services, AI-leaders "twice as likely as the least mature segment to benefit from applying these breakthrough technologies" (Azhar 2020).

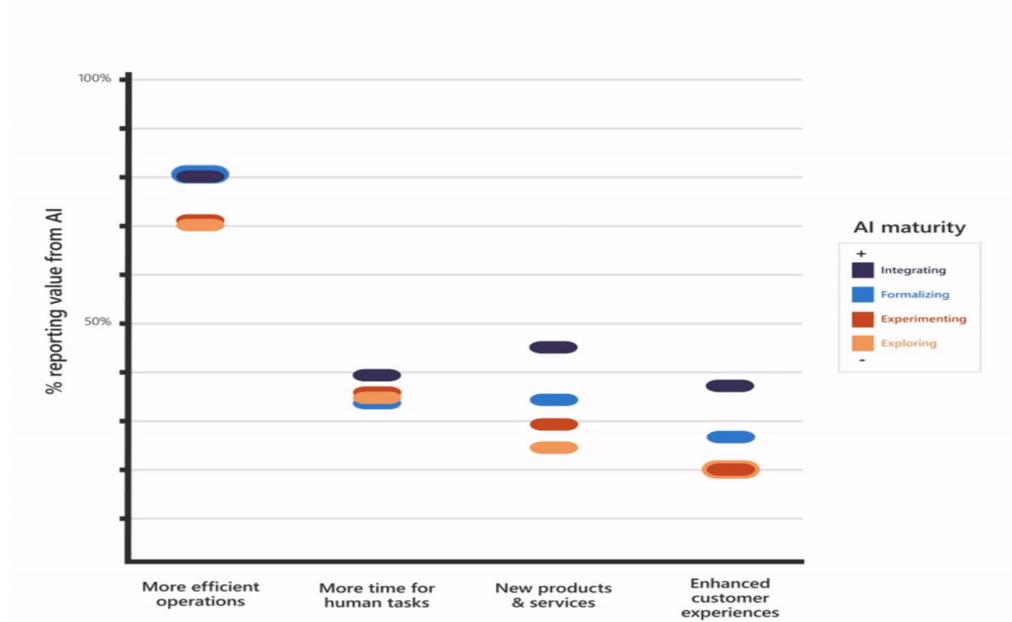


Figure 2.2. Business Impact Based on Companies AI Maturity

AI Risks and Implications: Society and Business

Notwithstanding the heightened future expectations and potential current benefits to AI, there are various possible side effects, downsides, or emerging issues facing its wholesale adoption. Practitioners should engage in a concerted effort to identify, escalate, debate, and mitigate these potential issues. Leading technologists like Elon Musk and technology luminaries like Stephen Hawking have warned of the problems associated with going full steam ahead without stopping to plan for its unforeseen consequences. Max Tegmark, an MIT professor, summed it up when he said,

When we got fire and messed up with it, we invented the fire extinguisher. When we got cars and messed up, we invented the seat belt, airbag, and traffic light. But with nuclear weapons and AI, we do not want to learn from our mistakes. We want to plan ahead.

Various think tanks and research groups composed of academics, researchers, politicians, and leaders from business and not-for-profit institutions have been formed under the 'responsible AI' rubric. For example, Harvard Kennedy School's Belfer Center for Science and International Affairs, along with Bank of America, formed the Council on the Responsible Use of Artificial Intelligence (AI) in 2018 to “address critical questions surrounding the evolving application for data and technology in society and businesses.” Advocacy and policy groups¹⁰ have been formed whose mission includes conducting research, formulating policy, and lobbying to proactively mitigate the unintended consequences, malicious issues, and other technical or societal limitations associated with AI use. Building upon Isaac Asimov,¹¹ Brooklyn Law School Professor Frank Pasquale (2020) developed four new laws of robotics that state that robotic systems and AI: should complement professionals, not replace them; should not counterfeit humanity; should not intensify zero-sum arms races; and must always indicate the identity of their creator(s), controller(s), and owner(s). These laws place ethical boundaries on AI before they become so pervasive and integrated into the political, social, and economic fabric that they become unmanageable. Three critical issues related to AI include the following:

Inherent Biases

The machines may have hidden biases derived not from the designer’s intent (even though many of the programmers are males) but from the data initially provided to

¹⁰ Some of these include the Future of Life Institute, Stanford University’s Human Centered Artificial intelligence, AI Now Institute at NYU, Data & Society Research Institute, Human AI, Black in AI, Data for Black Lives, Algorithmic Justice League, Partnership for AI, Open AI, Center for Human Compatible Artificial Intelligence and Machine Intelligence Research Institute.

¹¹ Isaac Asimov was a science fiction writer who introduced his “three laws of robotics” in a 1950 collection of stories *I, Robot*. The first law is “A robot may not injure a human being or, through inaction, allow a human being to come to harm.” The second law is “A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.” The third law is “A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.”

train the system. For instance, if a system learns which job applicants to accept for an interview using a data set of decisions from the past, it may inadvertently learn to perpetuate their racial, gender, ethnic, or other biases (Brynjolfsson & McAfee, 2017). Recently, Amazon ended its experiment using AI in its hiring process, citing as a main reason that the technology favored candidates who described themselves using verbs more common on male candidates' resumes. This was partly due to the many male technologists screened and hired over the past ten years, and because fewer women were employed in the past. Because men had higher performance scores, the algorithm was selecting our women and those with attributes associated with women (Tambe et al., 2019). Meredith Whittaker, founder, and director of the AI Now Institute at NYU, said, "It [Amazon] was penalizing résumés that had the word 'women' in it, such as if you went to a women's college, your résumé was spitting out" (NY Times: June 17, 2019). A second unintended bias occurs when the data available is not representative of the situation that it purports to represent (due to inaccurate measurement methodologies, incomplete data gathering, non-standardized self-reporting, or other flaws in data collection). Biases can be rectified by improving the data collection process or ensuring clean data (The AI Now Report: The Social and Economic Implications of Artificial Intelligence Technologies in the Near-Term: 2016).

On the other hand, an AI-based decision system will be free of any such cognitive predispositions (compared to humans). Therefore, it will be better at letting the data tell its own story, thus producing a visualization that is a more accurate representation of the data rather than a mere cognitive perception. Furthermore, any data missing in the analysis of the leader will be made more explicit in examining the output of an AI-based

decision-making system (Parry et al., 2016). However, in so doing, new technologies that reflect and reproduce existing inequities are promoted and perceived as more objective or progressive than the discriminatory systems of a previous era (Benjamin, 2019).¹²

Privacy

Many consumers and citizens are concerned about the data that I directly or indirectly supply via social media, which could be used with or without our knowledge. For example, Cambridge Analytica accessed records of 30 million friends via those Facebook participants who completed a personality questionnaire app (Thompson & Vogelstein, 2019). China has embarked on a large-scale effort to implement face recognition software to identify militants and keep their state-controlled security in place at the country level. On the more positive side, the EU put in place the Europe General Data Protection Requirement (GDPR) effective May 2018, which is "to protect all EU citizens from privacy and data breaches" with some stiff penalties to organizations that violate this policy (Accessed July 2019: <https://eugdpr.org/the-regulation/>). Employees leave a digital footprint in the workplace that employers can access, collect, analyze, and assess. Employers are mining employee data (e.g., emails, instant messages, survey respondents, etc.) (Zielinski, 2018) to understand social interaction patterns, create organizational network analysis, and predict employee retention. This data has driven the field of talent analytics as a critical component of human capital management.

¹² Arvind Narayanan commented further on the use of AI powered employment decision when he said that "human decision makers might be biased, but at least there's a diversity of biases. Imagine a future where every employer uses automated resume screening algorithms that all use the same heuristics, and job seekers who do not pass those checks get rejected everywhere" (Benjamin, 2019).

Accountability

One of the critical issues facing software developers, technology providers, executives, and managers is determining who is ultimately accountable when AI or other emerging technology systems behave not as intended, malevolently or irresponsibly. By both nature and design, AI and other computing technologies are complex systems where assigning fault, blame, or accountability to a solitary person is difficult. For example, software code is written by a variety of individuals as part of open software development. This is the 'problem of many hands,' where the connection between the outcome and the one accountable is obscured (Nissenbaum, 1996).

There is a tendency to blame computer systems when something goes wrong because they personify human interactions, and computers are usually the primary interface between humans and machines. Madeleine Elish introduced the concept of a moral crumple zone whereby the responsibility for an action is misattributed to a human actor who had limited control over the behavior of an autonomous system (Elish, 2019). Elish cites examples like Three Mile Island, accidents involving self-driving cars, and Air France Flight 447, where human operators are blamed for errors or accidents not solely within their control. System designers need to be held accountable and to feel morally blameworthy for given harm if that happens on their watch (Feinberg as cited in Nissenbaum 1996)¹³. One prominent example was the financial crisis of 2008 when the designers of mortgage-backed securities and the regulators who assessed them as safe did

¹³ Per Feinberg, a person is morally blameworthy for a harm if: 1.) his or her actions caused the harm or constitute significant causal factor in bringing about the harm. 2. his or her actions were faulty. He also states that faulty actions cover actions that are guided by faulty decisions or intentions as well as reckless and negligent actions. We judge actions negligent if a person does not consider probable harmful consequences.

not understand the long-term ramifications and downstream implications of their decisions. Additionally, machine learning systems often have low interpretability, which means humans have difficulty figuring out how the systems reached their conclusions. Deep neural networks may have hundreds of millions of connections, each contributing a small amount to the ultimate decision. As a result, these systems' predictions tend to resist simple, clear explanations, therefore hard to determine ultimate accountability.

There are many questions that need to be resolved. When AI goes wrong, who should be held accountable? Is it the theoretician who created the algorithm? Should it be the developer who wrote the code? The engineer who trained and tested the machine learning “black box”? The human factors expert who helped design the system? The company that integrated the AI software into its product? The human operator of the system who worked alongside the AI and was present, presumably, to catch any mistakes that arose and take control in time to avoid disaster? The answer is “any or all of the above,” although there seems to be an early tendency to blame the human operator (Jenkins & Mitchell, 2020).

Senior leaders and government policy leaders bear the ultimate responsibility to manage the existing and emerging risks. They need to implement checks such as comparing the quality of decisions made by the algorithms with those made in the same situation without employing them. They need to monitor these tools continuously to ensure they behave within appropriate limits (Babic et al., 2021) and have a community-based participatory approach to building AI products. This approach involves ethically partnering with marginalized communities (Martin & Moore, 2020), including diverse

stakeholders in forming products or solutions. (Prabhakaran & Martin, 2020)¹⁴ What is at stake is not the risk of AI superintelligence: It is idiot savants with power, such as autonomous weapons with power, weapons that could target people, with no values to constrain them, or AI-driven newsfeeds that, lacking superintelligence, prioritize short-term sales without evaluating their impact on long-term values. The only way to get out of this potential mess is to begin building machines with common sense, cognitive models, and powerful tools for reasoning (Marchs & Davis, 2019)

AI and the Workforce

This "third era of automation" could be more damaging by all accounts and be more far-reaching due to the potentially drastic changes (both positive and negative) foreseen from previous technology. No matter the degree of change that will ultimately occur, all employee base levels will be affected by the C-Suite to front-line employees. Some of these changes will result in anxiety due to a loss of individual autonomy; a diminution of freedom to exercise judgment and decision making; a lack of potential privacy in the workplace depending on how AI is deployed; real or perceived perception individuals could be displaced due to automation (or elements of the role could be eliminated). Also, there will be a need for individuals to be reskilled (training employees in something new and upskilled (taking the essence of what employees do and improving it) (Hancock et al. 2020)¹⁵ in new capabilities or technology tools to keep one's career

¹⁴ These authors have proposed a "community based-systems dynamics (CBSD) as practice that could supply diverse sources of causal theories to core decision making steps during the machine learning development process. CBSD is a participatory method that relies on group modeling sessions involving diverse stakeholders, the goal of developing a shared understanding of a complex adaptive problem by making the causal theories held by participants explicit. (Prabhakaran & Martin, 2020)

¹⁵ In a private conversation with Philip Campbell (CEO of EngimaFIT Corporation), he makes the distinction between reskilling and upskilling. According to him, reskilling is about acquiring new knowledge through language which he calls "book smarts" and upskilling is about upgrading existing cognitive capabilities because of one's brain plasticity which he calls "street smarts".

contemporary.¹⁶ These concerns are echoed by recent surveys stating that "55% of people are worried about automation or other innovations will take their job away" (Edelman Trust Barometer, 2019).

On one end of the scale, some prognosticators predict the demise of millions of jobs, including those held by administrative or transactional workers and highly skilled knowledge workers. McKinsey's Global Institute in 2017 stated that "about half of the work activities people perform could be automated with current technology." Michael Webb analyzed 16,400 AI patents containing keywords, such as "neural network in their titles or abstracts." He used an algorithm to extract 8000 verb-object pairs, such as "diagnose disease" (Muro et al., 2019) within those abstracts and compared these terms against the U.S. Dept of Labor's O*NET database. He determined that 740 of the 769 occupational descriptions contained a capabilities pair match with the AI patent language pairs. In his estimation, Webb's research found that specific job tasks, including white-collar workers, will be impacted by AI either augmented by AI or replaced by AI. (Muro et al., 2019). Frey (2019) from Oxford University analyzed the share of jobs with the highest risk of automation, due to Machine Learning and Mobile Robotics, against the share of total U.S. employment percentage. Figure 2.3 offers an overview of those roles that have the highest risk of automation (horizontal axis) and the share represented in the U.S. employment marketplace (vertical axis).

¹⁶ Tom Davenport identified "five paths toward employability" that he dubbed "step up, step aside, step in, step narrowly and step forward". For example, if you decide on the step-in path, his advice on how to add value includes "understand how software makes routine decisions, so you monitor and modify its function and outputs".

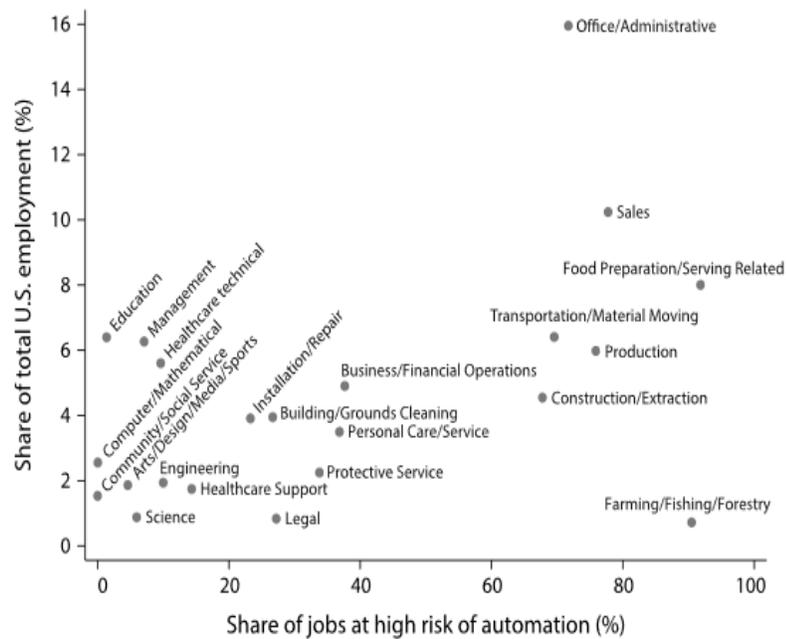


Figure 2.3. Jobs With the Highest Risk of Automation

The jobs with the highest degree of routine administrative, mechanical, or operational processes tasks vs. cognitive or highly relationship-oriented are at most significant risk of some degree of automation. Even though jobs can be technically automated, other factors might impact the decision to automate, such as the costs or benefits and the relative scarcity, skills, and costs of workers who might otherwise do the activity (Davenport, 2019). There has also been a growing movement to focus not on jobs but on the tasks or actions that comprise jobs that will be transformed as technology takes over duties (Malone, 2020). In the middle of Figure 2.3, there are business/financial operations roles with a high risk of automation. To further illustrate the point about the impact on financial tasks, operations, and processes, Figure 2.4 lists several financial sub-processes (e.g., Financial Accounting, Reporting and Analytics, Risk, and Compliance)

that AI tools will positively influence. These include expert systems, machine learning, and robotic process automation (Reinhardt, 2018).

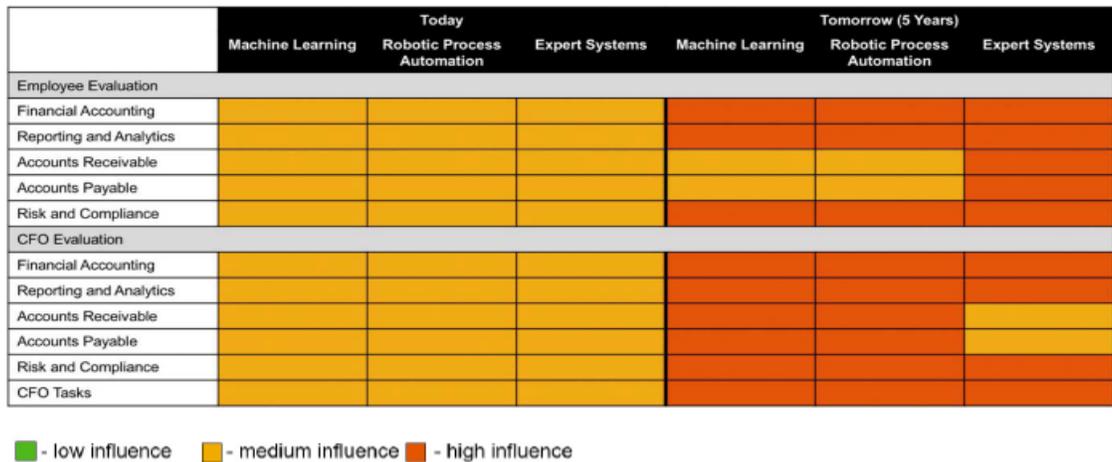


Figure 2 – Potency of the Effect of AI Technologies on the Subprocesses in Financial Management (Comparison Between Today and the Effects in 5 Years, Survey 07/18)

Figure 2.4. Artificial Intelligence in Financial Management Processes

Huang and Rust (2018) theorize that four categories of intelligence are required for service tasks: mechanical, analytical, intuitive, and empathetic. AI is developing in a predictable, staged order starting with the mechanical task and eventually leading up to empathetic tasks, as seen by the graph in Figure 2.5. At each successive stage, AI is replacing the previous set of functions with the latest phase. This reflects either a total replacement or, realistically, a blending between AI tools with workers' skills, capabilities, and knowledge job replacement.

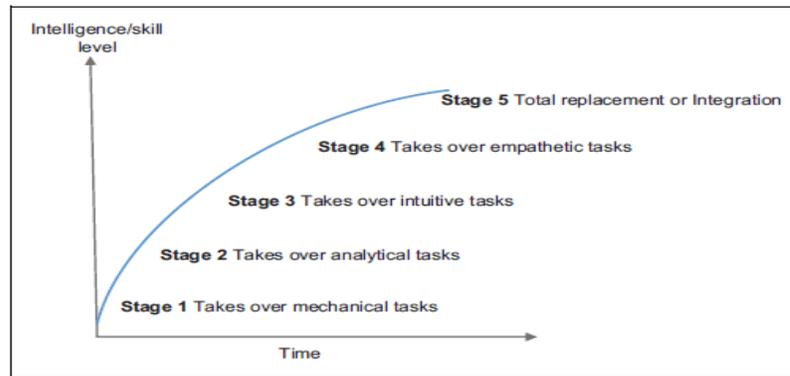


Figure 4. Stages of artificial intelligence job replacement.

Figure 2.5. Stages of AI Job Replacement

At the 2020 Aspen Institute Roundtable on Artificial Intelligence, participants took up the question of the human-machine relationship and how concepts like affect, emotion, and empathy are not only in the human domain anymore and what potentially "differentiates humans from machines is negligible" (Gloria, 2020). One of the participants summed up the conundrum, "for it is our nature to project humanity onto these humanoid objects that have none, but which nevertheless push our Darwinian buttons to relate to them as human" (Gloria, 2020). Therefore, interacting and relating to machines with human or emotional qualities can be considered artificial intimacy. At the same time, Stanford University developed Woebot, a chatbot therapist that uses machine learning and a standard cognitive-behavioral approach to talk users through their problems showing significantly reduced symptoms of depression and anxiety in users (Roose, 2021).

Simultaneously, some more sanguine futurists believe a net macro "economic difference between being mostly automated versus being completely automated" for the

overall economy (Bessen, 2016)¹⁷. These new technologies that create jobs will also be a net benefit for job creation, resulting in new or different roles and capabilities. For example, software developers will be able to identify new spam flags and manually write rules for spam detection. See Figure 2.6 for additional examples.

In the middle of the spectrum are those management theorists and researchers who believe that AI's impact will depend on the specific duties of the role. "For individual workers, the relative importance of these forces will depend on the degree to which the core skill they bring to their job is predicated on prediction" (Agrawal et al., 2019). Workers whose core skill is something other than a prediction, such as highly skilled experts such as radiologists, brain surgeons, and financial traders, may find that automated prediction enhances their occupation value because they can bring more informed decisions or recommendations to bear on complex issues. When one evaluates the various theorists and practitioners, the share of jobs and occupations that can be fully automated in terms of all their constituent activities is actually relatively small, at least for the next several decades (Lynch, 2020)¹⁸

Also, humans and machines will act as complementary forces (Daughtery and Wilson 2019). For example, humans will serve as explainers who "analyze algorithms to uncover the machine's heuristics. In other situations, AI will augment humans with additional capabilities.

¹⁷ Bessen, J. E. (2016). How Computer Automation Affects Occupations: Technology, Jobs and Skills. *Boston University School of Law, Law and Economics Research Paper*. 15-49. Bessen cites the example of weavers in the 19th century when 98% of the labor required to weave a yard of cloth became automated, the number of weaving jobs increased because of falling prices which increased the demand for cloth.

¹⁸ This is statement is a quote by James Manyika (senior partner at McKinsey & Co.) at Stanford University HAI Directors' Conversation)

The evolution of work and the elevation of workers.



Source: Accenture Future Workforce Ethnographic Study 2017

Figure 2.6. Evolution of Work and The Elevation of Workers

For example, humans will act as amplifiers by providing "extraordinary data-driven insights" that identify trends or patterns as they occur" (Daugherty & Wilson 2019).¹⁹

Armed with machine learning, a manager becomes a super manager; a scientist, a super scientist, an engineer, a super engineer. The future will belong to those who understand how to combine their expertise with what algorithms do best (Domingos, 2015).

At a minimum, there will be a need to reskill and upskill employees into technical and soft skills, which will soon be required to perform effectively. For example, employees will need advanced data analytics and visualization skills, and be agile, open to change, and embrace ambiguity (Reinhardt, 2018).²⁰ In recent year, IBM has identified the current skills needed for employees, showing a shift from digital and technical skills toward more behavioral skills. Figure 2.7 provides a list of such skills. Unlike in 2016, a 2018 survey showed that global executives seek a greater degree of flexibility, time management, collaboration, and communication.

¹⁹ Daugherty and Wilson, from Accenture, have termed this "the missing middle" which is a combination of human and machine hybrid activities.

²⁰ Another example is Microsoft who has built the AI Business School to share knowledge and insights from top executives and thought leaders on how to strategically use AI in organizations (De Cremer 2020) as well as the site is a platform on educating the marketplace on Microsoft AI services too.

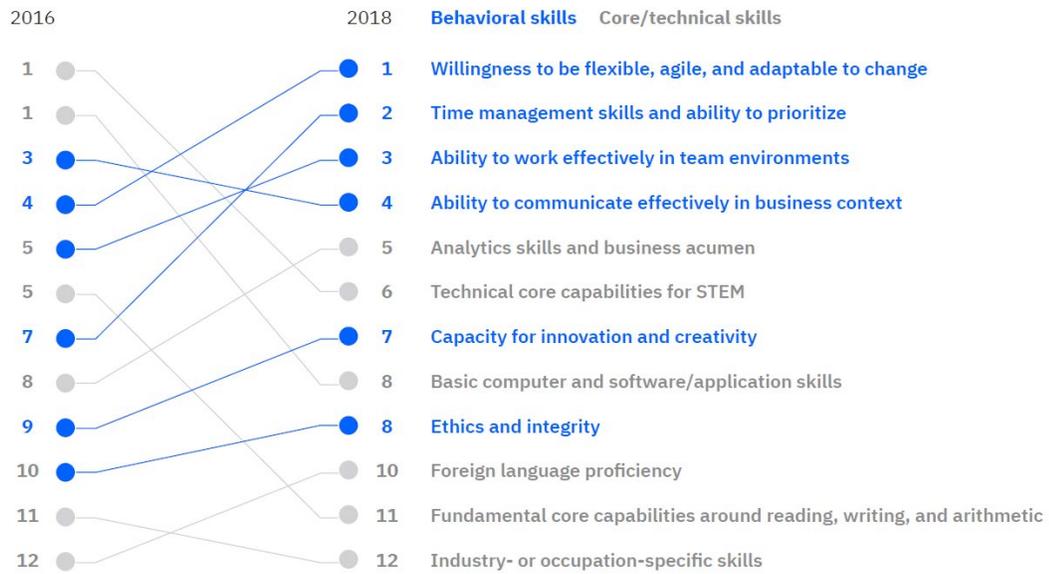


Figure 2.7. IBM Survey of Key Skills

Organizations need both technical and human skills to remain agile and innovative in response to technological and marketplace changes.²¹ Hybrid roles will be in greater demand, becoming some of the most technology and data-driven and more dependent on judgment and creativity (Siegelman et al., 2019). One senior practitioner²² has postulated that individuals need to become more Pi(π) shaped vs. T-shaped in their expertise (Hill, 2021). The horizontal part of T-shaped individuals has the broad general knowledge that is not specific to a particular domain. Individuals who have received a liberal arts education would be an example of individuals who have amassed

²¹ For argument’s sake, let us assume that soft skills are increasing in their importance which is consistent with other researchers, then managers will need to have expertise in these areas too in order to coach and train individuals. In the section on managerial capabilities required to lead in an AI environment, we identified a set of “soft skills” and personal attributes such as humility, curiosity, interpersonal orientation, and relationship building as well as social/creative intelligence (see Table 2.2)

²² Private conversation with Craig Hill who told me about the concept of π -shaped individuals that he described in a recently edited book in which he contributed a chapter (Hill, 2021) He used the π -shaped notion in the context of social science researchers, but I think the concept could be broadened to other professional disciplines.

comprehensive knowledge. At the same time, individuals have compiled in-depth expertise or knowledge in a particular discipline (vertical part of the T). What is different and new about being Pi or π -shaped (vs. T-shaped) is the need to add another vertical set of capabilities in statistics and computing (Hill, 2021) that should become part of one's academic/professional training.

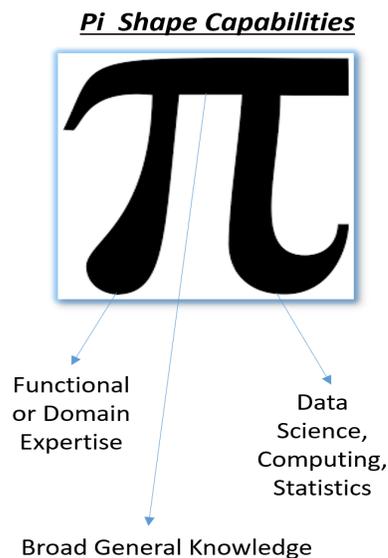


Figure 2.8. Pi Shape Capabilities

McKinsey's consulting firm also identified quantitative and statistical skills and advanced IT, programming, data analysis, and mathematics skills as necessary future skills (Bughin et al., 2018)²³. One banking organization offered data science training tailored for business managers at all levels, which was taught by the head of the data science unit (Josh et al., 2021). Due to the implementation of AI and digitization,

²³ McKinsey also advocates the need for individuals to become “M” shaped where they need to build broad competencies and deep expertise over the course of their career (Brassey et. al, 2019)

organizations will require their employees to be facile with data management or visualization and think in a probabilistic manner. Therefore, this transformation will require employees to continuously adapt to new situations and increase their need for agility, requiring an increased demand for lifelong learning (Schwarzmueller et al., 2018). Therefore, leaders must own the skills agenda for employees and continuously assess where new skills are needed and how best to help employees acquire those skills (IBM 2020). Those companies that implement AI widely across their whole organization offer a wide range of training (Ransbotham, 2019). One example of a global firm undertaking a significant retraining effort is Amazon. The company announced plans to spend \$700 million over about six years to retrain a third of its U.S. workforce as automation and machine learning upends the way many of its employees do their jobs (Wall Street Journal, July 11, 2019). Based on research at MIT's Center for Information Systems Research (Dery et al., 2020), developing a future-ready workforce pays off. Companies with a future-ready workforce deliver 19 percentage points higher revenue growth and 15 percentage points higher net margin than their industry average (Dery et al., 2020).²⁴

There is no doubt that automation will increase labor demand (new jobs) and change the nature of existing jobs. Still, workers' reallocation from existing jobs and tasks to new ones is complex and slow (even with reskilling & upskilling). At the same time, there has to be "an increase in a set of tasks in which labor has a comparative advantage," and the reality is that automation will pace ahead of new job creation hence reducing "the share of labor in national income" (Acemoglu & Restrepo, 2019). Peter Drucker was

²⁴Their report highlighted two distinct ways that companies are changing their workforces through the "Digitization of Work" (e.g., equipping employees with the right digital tools to do their work of today and to redesign their work of the tomorrow) and "Digital Fitness" (e.g., empowering and developing employees to work effectively in a company that is increasingly transforming to be digital). (Dery et al (2020).

prescient in 1946, he said, "however, the full picture, as in all technological revolutions, only emerges if both — the better life for those who can adjust themselves and the suffering of those who are pushed out — are seen together and at the same time" (Wartzman, 2015).

Because AI will fundamentally change the nature of employees' roles and their skills, the implementation of AI is fundamentally a change effort. Therefore, leaders need to be mindful of implementing a robust change effort that builds employee commitment and acceptance. Employees directly involved in the change effort by providing input into redesigned processes increase the probability of their commitment, buy-in, and utilization of the tools. The same is said for algorithms when employees suggest improvements, tiny tweaks, and changes that increase trust (Hosanagar, 2019). Another way to gain commitment is to demonstrate the potential impact of the specific AI application for users. Showing them prototypes of the tool or the technology's outputs would create enthusiasm and how the AI tool would help them in their day-to-day responsibilities. Employees feel digitally empowered when they receive support from managers and organizations to embrace the new digital technologies in their jobs thoroughly. The more positive the employees' perceived digital empowerment is and the more they get actively involved in the process right from the beginning, the higher the motivation and willingness to change and achieve the desired action or state (Gfrerer et al. 2021). Lastly, one way to ensure AI's commitment and energy are to access all employees' AI tools and data. Researchers (Zeng & Glaister, 2018) have called this "data democratization defined as firm's capability to integrate data across the firm and enable a broader range of employees to access and understand data where it is needed at any given time". If data

and tools are readily available, employees will be able to extract real value from AI because they will have the information and the empowerment to make final decisions aided by AI and act on those decisions (Di Fiore, 2018).

As seen by this section, AI has a significant impact on employees' roles and tasks, which will be required an increase in their skill set to succeed in this new environment. Also, they will need to adapt to and be willing to change to accept the latest technology deployed in their workplaces. Therefore, this leads credence to one of the three focus areas for this research: “Managers will continue to assume an essential role in employee development, engagement, and inspiration because of the potential impact of AI to work design and employee's motivation to embrace AI” (Focus Area 2)

Human Decision Making, AI, and Augmented Decision Making

Computer scientists have used human mental processing and decision-making as a cornerstone of their approach to designing AI systems and tools. This section will cover four areas. First, I will start by describing the fundamental elements that comprise human decision-making—followed by a discussion of the mutual integration of decision making with AI, including utilizing the brain's neurological mechanisms as a conceptual model to build AI systems. The third area will focus on how humans and AI work together in an augmented, synergistic fashion resulting in 'collective intelligence.' The last section will briefly discuss the challenges of training and ensuring AI operates at a higher degree of fairness, justice, and moral reasoning.

Human Decision-Making Core Elements

At the most basic level, rational decision-making consists of three core elements:
(1) Using relevant information to make decisions; (2) using the correct logic to conclude;

and (3) optimizing the decision process, including maximizing utility (Marwala, 2015). AI makes all three happen faster and more effectively in most circumstances. Creating an optimized human decision is, in most cases, not practical because the information is incomplete, and one does not have all the necessary mental processing infrastructure, including time or resources, to make sense of it. Herbert Simon called this "bounded rationality," which causes individuals to make sub-optimal decisions. At the same time, human decision-making is a team effort, coupling the ancestral parts of the brain most closely related to the body and emotions with the "reasoning" part through the frontal cortex acting as an integrating agent (Pomeroy & Adams, 2008). Therefore, human decision-making is an overly complex cognitive process resulting in a belief or course of action among several alternative possibilities, influenced by experience, decision complexity, emotions, and many cognitive biases. (Rosenfeld, 2018).

In *Thinking Fast and Slow*, Kahneman (2011) argued that there are two types of cognitive processes called System 1 (Fast) and System 2 (Slow). System 1 thinking characteristics include being "automatic, effortless, emotional, parallel, implicit, unconscious, governed by habit, therefore difficult to control" (Kahneman, 2003). In System 1, the decision-making process appears intuitive, which "depends on the use of experience to recognize key patterns that indicate the dynamics of the situation" (Klein, 1998) and can quickly act, especially in non-novel circumstances. On the other hand, System 2 is "slower, serial, effortful, orderly, requires attention, consciously monitored and deliberately controlled" (Kahneman, 2003). Consequently, these activities require deep thinking, concerted attention, mindfulness, and the practice of "deep work" (Newport, 2016). In addition to the lack of focused reflection, there are a series of

cognitive biases that get in the way of exercising effective decision-making and reasoning. Some of the more prevalent ones include the following (Rosenfeld & Kraus, 2018; Kahneman, 2003):

- *Self-Interested Bias*: Individuals are making recommendations or errors because they are motivated by conscious or unconscious self-interest.
- *Affect Heuristic*: Individuals have fallen in love with their proposal, and they cannot be objective on the merits or demerits.
- *Confirmation Bias*: Look for information that reinforces one's decision or actions.
- *Groupthink*: Minority or dissenting opinions were not heeded, heard, or considered.
- *Framing*: A phenomenon where individuals may make different decisions based on the same information, depending on how they are presented or framed.
- *Saliency Bias*: The diagnosis or decision is overly influenced by an analogous situation that is memorable.
- *Loss Aversion*: The tendency of individuals to avoid losses over acquiring equivalent gains.
- *Anchoring Bias*: The tendency of decision-makers to rely too heavily on a focal or "anchor" piece of information when making decisions or negotiating.

Certain behaviors distinguish an average individual from an individual with superior competence in decision-making. For example, one difference is recognizing the limitations to what one knows neither being underconfident or overconfident (Fischhoff, 2007). Another difference is individuals' awareness of their own cognitive biases, such as resistance to framing (Fischhoff, 2007), which means decision-makers are not affected by

irrelevant variations or facts presented in problem descriptions. A third difference is the awareness of their decision-making style. For example, when they approach a problem or situation, their first inclination is to converge on a probable answer instead of diverging to generate a range of possible ideas or solutions.²⁵ Because decision-making is fundamentally a learned skill, individuals can build their mental or cognitive capabilities with focused, deliberate practice²⁶ (Ericsson & Charness 1994). Some improvement techniques include treating each decision as an opportunity to learn vis-à-vis the decision's goals and evaluation criteria; conducting formal postmortems after significant decisions; keeping a journal to capture reflections by reviewing prior experiences to derive new insights from mistakes, and obtaining feedback that is accurate, diagnostic, and timely (Klein, 1999).

Integration of Human Decision Making and Artificial Intelligence

Computers, algorithms, and human decision-making, including the neurological processes that underlie thinking and deciding, have been mutually influenced by each other. Artificial Intelligence has become a more significant part of individuals' vernacular and daily practices, whether in the workplace or personal lives. For example, 'algorithmic thinking' has become defined as a "logical, organized way of thinking used to break down a complicated goal into a series of (ordered) steps using available tools" (Lockwood et al., 2016).²⁷ Computer scientists, software engineers, and data analysts have particularly

²⁵ David A. Kolb has written extensively on this topic and has created a self-reporting instrument called the "Learning Style Inventory" which provides feedback on learning styles and its impact on problem solving and decision making.

²⁶ Ericsson's work reached a mass audience when Malcolm Gladwell cited his work and titled one of his chapters "The 10,000-hour Rule" in his book "Outliers: The Story of Success"

²⁷ A related concept is the notion of is "computational thinking defined as "taking an approach to solving problems, designing systems, and understanding human behavior that draws on concepts fundamental to computer science." (Lockwood 2016)

required this capability. Still, algorithmic or computational thinking will become more of a regular practice in other business disciplines in the coming decade. Also, Brian Christian and Tom Griffiths wrote a book titled *"Algorithms to Live By: The Computer Science of Human Decisions."* In this book, they explored the idea of 'human algorithm design.' They provided insight drawn from statistics and algorithms to help individuals face challenges and solve day-to-day issues such as managing finite time, limited attention, incomplete information, etc. (Christian and Griffiths, 2016). Their book demonstrated how algorithms, computational thinking, and logical thought processes could help individuals in their day-to-day challenges.

On the other hand, human decision-making, including the neurological processes that underlie thinking, has shaped Artificial Intelligence tools and methodologies. In terms of neuroscience,²⁸ the current AI techniques of deep learning and reinforcement learning are based in brain functionality (Hassabis et al., 2017). For example, biological brains are modular, with distinct but interacting subsystems underpinning memory, visual processing, language, and cognitive control (Hassabis et al., 2017). In the first generation of deep learning network models that analyzed visual imagery, they gave equal priority to all images when processing them, which was very inefficient. Building upon the insight from human optical systems, where one's attention shifts among location and objects, centering process resources and representation coordinates on series of regions in turn. (Hassabis et al., 2017). Now, AI "architectures take glimpses of the input image at each step, update internal state representations, and then select the next location to sample"

²⁸ Neuroscience to "include all fields that are involved in the study of the brain, the behaviors it generates, and the mechanisms by which it does so, including cognitive neuroscience, systems neuroscience and psychology". (Hassabis, et al 2017)

(Hassabis et al., 2017). In addition to building upon neurological processes to build AI tools, software engineers who designed intelligent agents, who interact proficiently with people, necessitates understanding the prediction understanding of human decision making (Rosenfeld & Kraus, 2018) to mimic the thinking processes. Rosenfeld articulated three paradigms (e.g., expert-driven, data-driven, and hybrid) to predict human decision-making.

For example, in the expert-driven model, "predicting human decision-making is a mathematical formulation, articulated by an expert, which is assumed to adequately predict people's choices in a given setting or across different settings" (Rosenfeld & Kraus, 2018). For example, bounded rationality states that individuals do not use a purely analytical optimizing approach to solving problems but rely on a set of heuristics. Consequently, this leads to suboptimal decision-making because individuals do not have complete information, enough time to collect the data, or the cognitive capability to process it. With recent advances in Artificial Intelligence, incomplete information can be completed using missing data estimation methods. The finite time of making decisions can be accelerated, given the advances in computing power (Marwala. 2014). For example, several agent design models have been created to deal with bounded rationality, such as "logit quantal response, level-k model, and cognitive hierarchy model" (Rosenfeld & Kraus, 2018).

Human and AI Decision-Making Collaboration

Due to the power speed of AI along with the judgment, creativity, intuition, and innovativeness of humans, the human-AI symbiosis means interactions between humans and AI can make both parties smarter over time (Jarahi, 2018). Other theorists have

labeled this same combination 'hybrid intelligence,' defined as the "collective intelligence of humans and elements of AI working in close collaboration to serve the purpose of an organizational unit (Leodolter, 2017). Another term for these human-computer groups is super minds (Malone et al., 2020).²⁹ The uniting of AI's formal rationality with human beings' "substantive rationality, which is the capacity of humans for value-rational reflection and analysis" (Lindebaum, 2020), is another critical element of human-AI symbiosis. However, AI's algorithms' presumed rationality and objectivity might cause managers to adhere to the machine's recommendations without stopping to reflect and consider other matters, therefore transforming or subsuming substantive under formal rationality (Lindenbaum, 2020). AI tools will recommend possible actions, but it will be up to managers to consider other types of information, along with their intuition and judgment, before executing a course of action or decision. Combining analytics with intuition—shaped and provided by the individual's subconscious mind—will be a crucial feature of hybrid intelligence that gives humans the ability to control the outcome (Leodtler, 2017).

In terms of decision-making collaboration, AI technology is better positioned to tackle complex³⁰ issues that include large amounts of objective structured and unstructured data to analyze. On the other hand, humans are better situated to focus on

²⁹ Malone is one of the leading researchers in the field of collective intelligence where he leads MIT's Center for Collective Intelligence. This center "explores how people and computers can be connected so that – collectively – they act more intelligently than any person, group, or computer has ever done before." He is also the author of many articles and books including "Superminds: The Surprising Power of People and Computers Thinking Together" (2018).

³⁰ There is a distinction between complicated systems which have moving parts but operate in a patterned way vs. complexity where interactions are continually changing. Complex systems have the following properties: multiplicity (number of potentially interacting elements); interdependence (how connected these items are) and diversity (degree of heterogeneity). (Source: Learning to Live with Complexity by Gokce Sargut & Rita Gunther McGrath. HBR September 2011)

issues or problems that are in the realm of uncertainty and equivocality decisions. Figure 2.9 illustrate these three sets of circumstances (Jarrahi, 2018).

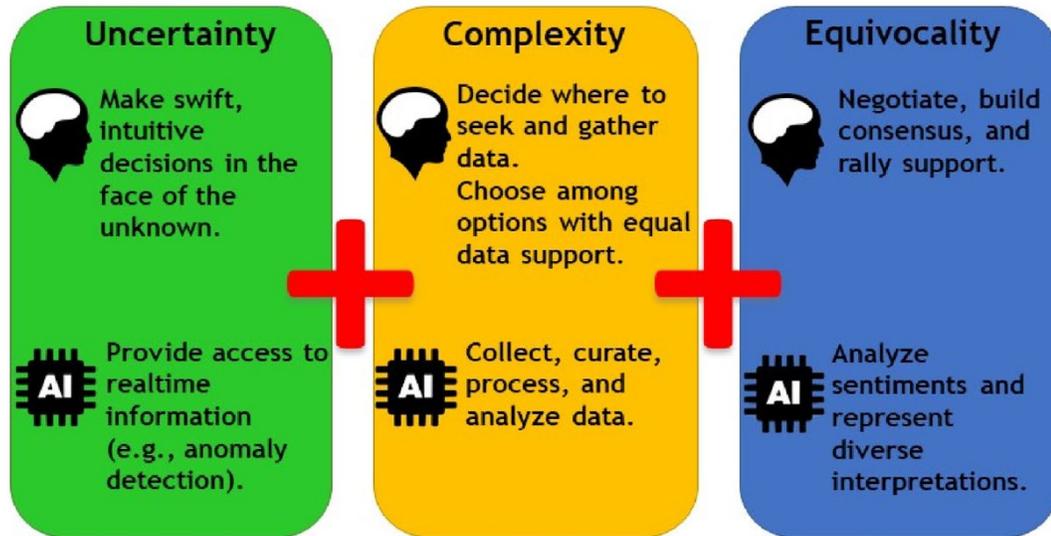


Figure 2.9. Circumstances That Dictate AI and Human Interactions

At a systems level, this Humans–AI hybrid can work together in four different ways, with humans playing a distinct role in each of the quadrants, as noted in Figure 2.10.

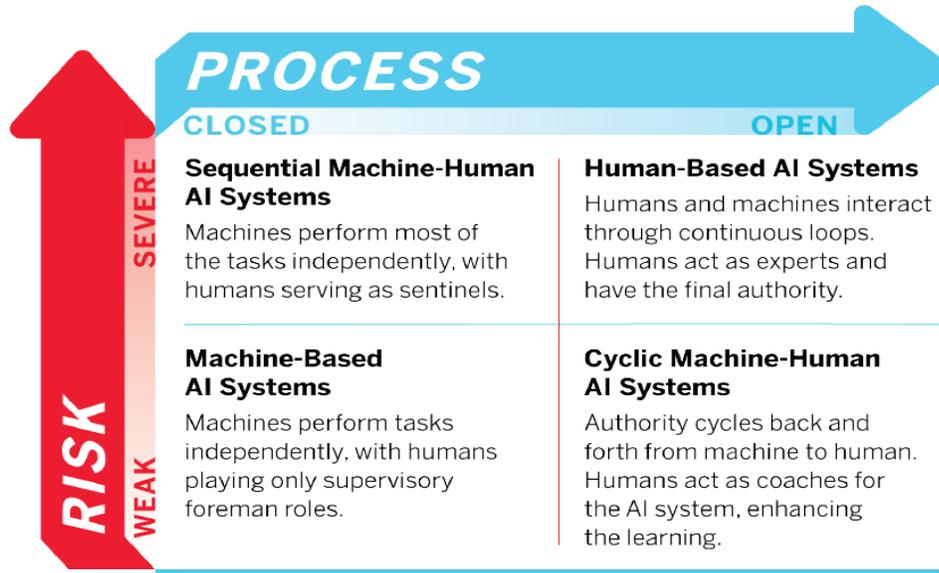


Figure 2.10. Human-AI Interactions

The top right quadrant—Human-Based AI Systems—is where risk is highest. The organizational decision processes are open, more complex, which necessitates that the final decision-making authority rests in humans' hands. In this quadrant, humans need to have a tremendous sense-making capability, project the future impact of recent decisions, and understand their cognitive biases, especially in stressful situations. In the bottom right-hand corner, machine-based AI systems can perform tasks independently in low-risk cases. One example is a recommender system that underlies Amazon and Netflix's suggestions for our entertainment consumption. In these circumstances, these companies generate an overall recommendation and present it to the chooser, sometimes offering an explanation (e.g., other customers searched for related titles) with the chooser determining the possible course of action (Jameson et al. 2015).

Creating a Just and Fair AI Decision Making Process

As stated above, integrating AI and humans in certain situations represents the optimal mechanism to provide recommendations or actual solutions that are highly efficacious and efficient. On the efficacious side of the equation, machine agents will need to produce predictions or recommend actions that reflect the application of universal moral traits as prudence, temperance, justice, courage, faith, hope, and love (Neubert & Montanez, 2020).

There are several challenges to designing and operating consistent with these moral traits. First, designers of these agents must provide 'an operationalizable and presumably quantitative theory that specifies which particular actions are morally right or wrong in a wide range of situations or domains, rather than every nuanced feature relevant to isolated scenarios' (Conitzer et al., 2017). Second, one must implement an approach, such as a machine learning framework, to arrive at procedures to train the agents to make moral recommendations or decisions. Some solutions would entail providing a labeled dataset of ethical dilemmas that offer explanations for why the actions are morally right, how ethically wrong the step is, and an assessment of how probable it is that the action is morally wrong (Conitzer et al., 2017). Third, these designers need to be self-reflective to understand their biases and blind spots because it shapes their epistemology (Dobbe et al., 2018). Part of this self-reflection includes doing operational audits to understand any biases present in the software. For example, Accenture advises its clients to review algorithms for bias in its programming and examine the data it was trained on to identify the correct potential biases (Neurbert and Montanez, 2020). Fourth, greater transparency is necessary. The lack of transparency

makes it nearly impossible to establish whether a faulty proxy, data set, or another reason causes unfairness. (Zarsky, 2016). Hence, individuals need to understand the underlying factors and algorithmic processes utilized by the AI system, the nature of the data sets, and the statistical error rate in predicting the outcomes (Zarsky, 2016). When users understand the inner workings of the decision aid—the why and how the system is behaving—it builds trust, which may increase the judgment and decision-making performance of the individuals and the intelligent agent (Seong & Bisantz, 2002).

Another dimension of maintaining a just, fair, and ethical AI ecosystem relates to the idea of gaming, defined as a "purposeful change (by the user) to alter the algorithm's estimates without causing any change to the key characteristic that the algorithm is attempting to measure" (Bambauer & Zarsky. 2018). Within limits, people game algorithms for a range of altruistic and self-serving reasons. Not to be outdone, algorithm designers game systems right back, using countermoves to thwart or minimize the impact of gaming (Bambauer & Zarsky, 2018). For example, Fintech companies use access location-based data to assess their customers' creditworthiness and utilize health data via Fitbit-like devices. One way that customers can game the system is by altering their behavior by "switching their devices off when visiting high-risk locations like casinos or liquor stores" (Bambauer & Zarsky 2018). One of the consequences of gaming (by the user and the agent developer) is that the algorithm will be less predictive, less accurate, and potentially render the system arbitrary.

Role of the Manager and AI's Impact

As noted above, managers at all levels will be impacted by introducing AI in the workplace. They will play a role in its adoption and implementation at the organization

and team levels. At the senior organization levels, such as the Board and C-suite, executives must be mindful of AI's capabilities during implementation. One analysis of leading vs. laggard AI implementation found that senior leader support, especially CEO support, was one of the differentiators for successfully implementing digital transformations (Brock & von Wangenheim, 2019).³¹ Leaders need to cultivate a "fertile environment" for AI tools to be used by non-technical leaders and business users and create business value (Ranbotham et al., 2019). Like any technological change, senior leaders must be mindful of the cognitive frame that they bring to this activity, formed by their previous experience, level of knowledge, and organizational culture (Kaplan & Tripsas, 2008). Also, AI high-performing organizations have engaged and knowledgeable champions at the C-suite, as evidenced by being fully aligned & commitment to the organization's strategy (Balakrishnan, 2020). According to upper echelons theory, organizational outcomes, such as AI, are influenced and partially predicted by the beliefs of top-level management teams. (Gfrerer et al., 2021). The consulting firm Oliver Wyman posed five critical questions that the board and senior executives need to debate across their organizations, which include the following:

1. Do we understand where AI could deliver the ***most significant business benefit*** and where a competitor's use of AI might most disrupt our business?
2. Do we have the necessary ***skillset and infrastructure*** to successfully deploy AI in areas where we think there is an opportunity?

³¹ The other factors that were significantly different among AI leaders include the following: organizational agility, engagement of skilled staff, support from technology partners, investment, culture, alignment of new digital technologies with existing IT, and learning from failed projects (Brock and von Wangenheim, 2019).

3. What are the *most significant risks* we face as we adopt AI to improve our business's effectiveness and efficiency?
4. Do we have the necessary *governance and control* framework to monitor and manage the risks created by AI adoption?
5. What are the *"unknown unknowns"* that we might be missing, and how will we make sure we *surface them* before it is too late?

By answering these questions, senior executives will understand the limitations, risks, and benefits of implementing AI in their respective organizations. Like any strategic investment with upsides and downsides, especially when risking an organization's reputation in the marketplace, executives need to be accountable for mitigating and solving issues that might present themselves. One example of managing reputation risk is when Mark Zuckerberg came under intense scrutiny due to Facebook's role in the November 2016 elections (Thompson, 2019).

One of the critical roles of senior executives is to help managers adjust to new, intelligent technologies by involving them in the initial experimentation with and implementation of AI, which will allow managers to familiarize themselves with the potential solutions driven by AI and human input (Kolbjørnsrud, 2017). Managers will have more pertinent information at their disposal to augment their decision-making and predictive capabilities. Additionally, robotic process automation software could take over much of the administrative and clerical work done, freeing up some of the manager's time (Walsh, 2019). There could be better tasks for "robots" than managers (Oracle & Future Workplace AI@Work Study 2019). Figure 2.1 illustrates differences in manager's and robots' skill sets.



Figure 2.11. Robots vs. Manager Role Preferences

The findings illustrated in Figure 2.11 are consistent with findings from another research study's conclusions. This study stated that "humans are seen as a better source of intuition, better at social skills, and better at taking another person's perspective, but algorithms can provide information about who to trust in cases where that information is less intuitive and more factual" (De Cremer et al., 2019). Machines can do very difficult tasks for humans, such as solving complex problems or translating sentences between hundreds of languages; however, AI is harder than we realize for AI to replicate human thought because we are largely unconscious of the complexity of one's thought processes (Mitchell, 2021). Some of these thought processes include looking out in the world and making sense of what we see, carrying on a conversation, walking down a crowded street without bumping into anyone which turn out to be the hardest challenge for machines (Mitchell, 2021). These mental processes are the *sine qua non* of managing (Mitchell, 2021). Malone (2018) argued "human managers delegate tasks, give directions, evaluate

work, and coordinate others' effort. Machines can do all these things, too, and when they do, they are performing as automated managers. At the extreme, by 2024, new technologies have the potential to replace as much as 69% of the tasks historically done by managers, such as assigning work, approving expenses, onboarding employees, and nudging productivity (Kropp et al. 2021). One cautionary example of how AI is encroaching on managerial accountabilities is at Amazon, where their 125,000 warehouse employees are given targets created by algorithms (Cappelli, 2020)³². Amazon's system tracks each associate's productivity rates and automatically generates warnings or terminations based on quality or productivity without input from supervisors. Any system feedback, automatically generated warnings, or termination notices are required to be provided to associates within 14 days (Mukherjee, 2020). The Amazon manager would have the final decision, especially if the policy were misapplied. A more positive example of how AI is complementing managers is how MetLife uses Cogito, an app-based AI coach, to provide call center employees with real-time feedback. If the call center person is talking too fast, a window flashes a speedometer, or the call center person sounds sleepy; the app flashes a coffee-cup icon. Also, if the call center person is not connecting with customers, it might show a heart icon—an empathetic cue—to encourage the mirroring of the customer's emotion (Roose, 2021).

Middle management will assume a pivotal role in ensuring the successful adoption of AI. Middle management is defined here as managers that are at least two levels below the CEO and one level above first-line supervisors (Huy, 2002), especially those who manage individuals assigned to routine administrative tasks. (First line

³² Another example is from Uber where bad drivers are not longer fired by a human, but they are deactivated by an algorithmic scoring tool (Pasquale, 2020).

supervisors, who lead highly technical knowledge workers, their role and impact are more consistent with middle managers.) Middle managers are usually "responsible for interpreting and communicating strategy and policy that originates at the executive level" (Kaiser et al., 2011). Some organizations have implemented self-directed teams (e.g., Zappas's holacracy organizational model), and other organizations have questioned managers' contributions. One highly publicized example was when Google was asking the importance of managers and whether they were necessary. They undertook a multi-year study dubbed 'Project Oxygen' to prove managers' worth and statistically studied the value-added benefits of a good manager and determined that managers indeed mattered (Garvin 2013).³³ Middle management is part of the fabric of an organization's leadership pipeline, which should be coveted, nurtured, curated, not eliminated (Hancock et al. 2021)

Other research has both corroborated the benefits of good managers or the negative impact of bad managers. These include:

- Companies with quality managers see a 48% increase in profitability and a 22% increase in productivity. (Source: Gallup's 2015 State of the American Manager Report)

³³ Based on this study, they initially identified approximately 8 behaviors which has grown to 10 when they updated the original study. Google found that the qualities of a great manager had grown and evolved with along with the company. The 10 Oxygen behaviors of Google's best managers (behaviors 3 and 6 have been updated and behaviors 9 and 10 are new): 1. Is a good coach. 2. Empowers team and does not micromanage. 3. Creates an inclusive team environment, showing concern for success and well-being. 4. Is productive and results oriented. 5. Is a good communicator — listens and shares information. 6. Supports career development and discusses performance. 7. Has a clear vision/strategy for the team. 8. Has key technical skills to help advise the team. 9. Collaborates across Google. 10. Is a strong decision maker. Source: <https://rework.withgoogle.com/blog/the-evolution-of-project-oxygen/>

- Effective managers are three times more likely to have high performing teams (Source: CEB's 2017 New Manager Mandate Study)
- Employees with effective managers give 38% more discretionary effort (Source: CEB's 2017 New Manager Mandate Study)
- 28% of employees leave due to bad managers (Source: CEB's 2017 A New Manager Mandate: Building Connectors Managers Study).
- Relationships with management are the top factor in employees' job satisfaction (Allas & Schaninger, 2020).³⁴

This evidence lends credibility to the claim that managers play a pivotal role in workforce management. Line managers directly control two aspects that constitute a pleasing workplace. First, managers impact good work organization, providing workers with the context, guidance, tools, and autonomy to minimize frustration and make their jobs meaningful. Secondly, managers affect psychological safety, which is the absence of interpersonal fear (Allas & Schaninger, 2020). The need for psychological safety is necessary during periods of change, such as AI or technological disruptions, which by its nature will evoke stress, uncertainty, and impact productivity.

Managerial Mindsets, Roles Tasks, and Capabilities in an AI Environment

This section will articulate the key mindsets and roles, tasks, and capabilities that managers need to master, which will result in the successful implementation of AI or other forms of technological change in their organizations. The below graph illustrates this reinforcing relationship between these various building blocks. Individuals need to

³⁴ At the same time, those employees who described themselves as having very bad or quite bad relationships with management reported substantially lower job satisfaction (Allas & Schaninger, 2020).

have the right mindset as they undertake their significant roles. Based on their mindsets and roles, it directly impacts their tasks, responsibilities, or duties ("the what") and the requisite skills, capabilities, or behaviors ("the how"). Each of these three elements is mutually reinforcing and necessary for managers to develop, demonstrate, and master to succeed in the "third era of automation." Figure 2.12 (Managerial System) illustrates these elements with short descriptions of each component.

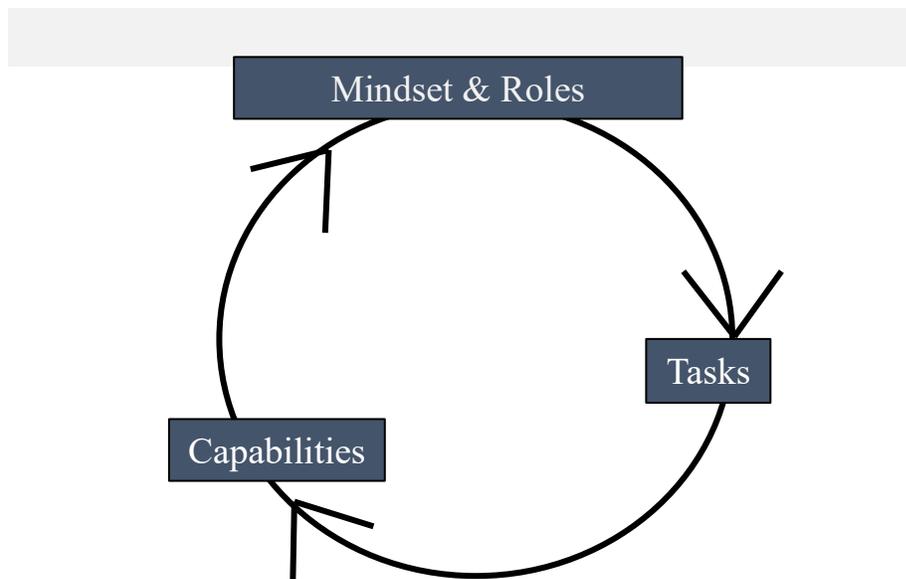


Figure 2.12. Managerial System

Mindsets and Roles

At the strategic level, managers in an "AI-powered operating model" assume the following roles and mindsets that are the prerequisite for operating effectively in this new environment (Iansiti & Lakhani 2019; Ready et al. 2020, De Cremer, 2020). These roles include the following:

- Managers are **designers**, shaping, improving, and (hopefully) controlling the digital systems that sense customer needs and respond by delivering value.
- Managers are **innovators** as they envision how these digital systems will need to evolve.
- Managers are **integrators and connectors**, as they work to connect disparate digital systems and identify new connections between the firm's operating model and the customers it serves. They also create trusted partnerships, develop networks, and create a sense of belonging.
- Managers are **guardians** as they work to preserve the quality, reliability, security, and responsibility of the digital systems they control.
- Managers are incurably curious **explorers**, seek broad input, and bring an attitude of test, try, learn, and repeat.
- Managers are **producers** who are obsessed with customers, are digitally savvy, and excel at executing.
- Managers act as orchestral **conductors** to have humans and algorithms work together in symphony.

Ready et al. (2020) argued that mindsets are the 'mental operating systems' or unspoken assumptions that drive behavior. Leaders need to change attitudes and beliefs (their mindsets) about what leadership looks and feels like if they want to produce behavior change that lasts over time. Therefore, managerial behavior is a function of their mindsets.³⁵ In all likelihood, these mindsets and roles are aspirational for several reasons.

³⁵ Similar to Doug Ready's description of mindsets, two other researchers described them as "leaders' mental lenses that dictate what information they take in and use to make sense of and navigate the situations they encounter. Some types include—**Growth and Fixed Mindsets**: A growth mindset is a

First, the firms have just begun to implement AI or other emerging technologies on a large-scale effort. Second, organizations have not yet developed the organizational sophistication or maturity in building the necessary mindsets or roles. Third, managers have not been required to operate in this fashion or capacity yet.

Tasks, Responsibilities, and Duties

As a natural extension of the required mindsets and roles, the next building block articulates the required tasks, responsibilities, and managers' duties. Table 2.1 identifies those 'vital few'³⁶ day-to-day operational tasks, taken as a collective whole, increasing the probability of maximizing AI's potential and ensuring employee acceptance of AI. The six broad categories include:

1. *Performance and Process Management*: How managers evaluate performance and manage their critical business processes
2. *Change Leadership*: How managers have a game plan to manage the current to the future state.
3. *Capability Development*: How managers build the needed skills needed on their teams.

belief that people, including oneself, can change their talents, abilities, and intelligence. Conversely, those with a fixed mindset do not believe that people can change their talents abilities and intelligence. **Learning and Performance Mindsets**: A learning mindset involves being motivated toward increasing one's competence and mastering something new. A performance mindset involves being motivated toward gaining favorable judgements (or avoiding negative judgements) about one's competence. **Deliberative and Implemental Mindsets**: Leaders with a deliberative mindset have a heightened receptiveness to all kinds of information as a way to ensure that they think and act as optimally as possible. Leaders with an implemental mindset, as the name suggests, are more focused on implementing decisions, which closes them off to new and different ideas and information. **Promotion and Prevention Mindsets**: Leaders with a promotion mindset are focused on winning and gains. They identify a specific purpose, goal, or destination and prioritize making progress toward it. Leaders with a prevention mindset, however, are focused on avoiding losses and preventing problems at all costs" (Gottfredson and Reina (2020).

³⁶ Vital Few term comes from the Pareto Principle where 20% of the factors cause 80% of the outcome.

4. *Decision Making*: To what degree do they make effective decisions based on the data/prediction information that is provided to them.
5. *Personal Capacity Management*: How managers allocate and reinvest their time.
6. *Boundary Management*: How well do they work across their total ecosystem.

As stated above, additional categories underlie the manager's responsibilities, but these are the most critical for implementing AI. Table 2.1 provides an overview of the specific duties and accountabilities that comprise each of these areas.

Table 2.1.

Managerial Role Categories and Activities

Category	Activities
Performance & Process Management	<ul style="list-style-type: none"> • The efficacy of the AI system will depend on the human/machine interface and its complementarity (Daugherty) so, therefore, managers will need to be vigilant in evaluating the organization's cognitive systems and understand where "humans excel relative to machines" (Walsh 2019) performance as well as monitor AI decisions in order to recalibrate them against one's own experience, insight, and intuition (Tarafdar 2016). • Need to have clean data so managers need to play a vigilant role to ensure that the data under their control is robust (e.g., data availability, acquisition, labeling, and governance (Walsh 2019) as well as democratize the data enabling a wider range of employees to access the data where and when needed (Zeng 2018). • Shape team structures by deciding which tasks are allocated to AI and which ones to human agents. (De Cremer 2019).
Change Leadership	<ul style="list-style-type: none"> • Depending on the roles and processes, AI will displace roles/duties, managers will need to prepare for dealing with a high degree of anxiety especially during the earlier stages of AI implementation. Managers need to balance implementing change with organizational continuity (Huy 2002) while creating a climate of psychological safety. • Construct an overall change strategy so stakeholders understand how new technologies fit into the greater strategy of continuous improvement and organizational health. Provide a strategic context for the work which acts as a "North Star" and ensures an understanding of the 'why' behind organizational decisions. (Morieux 2018). • Able to tell a persuasive fact-based story on the business case, merits and logic of utilizing AI tools and techniques. • Manage employees' emotions in their interaction with algorithms to ensure optimal performance (De Cremer 2019).
Capability Development	<ul style="list-style-type: none"> • AI will require a reskilling of employees therefore managers will need to be on point to ensure skill building and developing a comprehensive learning system is implemented. • A critical element in implementing AI straight through processing. Managers will need to ensure that they demonstrate a process mindset & activities including rigorous discipline in optimizing, monitoring & creating new processes rather than automating non-value-added activities Daugherty & Wilson, et al 2018). • Even though manager's will need to have a threshold set of technical/functional skills, their emotional intelligence capabilities (e.g., empathetic, communication, humility) will be essential.
Decision Making	<ul style="list-style-type: none"> • The power of AI is its ability to provide more information/insight/predictions as input for decision making so managers will need to exercise prudent & ethical judgment to maximize AI's potentiality.
Personal Capacity Management	<ul style="list-style-type: none"> • Once AI is implemented, managers will theoretically have more time, potentially freeing up their capacity (e.g., reevaluating their product or service offering; sensing the external environment; etc.) for higher order value added activities to best support the organization's objectives, activities (Weick, et al 2005).
Boundary Management	<ul style="list-style-type: none"> • AI demands a more connected organization therefore managers will need to collaborate between and among functions to include software developers, IT architects, external solution providers, finance professionals who will be responsible for the development, implementation or evaluation of the AI tools (MIT SMR Report 2020).

For example, under the Performance and Process Management category, one of the critical success factors is the ability for individuals to work in unison with AI, which has been labeled as the "Human + Machine" interface or another term called 'cyber-human systems'³⁷. An example drawn from the chess world that exemplifies the benefits of humans and computers comes from Garry Kasparov, who states, "When playing with the assistance of computers, we could concentrate on strategic planning instead of spending so much time on calculations. Human creativity was even more paramount under these conditions. The result is chess is played at a higher level than has ever been seen before. Perfect tactical play and beautiful, meaningful strategies" (Fry, 2019).

Managers will need to monitor both the machine's effectiveness and the employee's interactions with the technology. AI will dramatically impact individuals' jobs, and there is potential anxiety of job loss or diminution. Therefore, managers need to ensure that they need to display effective change leadership behaviors and build the necessary capabilities for their employees.

As seen in this section, some aspects of the manager's role are still relevant to people management and creating an empowered environment. In particular, AI will turbocharge other factors related to data management, managing cross boundaries, change leadership, and process management. Also, managers will need a multi-dimensional mindset than what might have been expected in past technological eras.³⁸

³⁷ MIT's Tom Malone named this term which takes advantage of the strengths of people and computers. Malone has identified four distinct roles that computers can play to make what he calls a supermind smarter as a tool, as an assistant, as peers and as managers. (Adler, 2020)

³⁸See page 53-55 in the section titled "Summary: Managing in the AI Environment Versus Other Technological Eras" which describes how leadership requirements are similar and different across technological eras.

The literature review supports and gives credence to one of the research focus areas: “There will be a moderate to a significant change to the manager’s role (e.g., their tasks, how they allocate their time, and focus) due to the utilization and power of AI” (Focus Area 1).

Capabilities

The other half of the coin is the capabilities needed to succeed in this next era of automation. MIT Sloan Management Review, along with Cognizant, conducted a global executive survey of 4000 leaders about 'preparedness to lead in the digital economy,' highlighting the below findings (Ready, 2019) in Figure 2.13.



Figure 2.13. Preparedness to Lead in the Digital Age

This data illustrates a gap in skill development and the organization's readiness to compete effectively in the digital (AI) economy. Figure 2.14 illustrates how leaders are needed at every stage of an organization’s digital maturity levels (MIT SMR/Deloitte Report on Digital Business, June 2018).



Figure 2.14. AI Leadership Gap

As a follow-up to their initial report, MIT Sloan Management Review published a study titled “The New Leadership Playbook for the Digital Age” (Ready et al., 2020). This report identified the "eroding, enduring, and emerging leadership behaviors" that will be required to succeed in the "digital age.

Second, Giraud et al. (2019) worked with a practitioner from to study how the rise of AI in organizations affects managerial skills. They came up with a construct that was similar to Doug Ready’s regarding how AI will impact managerial skills, grouped into five broad categories: 1) Managerial skills likely to be replaced by AI; 2) Managerial skills likely to be augmented by AI; 3) Managerial skills unlikely replaced by AI; 4)

Technical, managerial skills to optimize the use of AI; and 5) Non-technical managerial skills to maximize the use of AI.³⁹

Third, a book published in March 2020 by David De Cremer (Professor at National University of Singapore) titled *Leadership by Algorithm: Who Leads and Who Follows in the AI Era?* De Cremer (2020) did not cite any academic research about AI related to the manager's role per se. However, he did construct a leadership model that is focused on similar capabilities to the above two references, primarily focused on the "human-centered" aspect of leading. His main argument is that algorithms concentrate mainly on the management domain because of their ability to process large amounts of data, be objective, and continuously learn from the data. Algorithms cannot lead because they do not understand the context, are devoid of purpose and are not human. He makes the case that humans and machines must be considered colleagues. He cited many academic articles that deal with AI (e.g., bias, explainability, decision making) and various leadership components. He identified eight critical skills: critical thinking, curiosity, agility, imagination, creativity, emotional intelligence, empathy, and ethical judgment.

Because AI is a subset of the broader digitization that has occurred over a more extended period, researchers have studied the leadership skills to operate in a “digitized world.” A meta-analysis of 54 articles (Corellazzo et al., 2019) identified the skills that e-leaders lead included the following skills and behaviors: creating a high involvement

³⁹ The sub-categories include the following: managerial skills likely to be replaced by AI (simple decision/action-making, administrative ability, information searching & gathering); Managerial skills likely to be augmented by AI (complex decision/action-taking, innovation, knowledge of job/business, communication); managerial skills unlikely replaced by AI (critical decision-making, imagination); technical managerial skills to optimize the use of AI (basic AI knowledge, define needs and business case, judgement & ethics); non-technical managerial skills to optimize the use of AI (risk-taking, openness-mindedness, organizational change management, communication & collaboration skills).

organization or empowerment, inspiring & motivating employees, collaborative, decisiveness, tolerate ambiguity, processing and analyzing high amounts of data for decision-making, and managing change and connectivity (Cortellazzo et al., 2019). As a way to synthesize the academic research to date, Figure 2.15 places those behaviors and skills into three buckets.

Eroding/Less Important	Enduring	Emerging
<ul style="list-style-type: none"> • Asks for Permission • Has No-Exception Protocols • Reinforces Command and Control • Manages Top Down • Micromanages • Avoids Transparency • Takes A One Size Fits All Approach • Simple Action & Decision Making • Information Search & Gathering 	<ul style="list-style-type: none"> • Critical Decision Making • Imagination & Creativity • Creates a Clear Vision • Is Customer Centric • Leads by Example • Demonstrates Ethics & Integrity • Takes Responsible Risks • Leads Change • Defines Needs & Business Case • Is Results Oriented • Builds Relationships 	<ul style="list-style-type: none"> • Is Purpose Driven • Nurtures Passion • Makes Data-Driven Decisions • Exercises Judgment • Demonstrates Authenticity • Demonstrates Empathy & Humility • Employs A Diverse & Inclusive Approach • Show Humility • Works Across Boundaries • Has The Threshold Set of Technical Knowledge • Builds Bridges Between Technology Solutions & Business Requirements

Figure 2.15. AI Managerial Capabilities

The emerging skills or behaviors are the most critical for managers and their leaders to master for our purposes. A sequence of steps would include conducting a thorough assessment, developing an individual learning plan, and executing an implementation approach through on-the-job experiences, formal learning solutions, learning from one's peers/colleagues, and being coached by experts. Parenthetically, one can also argue that the above set of capabilities is also relevant for leading in an increasingly networked global economy managing Gen Z and Gen Y employees. This

employee population has grown up with the internet and has had greater exposure to algorithmic suggestions in their day-to-day lives.

Figure 2.15 is conceptually in the right direction. To carry out the managerial tasks, managers will need to understand the specific set of capabilities (e.g., knowledge, skills, personal traits, and attributes) that ultimately lead to significant performance as they implement and operationalize AI.⁴⁰ Below is a set of 13 capability areas grouped into three clusters. Table 2.2 Managerial Capabilities Description provides a detailed description of those capability areas.

- Knowledge (e.g., Computational, Algorithmic and Design Thinking, AI and Emerging Technologies, Data Management, and Analysis and Change Management⁴¹)
- Skills/Behaviors (e.g., Conceptual Skills, Judgment, Interpersonal Orientation and Relationship Building, and Social and Creative Intelligence)
- Attributes (e.g., Humility, Curiosity, Passion for Diversity, and Questioning)

⁴⁰ In building capability models, they are usually more effective when they are relevant to the specific role/job duties; aligned with and supports the strategic era of the firm (which in this case is the successful implementation of AI) and is congruent with the organization's culture.

⁴¹ Decided to categorize change management as a knowledge area vs. a skill/behavior because of the need for managers to understand the underpinning of technology and the key levers are for making change in organizations. At the same time, if managers are able to develop and master the other set of capabilities that are expressed in this model, they will be successful in managing the change that AI will usher into their respective teams.

Table 2.2.*Managerial Capabilities Description*

<u>Capability</u> <u>Area</u>	<u>Description</u>
<i>Computational, Algorithmic, and Design Thinking</i>	Breaks a problem down to its core elements; finds patterns or trends; is comfortable in iterative problem-solving; learns quickly from rapid prototypes. Generates principles, rules, and insights for use in routine and novel situations. (Wing 2008)
<i>Artificial Intelligence and Emerging Technologies</i>	Has a competent understanding of AI tools, concepts (e.g., machine learning, natural language processing, deep learning, artificial neural networks, intelligent robotic process automation, etc.) and its potential/possible applications. Also, individuals have a foundational knowledge of emerging technologies such as the IoT (internet of things), cloud computing, predictive analytics, and agile software development. (Reinhardt 2018)
<i>Data Management and Analysis</i>	Understands the full gamut and use of data—its availability, acquisition, labeling, and governance (Walsh 2019), including its analysis and interpretation. Transform data insights into action that lead to the identification of new opportunities and engage in data experimentation, and monitor changes. (Zeng and Glaister 2018)
<i>Conceptual Skills</i>	Is proficient with ideas. Displays analytical, systems, and logical thinking as well as deductive and inductive reasoning. It can mentally represent complex information and manipulate it to form integrative concepts (Kaiser 2011).
<i>Cognitive Complexity and Diagnostic Capability</i>	Ability to digest large amounts of information, process it quickly, ask the right questions, and get at the essence of the issue (Javidan 2013). Is aware of one's cognitive biases.
<i>Change Management</i>	Understand the various levers (e.g., communications, governance, project management, motivation, personal leadership, and influence, lead by example, informal networks, quick wins, etc.) and brings the right combinations to bear in the proper sequence to affect change. Can manage in a VUCA (volatile, uncertain, complex, and ambiguous) environment.

<i>Judgment</i>	The ability of individuals to apply human experience and expertise to critical business decisions and practices, especially when the information available is insufficient to suggest a successful course of action. Or if the information is not reliable enough to recommend an obvious best course of action and anticipate the consequences of alternative courses of action (Kolbjørnsrud et al. 2016). ⁴²
<i>Interpersonal Orientation and Relationship Building</i>	Competence with people as demonstrated in coaching, communication, forming and maintaining relationships, and showing concern for the feelings and desires of others (Kaiser 2011) as well as create an environment of teamwork across a range of contacts (direct reports, peers, colleagues, etc.)
<i>Social and Creative Intelligence</i>	Ability to listen to others in an open-minded manner while seeking to fashion bricolages of ideas and hypotheses from inside and outside of the enterprise to shape solutions to their most pressing business problems (Kolbjørnsrud et al. 2016).
<i>Passion for Diversity</i>	Has an intellectual curiosity to understand other cultures and geographies (Javidan 2013) and bring diverse points of view when making decisions or gathering input.
<i>Curiosity</i>	Is open-minded, intellectually curious, and learns quickly from one's mistakes, decisions, and actions; committed to solving difficult problems (Ancona & Gregersen,2017).
<i>Questioning</i>	Is open-minded, intellectually curious, and learns quickly from one's mistakes, decisions, and actions, and asks genuine, open-ended questions to elicit feedback, information, and potential approaches.
<i>Humility & Trustworthiness</i>	Practices "humble leadership" that creates a more personal, trusting, and open culture build on more personal intragroup and intergroup relationships (Schein & Schein, 2018) and being competent, having integrity, and displaying benevolence (De Cremer 2020).

⁴² Developing the judgement to use the outputs of the machine (or ignore them entirely) is critical to optimizing the use of AI solutions. “As users process those exceptions—accepting, rejecting, and altering the AI suggestions as appropriate—two other important things are happening. First, the human worker is learning to have confidence in the solution, noticing what it is right and with what confidence level. Second, the worker’s interventions constitute vital feedback” (Ransbotham et. al. 2019)

Figure 2.16 attempts to link the specific managerial tasks related to an AI environment and the required capabilities to perform the capabilities. As the chart shows, several skills are potentially needed at various degrees of depth to implement one or more managerial functions.

	Capabilities												
	Knowledge				Skills & Abilities					Personal Traits & Attributes			
	CA & DT	AI & ET	DM & A	C M	I & R	J B	CS	S & CI	CC & D C	P D	C	Q	H
Leadership Tasks Summary													
The efficacy of the AI system will depend on the <i>human/machine interface</i> and its complementarity (Daugherty, 2015) so, therefore, managers will need to be vigilant in evaluating the organization's cognitive systems. (Walsh 2019).	x	x	x		x	x	x	x	x		x		x
A critical element in implementing AI (as well as Robotic Process Automation) is the power of <i>straight through processing</i> . Managers will need to ensure that they demonstrate a process mindset & activities (Daugherty & Wilson, et al 2018).	x	x	x		x		x					x	
Depending on the roles and processes, AI will <i>displace</i> roles/duties, managers will need to prepare for dealing with a high degree of <i>anxiety</i> especially during the earlier stages of AI implementation.		x			x	x		x		x	x	x	x
The critical success factor of an effective AI implementation will be the need to have <i>clean data</i> (versus "garbage in and garbage out") so managers need to play a vigilant role to ensure that the data under their control is robust (Walsh 2019).	x	x	x				x		x		x	x	x
AI will require a <i>reskilling of employees</i> therefore managers will need to be on point to ensure skill building and developing a comprehensive learning system is implemented.	x	x		x	x			x	x		x	x	
Once AI is implemented, managers will theoretically have more time, potentially <i>freeing up their capacity</i> (e.g., reevaluating their product or service offering; sensing the external environment; focusing on increasing their skills, etc.) (Weick, et al 2005).	x	x	x						x		x	x	
Construct an overall <i>change strategy</i> to help all parties understand how new technologies fit into the greater strategy of continuous improvement and organizational health (Morieux 2018)		x		x			x	x	x	x	x	x	x
The power of AI is its ability to provide more information/insight/predictions as input for decision making so managers will need to exercise prudent & ethical <i>judgment</i> to maximize AI's potentiality.	x	x			x				x		x		
Because AI demands a <i>more connected organization</i> managers will need to collaborate between and among functions who will be responsible for the development, implementation or evaluation of the AI tools (MIT SMR Report 2020).		x	x			x					x	x	x
<i>Key: Computational, Algorithmic & Design Thinking, Artificial Intelligence & Emerging Technologies, Data Management & Analysis, Conceptual Skills, Cognitive Complexity & Diagnostic Capability, Change Management, Judgment, Interpersonal Orientation & Relationship Building, Social & Creative Intelligence, Passion for Diversity, Curiosity, Questioning, Humility.</i>													

Figure 2.16. Leadership Tasks & Capabilities

As elucidated by the academic research that is related to leading in AI environment (or even in the digital age), this leads credence to the research focus area: “Managers at all levels will need to enhance their technical, leadership, and interpersonal knowledge, skills, abilities, and personal attributes to thrive in the AI environment” (Focus Area 3).

Summary: Managing in the AI Environment versus Other Technological Eras

Managing and leading in an AI technological environment (and within the digital era) in the early part of the 21st century is a step order difference from other previous technology eras. In the 21st century, there has been a confluence of several technology innovations, such as the Cloud, Mobile, Big Data, Analytics, Visualization, Internet of Things (IoT), and Smart Machines (See Figure 2.1). In addition to the technologies above, exogenous contextual factors also contribute to leading in the 2020s:

First, institutional leaders, at all levels, have to function within a VUCA environment (Volatile, Uncertain, Complex, and Ambiguous) (Bennett, 2014).

Second, the speed of change, compounded by the current pandemic posture, has resulted in leaders feeling perpetually in a ‘time-based competition’ race (Stalk & Hout, 1990) and feel pressured to make decisions quickly.

Third, leaders have more data at their disposal⁴³, requiring leaders to enhance their sense-making ability (Ancona et al., 2020). Fourth, organizations have implemented *agile* methodologies, starting first in software development⁴⁴, quickly becoming a

⁴³ By end of 2020, 44 zettabytes will make up the entire universe and in the last two years, 90% of the world’s data has been created. (Source: <https://techjury.net/blog/how-much-data-is-created-every-day/#gref>)

⁴⁴ The ‘agile manifesto’ laid out the key agile principles for software development (Source: <https://agilemanifesto.org/>) which was a departure from the longer cycle time of ‘waterfall development’.

management philosophy--rapid prototype deployment and feedback; creating minimum viable products; engaging end-users or customers in the design (Rigby et al., 2016).

Fifth, there is a shift from profits as the primary reason corporations exist (as stated by Milton Friedman in 1970) to giving equal weight to all stakeholder requirements, as expressed in 2019 by the Business Roundtable CEOs in their “Statement on the Purpose of a Corporation.”⁴⁵

Sixth, given recent advances in neuroscience, we know more about the underlying mental processes that cause individuals to feel threatened or rewarded due to social needs not being met (e.g., status, autonomy, certainty, relationships, or fairness) (Rock, 2009).

Considering these exogenous factors, along with the emergence of AI (along with the confluence of adjacent/complementary technologies such as Cloud, Mobile, Big Data, Analytics, Visualization, IoT, and Smart Machines), managing and leading are different in this era compared to other technology periods. One way of characterizing the stages of technology eras or innovations is noted in Figure 2.17 (Cascio & Montealgre, 2016) corresponding to the dimension of societal impact or business impact (Swanson, 1994) along a certain time continuum.

⁴⁵ Source: <https://www.businessroundtable.org/business-roundtable-redefines-the-purpose-of-a-corporation-to-promote-an-economy-that-serves-all-americans>

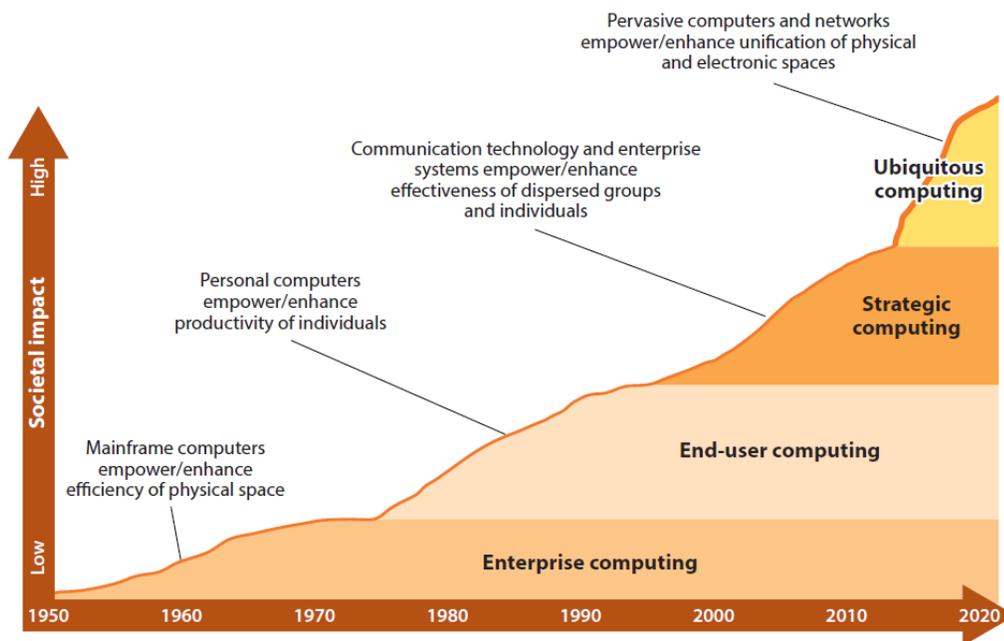


Figure 2.17. Technology Eras

The first stage, enterprise computing, was based on mainframe computing that runs enterprise planning systems such as MRP or CRM.⁴⁶ The second stage, end-user computing, was based on personal computers. The third stage, strategic computing, was based on communications technology with the internet as the critical connector with enterprise application systems. The fourth stage, ubiquitous computing, refers to how computing technology permeates almost everything that allows a level of complexity, speed, and quality not possible before (Cascio & Montealgre, 2016). Ubiquitous

⁴⁶ One research (Swanson, 1994) created a typology of IS innovations: Type I innovations confined to the IS task. Type II innovations supporting the administration of the business and Type II innovation is integrated into core business processes or impact strategies that can directly impact the firm's performance (Ke & Wei, 2008).

computing infrastructure provides for the collection of structured and unstructured data (Cascio & Montealgre, 2016), which is the current state of technology in the 2020s

Along this period, as noted in Figure 2.17, leadership and technology interact with each other and enjoy a recursive relationship, each affected by the other; each is transforming and being transformed by the other (Avolio et al., 2014). Each period emphasizes and requires a set of leadership traits (e.g., who one is), behaviors (e.g., what one does), cognitions (i.e., what, and how one thinks), and affect (e.g., what one feels) (Avolio, et al., 2014) with a certain degree of consistency across the technology eras. They compared ‘traditional leaders’ and ‘e-world leaders.’ The traits of decisiveness, inspiration, adaptability, and intelligence were seen as universally necessary (Horner-Long & Schoenberg, 2002). All these qualities are essential in an AI environment. Looking at ERP specifically, successful installations need innovation and organizational culture of learning (Ke & Wei, 2008) required in an AI environment. Senior leaders who display a transformational leadership style positively influence a learning culture by creating a psychologically safe environment, ensuring employees participate in decision-making, and being open to others' opinions (Shao et al., 2017).

Three areas present a fundamentally different set of requirements for leading in the AI environment. First, there is a greater need to apply probabilistic or statistical thinking to the outputs generated and exercise judgment to understand whether these outputs are false positive or false negative. Compared to other technology eras, the outcomes of ERP or PCs did not require this skill to the degree that is currently needed. Second, the integration of human and machine technologies is more pronounced in AI than in other technology eras. The PC or ERP is used as a tool for productivity or

ensuring standard processes. In an AI environment, managers need to ensure that they are continually evaluating the outputs and training the models to meet the business problem better. Third, the explosion of data that is being created necessitates leaders deciphering the “signal from the noise” (Silver, 2012), which was not as required in other periods.

CHAPTER 3

STUDY ONE

Conceptual Model and Focus Areas

As stated earlier, the overall core research question is: How does the manager's role change due to the implementation of Artificial Intelligence?⁴⁷ The manager's role is expected to change, shift, or evolve along several dimensions: including the capabilities they require to manage in this new era; how their mindset will need to change so they can operate more effectively, including how managers champion this technology; how managers will coach their teams to higher performance; how managers oversee their workflows (e.g., processes, data, activities); how one manages relationships with internal and external customers; how managers make decisions, solve problems and exercise judgment; how managers measure the outputs of their AI tools; and ultimately how they allocate their time.

This question assumes that managers will continue to be a focal point in maximizing the potential of AI's power because of the critical role in shepherding the implementation and its utilization within their respective organizations. Based on the literature review and speaking with technology executives, line of business leaders, and external thought leaders, three overarching focus areas were developed to test in the research study. Focus area 1 focused on the potential evolution of the manager's role, including their responsibilities, activities, or time; focus area two focused on employee

⁴⁷ Research sites for this study would be drawn from knowledge intensive industries such as financial services, health care or pharmaceuticals where their major product or service is information based vs. a product that is a result of a manufacturing production process.

development, engagement, and inspiration/motivation. And focus area three deals primarily on identifying capabilities needed by managers to thrive in this new environment. The below chart Figure 3.1: Research Focus Areas lists those focus areas on the left-hand side, and the right-hand side chart is a subset of core managerial responsibilities (as noted on page 54).

Besides each task (at the bottom), I attempted to identify how each of the three focus areas ties to the managerial task to show the association between them. Also, I noted the academic research supporting the association.

Expectations of the Research Approach and Contributions

The first dimension reflects the lack of focused research or case studies on AI implementation and its impact on the manager's role. There have been various consultants' reports and musings on the subject, but detailed research has not been conducted on a micro-level. For example, it is unclear whether technical skills are the superordinate capability that managers need to develop or whether technical, leadership, and interpersonal skills align. Also, I expect to uncover some practical approaches or lessons learned that could be applied to organizations at a different stage in their maturity. If this occurs, it will increase the speed of adoption and minimize or avoid potential problems.

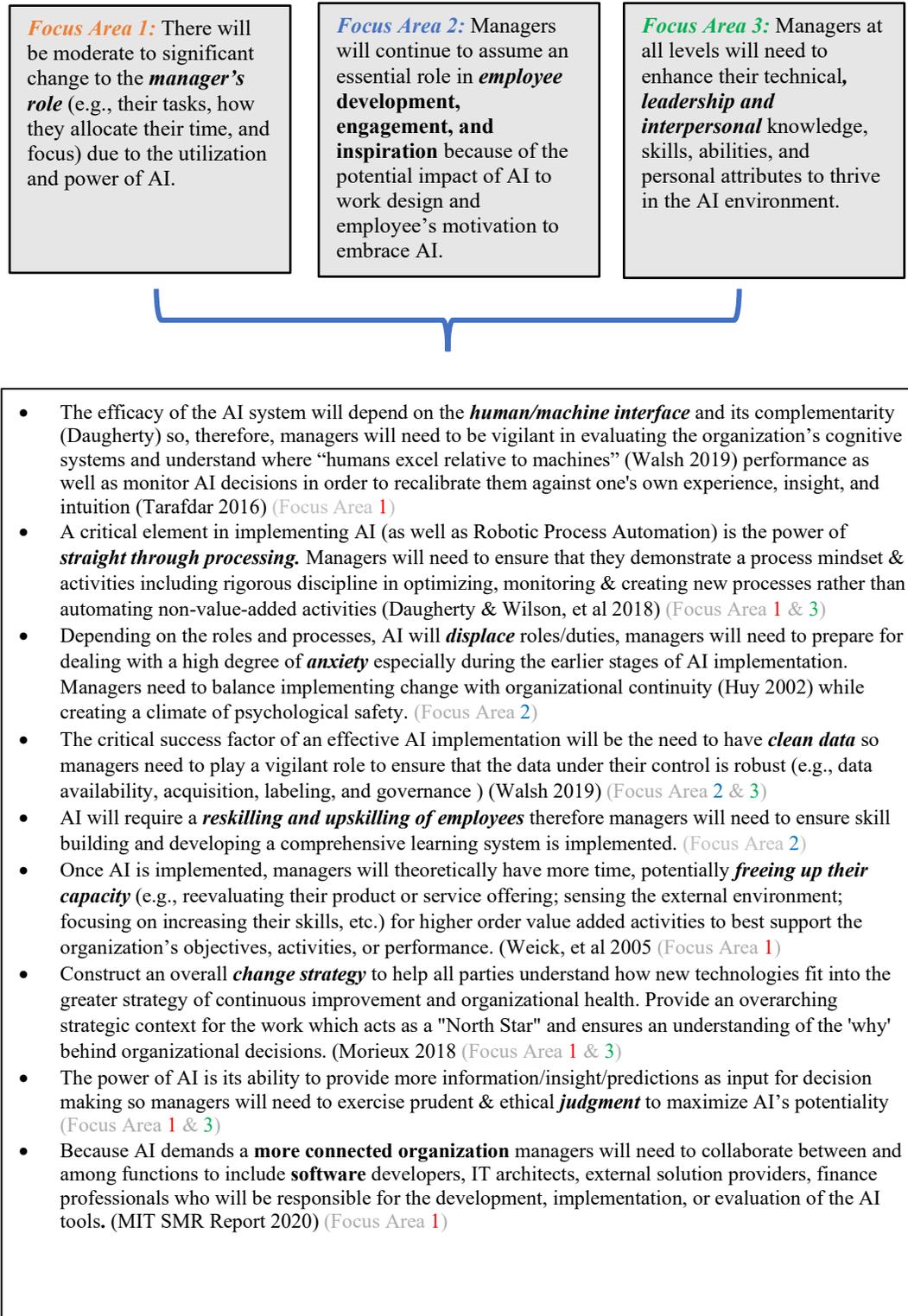


Figure 3.1. Research Focus Areas

The second dimension has to do with the audience interested in and consumers of the research. Some of these individuals include the senior line of business or functional executives (e.g., Chief HR Officers, Chief Transformation Officers, Chief Information officers, etc.), academicians (e.g., researchers or academic centers such as MIT's Media Lab), organizational consultants, and most importantly managers. They particularly need to manage through these changing times.

For each specific audience segment who would benefit from this research as potential consumers, Table 3.1 lists possible characteristics that they would find appealing. The main targets for the research are C-suite executives who are usually the change architects and are accountable for ensuring that the right operating model is in place to guide the change and achieve their business objectives. This research would also help them solve a contemporary issue of implementing AI in their respective organizations. Equally important, this research would benefit managers (who are either leading the change or the recipients of the difference depending on their level) to provide them with direction, tools, insights, and approaches. This research appeals to a cross-section of audiences because it is timely; addresses a pervasive need because all types of organizations will eventually face the issue of implementing AI/emerging technologies and would have interest across a variety of academic disciplines.

Table 3.1.*Audience Impact*

Audiences	Degree of Interest	What Would Be the Appeal of This Research
CIOs/Chief Transformation Officers (Target)	Hi	<ul style="list-style-type: none"> • Mitigate the Impact of a Future Trend • Would Have a Solution to A Vexing Problem • Provide the Potential Competitive Advantage
CHROs (Target)	Hi	Same as Above + <ul style="list-style-type: none"> • Can Be an Essential Component of Their Workforce Strategy • Raise the Firm's Profile as An Employer of Choice
Managers (Target)	Hi	<ul style="list-style-type: none"> • Practical Assistance to Improve Their Performance • Alleviate Stress as They Migrate to A New Way of Managing
Organizational Consultants	Hi/Med	<ul style="list-style-type: none"> • Provide Insight and Potential Solution Being Faced by Clients • Would Offer Some Research in An Emerging Trend Being Faced by Many Organizations
Academicians (e.g., MIT Center for Digital Innovation; organizational theorists)	Hi/Med	<ul style="list-style-type: none"> • Provide Insight and Potential Frameworks That They Can Further Test Out • Would Offer Some Research to Build Upon and Test with Their Sponsors and/or In Their Respective Disciplines • Would Have Potential Appeal to a Variety of Academic Disciplines (e.g., Information Technology, Organizational Change, Strategy and Behavioral Sciences) and Could Bring Them Together in a Multi-Disciplinary Approach

Description of Necessary Data and Methodology

Mixed-method research is being planned to answer the research question and shed light on the above-mentioned focus areas. I start with qualitative interviews--an “interpretivist case study qualitative research” (Venkatesh et al. 2013), followed by a potential quantitative survey to deepen the understandings and collect data across a larger sample of individuals. In all likelihood, the survey will be an element of the second research study. Myers defined "case study research in business uses empirical evidence from one or more organizations where an attempt is made to study the subject matter in context. Multiple sources of evidence are used, although most of the evidence comes from interviews and documents. Positivist case study research attempts to meet the requirements of positivist social science—case study research is seen as a method for testing and refining hypothesis or focus areas on the real world" (Myers, 2013). My usage of the term case study refers to the understanding of how AI is being implemented in several organizations. The mixed-method design will be exploratory to "collect quantitative data to test and explain a relationship found in qualitative design" (Venkatesh et al. 2013). Utilizing a mixed-methods approach "will help to make better and more accurate inferences—that is meta-inferences which is an "integrative view of findings from qualitative and quantitative strands" (Venkatesh et al. 2013)

Figure 3.2 is a summary flow chart of the specific steps undertaken, which I will elaborate upon in the following pages.



Figure 3.2. Research Process Steps Overview

Met with External Thought Leaders and Corporate Business & Technology Managers

As a first step in the research process, I conducted several conversations with external thought leaders from organizations such as BCG, Oliver Wyman, Deloitte, PWC, ICEDR/MIT, Microsoft, and business and technology managers. Through these discussions, I tested the research question that I was proposing to get their reaction and input on my topic. Every person, bar none, reinforced that my research topic has merit in the marketplace and provides insight on AI, digitization, and other emerging technologies. For example, I had an assumption that the first step in AI implementations

started with Robotic Process Automation and then proceeded to machine learning; however, a senior technologist disagreed and said that there are many instances of AI implementations that do not begin with an RPA installation. In addition, other experts said that AI would result in a flatter organization and that the ROI for automation would depend strongly on labor savings. If the breakeven point (usually labor costs is the primary driver) is too high, then automation would not be invested in that particular application. These conversations were also a way to beta test the approach before embarking on the official research process, which helped to sharpen the potential data/interview questions.

Identified and Refined Qualitative Data to Be Collected

As input to developing interview protocol, identified a set of potential salient data elements to collect and eventually analyze, including the following items:

- *The specific AI application that is being employed by this team, function, or unit:* This item would help to understand which business process or issue faced by the organization
- *The business case that influenced senior executives to fund this AI project/initiative:* This would help understand the original logic that greenlit the project.
- *Description of the expected outcomes for the AI installations:* This would help understand the magnitude of the effort and delineate whether it was a pilot project or part of a larger-scale implementation.
- *What is the stage of implementation to date?*

- *The impact on the role of the manager in implementing and operationalizing the technology:* This would help in understanding the various dimensions of the managers' position such as how they allocate their time, their interactions with their team; new or existing capabilities that they need to develop; future role expectations, etc.).
- *'Demographic' information on the use case examples and interviewers:* If possible, inquire about the following data elements: # of employees involved in the AI, skill capabilities, employee background, career experience, seniority, etc.

Developed Qualitative Interview Protocol

Based on the literature search, conversations with external thought leaders constructed a semi-structured interview protocol to collect qualitative data. The interviews will focus on five areas starting with discussing the business case and the problem (or opportunity) that AI would solve, then delving into the impact on managers, impact on employees, then closed by focusing on the implementation process and any outcomes. (See Appendix A for the initial set of questions).

Identified Potential Organizations and Interviewees

The sources for the potential research organizations and individuals were drawn from my current employer, former colleagues, extended network, and referrals. Forty organizations were contacted, with a significant majority from the life sciences or financial services organizations. See below for a bar chart (Figure 3.3: Research One Study Population Overview) that shows the results of this effort.

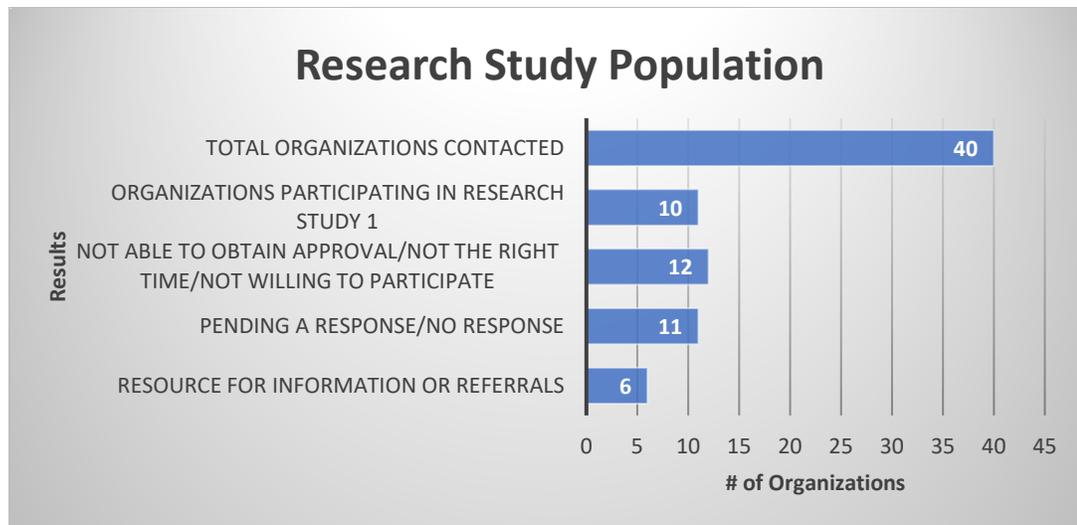


Figure 3.3. Research Study Population Overview

Out of the 40 organizations contacted, 12 individuals participated from 10 organizations. One significant lesson learned from this study was the degree of effort and difficulty in identifying interviewees, especially the length of time from initial contact to final disposition. Based on this experience, a key consideration for utilizing a survey in the second study is to mitigate the length of elapsed time in collecting data.

Interviewed Participants and Collected Data

Interviews were conducted online either through a Zoom platform or over the telephone. A semi-structured interview process was employed to provide additional context and depth and offer personal experiences and observations. The semi-structured interview format was optimal to allow the interviewee to expand on a particular topic for the interviewer to go more in-depth on a specific topic where the interviewer has a lot of energy, interest, or information. (See Appendix A for interview questions and Appendix B for the initial draft of an email invitation to potential participants.) The main advantage of face-to-face semi-structured interviews is the

opportunity to adapt the questions as necessary and ensure that the responses are appropriately understood by repeating or rephrasing the items and picking up on nonverbal cues from the interviewee (Sekaran & Bougie 2016).

At this stage in the process, interviews were selected and preferred because they provided an opportunity to understand more salient variables and probe to test some initial thoughts, focus areas, or working assumptions. For example, one of my inclinations is that managers would need to have a working knowledge of Artificial Intelligence to lead the implementation and usage of their teams' technology. This was true to a certain extent, but what I uncovered was the importance of the working relationship with technologists who, by collaborating with the managers, increased the 'collective intelligence,' which is more important than the individual's intelligence manager. Once I uncovered this information early in my interviews, I built this finding into my interview protocol and probed it explicitly in this area. Also, there was a need to be conscious of one's biases. One bias from the interviewer's perspective is to be aware of preconceived notions about the managerial tasks and capabilities impacted by AI identified in the previous section. Therefore, there was a need to keep an open mind instead of listening for information that confirms one's preconceived notions.

For this research, 12 'elite' (Harvey, 2011) individuals were interviewed and came from several industries or consulting firms. Twelve interviews were in the range of sufficiency because "16 or fewer interviews is enough for studies with relatively homogeneous groups" (Hagaman & Wutich, 2017). In terms of homogeneity, interviewees currently hold or have held senior technology, consultant, or business roles. Table 3.2 includes brief biographical information about each interviewee.

All of the interviewees had a broad technology and business background. They were well versed in all forms of emerging technologies, especially artificial intelligence, and data management. They all had insightful comments about technology's strategic and tactical implications on employees, managers, and the need for a comprehensive change management approach in implementing new technology. The interviewee took handwritten notes or typed the interviewees' comments directly into the computer in terms of data collection. There is no identifying information on the specific interview write-ups that can be traced back to the interview names.

Analyzed the Data

The data were coded and analyzed using the NVivo software package (QSR, 1999). In particular, by using NVivo, the intent was to ensure that the coding scheme was both "objective" (e.g., the codes and the categories require little inference or interpretation from the researcher) as well as "mutually exclusive and collectively exhaustive" (e.g., categories are mutually exclusive if none of the categories overlap one another and it is collectively exhaustive if it covers all possibilities (e.g., events, actions, and behavior) (Sekaran & Bougie, 2016). In the analysis of the collected data, a series of questions helped interpret the information: Are there differences in the manager's role based on the type of AI application being implemented? Is there a learning curve from the initial AI implementations to succeeding rounds of implementation? What was the extent of a change strategy on the implementation? Did the technical know-how of various individuals in the ecosystem (e.g., managers, employees, technologists) impact the application rate?

Table 3.2.*Research Organizations and Roles*

	<i>Industry/Organization</i>	<i>Role/Biographical Information</i>
1.	Pharmaceuticals	Chief Data Officer for Data Analytics and AI, Strategy and Operations for a Line of Business Unit
2.	Health Care	Technology Director Who Directly Implements Automation Efforts
3.	Pharmaceuticals (same organization as #1 interviewee)	Transformational Technology Leader Within the Company's Line of Business Operational Groups
4	Financial Services	Senior Technology/Data Management Leader Who Started up The Firm's AI Strategy
5.	Financial Services	Started the Firm's AI Program and Currently Leads Their Emerging Technology/Applied Research Development Group
6.	Consulting/Industrial	Leads the Firms Transformation Efforts and Is a Former Senior Technology Leader at A Global Industrial Firm. Also Started an AI Not for Profit.
7.	Private Equity/Industrial	Senior IT Operating Partner Who Works with Each of the Private Equity Firm's Companies on Technology Issues.
8.	Telecommunications	Line Leader That Implements Customer Quality Improvement Initiatives
9.	Financial Services	Executive VP Who Leads Data Science and AI Efforts for the Company
10.	Consulting	Chief Technology and Innovation Officer. Leads the Firms AI Initiatives for The Firm.
11	Financial Data Services	Line of Business CIO for The Major Business Unit
12	Financial Data Services (same organization as #11 interviewee)	Line of Business Customer Service Senior Leader

Construct A Proposed Theory

Based on the interviews, develop a proposed "theoretical perspective composed of constructs and relationships" (Venkatesh, et al., 2013) on how the manager's role will change due to AI's implementation. This construct will be informed by the literature review and the initial set of qualitative interviews. In the last section of this paper, there is the initial draft of a conceptual framework.

Determine Next Steps

After the analysis, there were several possible next steps, such as updating the literature review focusing on other potential topics. For example, are there specific change management techniques more successful in AI implementation than different technology innovation types? Another next step is to determine if there is a need to develop and execute a quantitative survey as part of a second research study. One goal will be to sample a larger population to validate the construct and draw some analysis that is generalizable to a larger population. The updated literature review will ensure that the survey construct's items are grounded in academic literature.

Analysis and Results

This section will provide an analysis of the qualitative interviews that were undertaken over two months. As mentioned earlier, each interviewer held senior-level technology, leadership, or consulting roles within each of their firms. Individuals who were in a consulting capacity, either at a global professional services firm or in a private equity organization, led AI or major technology implementations in their previous roles while in the industry. For the most part, the interviewers were well versed in the strategic

application of technology and knowledgeable and experienced in the challenges of implementing AI both at the micro and macro levels.

The interview data analysis fell into four major categories, as noted in Figure 3.4, and will describe the findings in each of these areas in the following sections.



Figure 3.4. Research Data Analysis Categories

Business Applications

Interviewers described in detail how AI was impacting their respective businesses or previous roles that they held. They could use case examples, business results, and several mentioned specific AI tools and techniques. One leader could articulate what he has learned and placed AI in the broader context of other business improvement tools. He stated,

We are on this AI journey; it is really exciting, and it is really challenging. This assignment is making me learn things, and it is a master cultural shift” It is making me learn that there are two kinds of schools of thought on who should use AI or who will be using AI. One school of thought is that there will be experts who are the only ones who know AI and then help the organization. The 2nd school is that everyone will do AI. Implementing AI is similar to when spreadsheets came in 8 years ago. Now, we look back, and spreadsheets are second nature in business. It is a productivity tool, and everyone is familiar with them. AI will be no different than EXCEL spreadsheets that we run in place today, and we need to harness the power of AI.

If AI becomes as ubiquitous and easy to use as Excel, then “AI is not going to replace humans, but those that know AI will replace those that don’t, and if you don’t adopt AI, the people who do will get the upper edge.” Another interviewer described how AI fits into the evolution of technology from a practical business perspective. He described a triangle composed of distinct elements—Transactional, Operational, and Analytical—located at each corner of the triangle noted below in Figure 3.5.

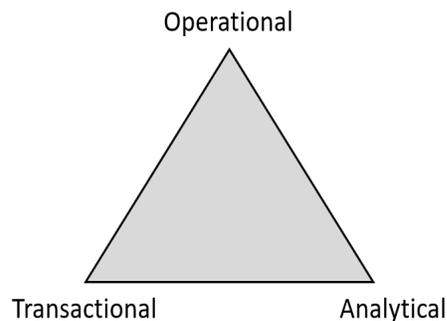


Figure 3.5. Technology Evolution

When technology was beginning to be implemented in organizations, these three components were managed separately across different technology systems. Over time, in operations-oriented environments, Enterprise Resource Planning Systems were

implemented, which helped in “understanding financial costs, the status of current orders, how materials flowed through the system,” which are activities that relate to the transactional and operational elements of the triangle. The ERP systems generated a lot of data without “making us better or smarter.” Next, the creation of data warehouses (the analytical bottom right part of the triangle) provided the ability of individuals to summarize data and provided information to create “pretty charts and tables.” With AI, “it gives us the computing power to connect all three of these elements.” Hence, organizations have the ability to better plan taking into potential constraints, and “intelligent automation can better understand what the underlying demand is.”

As mentioned earlier, each interviewee was able to identify various business problems or case examples drawn from their experiences. In particular, a senior financial services technology leader described a business application using AI in its customer-facing organization. He stated the following:

The main place that we are using AI is in the Call Center. AI has reduced the Call Center headcount as well as we can manage better client service. This is how it works. When the customer calls into the call center, the customer is first met with an IVR machine. This machine pulls up the information for the call center person on their respective screen. It routes the information to the right call center person based on the information that the customer expressed into the IVR. The machine picks up on the emotional intensity of the customer and routes the call to a supervisor. It is getting to the point where the computer can almost say, how can I help you. It has changed the game related to the expense side and customer side of our business.

Each interviewee was responsible for driving AI within their firms/divisions.

They were personally involved in implementing the specific cases through the use of AI tools (e.g., Intelligent Robotic Automation, ML for Optical Character Recognition (OCR), Image Classifiers, etc.) Based on the industries where the interviewers originated

from or experienced in, there was a variety of use case examples and business problems as noted in Table 3.3.

Table 3.3.	
<i>AI Use Case Examples</i>	
Industry	AI Use Case Example/Business Problem
Financial Services	<ul style="list-style-type: none"> • Anti-Money Laundering • Cybersecurity/Cyberfraud • Personalized Content for Customers • Transactional Information for Mobile Customers • Cash Flow Management • Customer On-Boarding Process • Call Center Operations
Industrial/Manufacturing	<ul style="list-style-type: none"> • Digital Twins for Aviation Maintenance • Health Care Equipment Servicing and Preventive Maintenance • Pricing Analytics Platform for European Customers • Vaccine Process Throughput Time and Yield Rates • Potential Leads for Sales Representatives
HR/Consulting	<ul style="list-style-type: none"> • Mining Employee Data to Identify Top Development Needs by Various Population Segments • Accountant Payable Outsourcing
Telecommunications	<ul style="list-style-type: none"> • Customer Call Routing • Predicting Customer Internet Outages

This particular set of interviewees was all bullish on AI's impact and could cite, quote, forecast, and be hopeful for intangible and tangible business results. Due to their position in the organizations, their technical and business background, and their track record, they were not surprised that they were cheerful and optimistic. On the intangible benefits side, AI is on the trajectory of “creating more capacity to do more value-added work,” as well as making more intelligent decisions with faster analytical engines. Also,

one interviewer talked in length about the power of AI to aid in speeding up potential operating decisions:

AI is shortening one's learning cycle dramatically and experiment with virtual versus physical products by creating digital twins. These digital twins can help in discerning patterns of behavior and can use the outcomes of various simulations to refine one's process and have operating models infused with intelligence. For example, one can virtually model certain parameters and have a determination on where you can put one's next warehouse basically overnight.

At the same time, individuals were able to identify tangible benefits, such as:

- Improved manufacturing yields in the 6-17% range (pharmaceutical industry)
- Increase of 12% of targeted customers for sales territories (pharmaceutical industry)
- Ability to predict which customers will have a 30% expected cashflow downturn (financial services)
- Reduced the customer on-boarding time from 36 hours to 24 minutes (financial services)
- Reduced each customer call by 25 seconds (financial services)
- Saved \$46 million due to not having to hire 2000 call center employees (financial services)

On the far end of the spectrum in terms of implementing AI was a senior leader who described the breadth and depth of their AI implementation when he stated the following:

We have over 100 use cases in flight or completed with 200 or more planned, ranging from HR to Technology to Finance to Compliance within every division is using AI. One example is HR, where we have development cards for each of my direct reports. We have 17000 development cards across the company, which are free-text documents. The CEO asked a question, "what are the five top development needs across the corporation." Who can really answer that question? Who can really distill all those development cards and answer that question in the US or other parts of the world? We wrote an NLP program, and we can tell it for the corporation at any level or any geography or any division, which would never be possible because no one has that much intellectual bandwidth.

Organizing for Success

In all the interviews, they described how their respective organizations implemented their various approaches to achieve the business results and implemented their AI installations. One leader described the marriage of the ‘socio-technical’⁴⁸ when he stated, “the building of the tool is technical, but the deployment is behavioral; they both need to come together.” The concern about integrating the human/behavioral with technical is a theme that underlies the various implementation approaches. Below are a list of common “best practices” highlighted in interviewee responses.

Senior Leader’s Role

Consistent with the success of other change efforts--senior leader involvement, how they frame the AI rollout, and their visible commitment—all set the tone and signal the AI effort's importance. In one organization, they held face-to-face company-wide meetings with the CEO present, where they described the AI journey that they are on and introduced their attempt to get individuals involved. They also stressed that this effort “was not an effort to replace people but to equip them.” Another senior leader framed their initiative as “Trustworthy AI,” described as a strategic initiative, so the organization “acts responsibly towards data usage, risk, checking for bias in the code.” This organization also assembled a council of senior executives where they articulated a set of “commitments to shareholders, employees and customers to be fair, accountable, transparent and trusted.” On a micro level, several interviewees described senior-level involvement. For example, the senior VP of the business unit had meetings with the AI

⁴⁸ The term socio-technical systems was originally coined by Emery and Trist (1960) to describe systems that involve a complex interaction between humans, machines and the environmental aspects of the work system—nowadays, this interaction is true of most enterprise systems (Baxter & Somerville, 2011)

implementation team, along with his direct reports, throughout the process, and this person had an “objective that AI would be implemented in his division.” Another senior leader invested an hour a week where the technology team “explained metrics, how the model works, and the correlations,” which has made this installation go much smoother.

Broad-Based Engagement

Several tactics were employed to enroll individuals “emotionally and actively” and to “spread the use of AI.” One of the tactics deployed was to run an organization-wide challenge (or contest), which resulted in over 1,000 individuals volunteering to work individually or on a team to submit proposals utilizing AI. All of the participants were at varying levels of programming skills. This organization created an internal web page with YouTube videos as a mechanism for individuals to easily access learning solutions to develop software programming capabilities. In this challenge, “the winning team employed Python code to predict with 100% accuracy if the new credit card logo meets corporate standards, as well as the AI tool was able to provide feedback to the local marketing teams on potential modifications vis-à-vis those standards.”

Change Management Process

Each of these organizations was tuned to ensure that there was a deployment of a purposeful change strategy and tactics that generated excitement about the AI tools' potential, increased employee capabilities, and attempted to minimize the concerns about job reductions or diminution of accountabilities. One leader described their effort as a “major cultural shift,” The degree of success is causally related to the individuals' willingness to support the effort. One change management tactic included an “agile or experimentation” mindset to “envision the art of the possible” by starting narrowly with

developing “minimum value products” via pilots or beta tests (vs. big bang solutions). While at the same time, the organization was operating the current process and eventually measuring the pilots' success against the everyday activities. Several interviewees cited this approach as a way to prove the benefit of AI tools in their organizations; to win over skeptical users, especially front-line operators who are not well versed in using technology (either in their personal or professional lives) as well as alleviating concerns that specific jobs would be eliminated. In one organization, they were deliberate in selecting automation pilots where the employees had a broader or deeper skillset to be redeployed if the AI pilots resulted in job displacement. However, on the other side of the equation, a financial services company had over “100 use cases in flight or completed with 200 more or so planned in HR, Technology, Finance, Compliance, and every division are using AI.”

Another change management technique was the involvement of those at the micro-level that would be impacted by the AI tools being implemented in their unit. As one interviewer said, “if you show them a cool thing, their eyes open up. You have to show them and need to expose them to a variety of possibilities”. Other ideas of generating enthusiasm included showing them prototypes of the reports that would be made based on the AI tools, getting their input as the algorithms are being built, and describing how AI will help them in their day-to-day accountabilities.

Another critical component of the change effort is the deployment of training to skill employees and a lever for broad-based communication. Several interviewees described a variety of tactics such: creating an internal web page with instructional videos; purchasing Coursera licenses that individuals can use “without adverse

consequences if they don't use the license within 60 days"; building-specific workstream content that they marketed "data smart" which helped to "demystify data" geared to fundamental or advanced levels (which was more mathematically oriented) with employees receiving a badge when they completed the curriculum; engaging their Chief Learning Officer and other third party suppliers to create content geared toward senior leaders and managers.

Lastly, a crucial element of the change management approach was the capabilities and active support of IT professionals who were able to: explain simply how the tools would be used; gain excitement about the potential AI applications; bridge the gap between the "technology and the business value" by "figuring out what are the top business problems and how these problems can be solved through AI" as well as possesses "business domain expertise (e.g., pharma, supply chain, commercial) along with technical expertise (e.g., Machine Learning) with a practical, delivery oriented approach due to working in a consulting firm or in a large company." One of the interviewees stated that there was a need for software engineers and data scientists who can "educate the team on how to use the data, how the machine works and can describe the black box" and be that expert who can explain concepts, outputs, and the technical process in simple terms. As an analogy, one interviewer compared this role to the Jonah Hill character (Peter Brand) from the 2011 movie Moneyball in which Hill is the sabermetric expert who provides counsel and advice to the Athletics baseball team general manager (Billy Beane).

Creating an Evangelist Role⁴⁹

Lastly, two of the organizations mentioned the importance of having an “evangelist” embedded in the specific unit where AI is being implemented who “can carry the torch.” In these two situations, they described the person as mid-level, trustworthy, and “the face of AI within the division.” This person has a unique set of capabilities to include knowledge of the technology (including AI tools) and specific domain business knowledge (e.g., finance, risk, compliance, operations, etc.). The person needs to be highly respected, well-liked, competent, believes in the AI solution, and has built up credibility. They play an important role, especially in convincing individuals who might be on the fence regarding the AI tools, and can meet with individuals, primarily when informal meetings occur after the formal sessions.

Role of the Manager

In one of my interviews with a senior technology leader, who is currently the IT Operating Partner for a private equity firm (in which he works with each of the firm’s operating companies), he framed the role of the manager as part of a broader “system” or “ecosystem.”⁵⁰ as graphically described in Figure 3.6 Managerial Ecosystem

⁴⁹ The role of an evangelist (and capabilities that is required) is similar to Jon Katzenbach’s notion of ‘authentic informal leaders’ as described in his book, *The Critical Few* (2018).

⁵⁰ System is usually composed of “set of interacting or interdependent component parts that form a complex, intricate whole” and an ecosystem is thought of as a “combined physical and biological components of an environment and their interdependencies”. In particular, “social ecosystems are generally an indivisible unit within a larger social, political, and economic environment in which those factors of society that affect interactions among people—including technology—function together as an indivisible system of exchange”. (Source: Pendleton-Jullian & Brown, 2018).

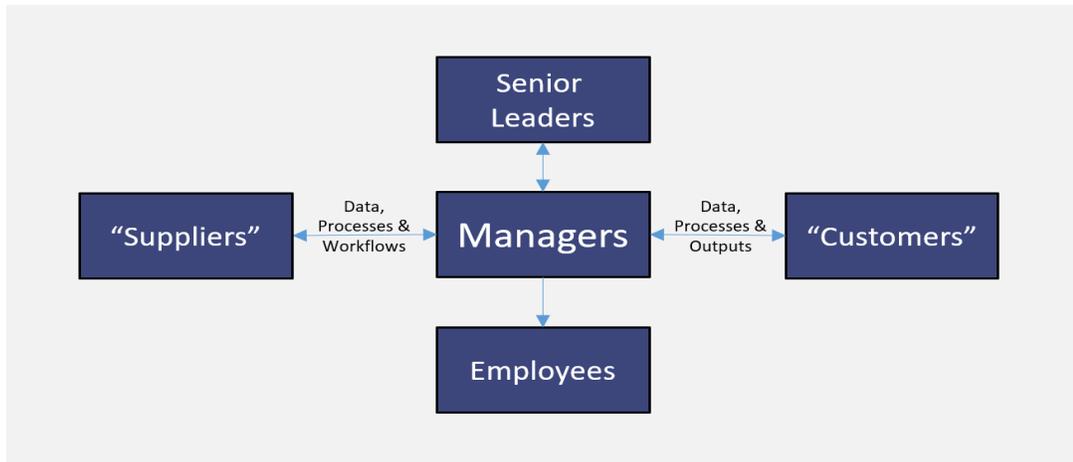


Figure 3.6. Managerial Ecosystem

His central argument is that the manager is the linchpin among the various key stakeholders surrounding their responsibility area. By the nature of where they are situated in the organization, they are managing the flow of information, processes, relationships, and data horizontally (with their suppliers and customers) and vertically (with senior leaders and employees). This construct is an apt description of the managers' role in an AI environment for several reasons.

First, a key element underlying a thriving AI environment is the flow and quality of data and information across boundaries, which flows horizontally and vertically. One of the interviewers described how there would be a need for all ecosystem partners, especially suppliers, to share information cross-boundary to build into the prediction models. Therefore, a principal managerial role activity is *process and data management*. The manager must create a feedback loop back into their organization from critical stakeholders to fine-tune the AI model or determine if one's decisions or actions were valid based on the AI tool. Another element of process management is using "intelligent business management" tools where the manager looks for opportunities to use data in

their decision-making or as input to other decision-makers in other parts of the workflow. Because managers are the crossroads of several data flows, they need to perceive themselves as ‘data stewards’ to ensure that they are collecting the correct data; providing that there is no “garbage in and garbage out” and they are thinking about “data from day 1” on the job. When managers are starting to use AI and Machine Learning, they need to understand that “everything is connected,” The data collected is feeding upstream processes and underlying AI algorithm models. For example, one of the interviewees described a scenario where the field services technician (in the telecommunications industry) manager needs to ensure that they are coding a “trouble call” the correct way because it feeds downstream data models. The manager plays a critical role in ensuring that their organizations ensure quality robustness under their watch.

Second, the manager has interdependencies with various stakeholders such as software developers or data scientists who supply the managers’ organization with AI tools for deployment. The manager needs to work with multiple technologists, such as data scientists and data architects, to ensure that the “chosen models have applied sensible techniques” relevant to managers' situations. Therefore, a second principal managerial role activity is *horizontal relationship management* or managing across boundaries characterized by a high degree of mutual trust. If managers develop this type of relationship, especially with suppliers and customers (be internal or external), the manager’s organization will receive informal or formal “preferential treatment.” A key ingredient in building a capability of “dynamic responsiveness” is getting timely service from one’s suppliers when there is a need to respond quickly to marketplace business opportunities or solutions. Another dimension of horizontal relationship management is

that managers, especially in external customer-facing environments, need to make strategic and tactical decisions on the level of service required for their customers. Due to AI's capability to analyze data and prediction modeling capability, managers will have better information in determining when and how much service to provide. One interviewee described scenarios (in the telecommunications industry) where customer service managers can predict specific customers' future internet outages. The senior line of business stated the following:

For a manager, there are some choices that one needs to make. For example, do you really want to reach out to the customer when there is a future potential problem because AI has alerted you to that fact? The manager needs to consider: what is the economics of the support model, need to prove out what is the impact to the business, especially what is the business case of chasing down internet interval issues; creating customer interactions that you would not normally do while potentially reducing some interactions that you might need to have. The manager has to decide at a high level what the thresholds are related to service, what we want to do, and what we are currently doing. The machine is still pulling together a recommendation, but the manager has to weigh those considerations based on the above examples.

In this case, the manager will need to consider the incremental cost vs. the return on investment of serving that customer, the timing of that service call, and the total return on investment. For example, if the customer is a financial services organization (which transacts online trades), an internet outage would cause a significant interruption to their business model. The manager will need to act because “an ounce of prediction is worth a pound of margin” in these types of situations. Lastly, managers need to ensure that they meet the needs of their internal and external customers because successful “execution equals credibility.” In the early phases of using AI, managers need to start with a “modest

win, build upon it and then expand to more aggressive opportunities in applying AI where there might be less transparency in terms of how the algorithm works.”

Third, labor economists, technology researchers, and external consultants are converging on the point of view that AI is having a direct impact on the workforce-- capabilities required, the design or roles, the nature of the work, the number of employees that will be deployed, and employees’ readiness to accept new technologies—which necessitate managers to display change leadership, enhance their communication approaches, and demonstrate effective management practices. Therefore, a third critical managerial role activity is *people, workforce, and AI tools management*. In terms of communication with employees, the manager plays a crucial role in summarizing the “various conversations they are having with the various stakeholders.” Managers need to create a motivating story to translate “what it means for employees such as what needs to change due to “the adjustments in the multi-generation plan to meet the outcomes” and help employees understand how AI impacts those multi-generation plans.” In deploying AI, one of their key roles is to architect how AI will be utilized in their units, mainly how employees will perform their day-to-day roles more effectively through AI. This activity is done in conjunction with software engineers, developers, and data scientists from a technical perspective.

From a motivational standpoint, employees need to be active participants. One of the interviewers cited an example of how in a call center (that provided outsourced services to their customers), they involved their “people in the automation” that resulted in successfully “automating 40% of the roles”. However, the manager’s role is to see the “art of the possibility” in utilizing AI technology. Managers need to understand that the

effective deployment of AI “increases the utility of lower-skilled workers to make important decisions” versus those “decisions flowing back to leaders.” Our interviewees cited two examples. First was the interaction between a customer and the airline ticket counter agent, where the AI tool is listening to the real-time dialogue. In this circumstance, the AI tool provides real-time help to the agent to augment the agent’s advice. The second was the “deployment of deep learning tools to identify false positives” in the loan approval process. Managers need to drive the use of these tools because “people have more work than they can do, and if they can do more work quicker and more accurately, this will increase employee morale.” However, managers need to equip their workforce because, over time, those “people who adopt AI will get the upper edge.” Lastly, managers need to understand that they now “managing people plus machines,” so the need to “measure the effectiveness of AI” as well as their employees.

In summary, this anecdote sums up the impact of the manager’s role:

AI is a new way for managers to look at their jobs. It is a creative way to use technology to solve customer problems. We use standard metrics for call centers to measure our success as calls dropped. Now, AI has up the game for managers. They do not just have to walk around, and some calls are routed to them automatically. Also, one thing they need to do is to think and determine what the software can handle in the future. Then need to have more of a technology understanding than they needed in the past.

Manager Capabilities

For this section's purposes, I define capabilities as knowledge, skills, personal traits, and attributes that lead to superior performance in support of the firm’s culture and strategy. Therefore, our emphasis will be on identifying those core capabilities aligned with the successful implementation of AI and possibly other emerging technologies. There is a sense of urgency to improve managers’ abilities, as one of the interviewers

expressed, who stated that “the good ones are getting better, and the gap is getting bigger.” The process of distilling the interviewees' capabilities was a combination of extracting those frequently mentioned directly or analyzing the use case examples.

Technology Knowledge: The most prevalent theme throughout the interviews was the need for managers to develop technologically oriented knowledge. Managers can characterize this knowledge as table-setting or foundational to lead in this environment. Areas mentioned included understanding software development lifecycle, blockchain, AI, basic statistical algorithms such as regression, data management fundamentals, design thinking, and experimentation. Without this foundation, managers will not be able “to be competent about the possible” uses of the technology, what the “AI tools have to offer,” or be able “to make suggestions to technologists on their business needs.” Also, one of the interviewees expressed the importance of managers being able to probe data scientists on the tools they are using. They can explain how they utilized the specific AI tools stakeholders to arrive at the recommendations or outputs.

Communication and Influence Skills: The second most predominant theme was the manager’s ability to communicate with and influence stakeholders' entire range. For example, managers have to explain and “help people understand how AI got to prediction” or similarly “take the talking points from data scientists to explain the AI inputs and outputs to explain how the algorithm works.” Also, they need to tell a closed-loop story starting from the “problem statement to how AI will be part of the solution and then to the outcome,” demonstrating credibility for the manager and their organizations. AI already has a reputation for being a “black box” model. Suppose managers can offer viable explanations on how AI works. In that case, this will go a long way in increasing

managers' chances of future AI installations because it will dissipate potential concerns and uncertainty by users.

Judgment: The third most predominant theme was the manager's ability to exercise judgment, which plays out in various ways. One dimension is how managers display "diagnostic capability" to ask the right set of questions to ascertain if AI tools are optimal for this specific business problem. As one senior line of the business leader said,

I think that judgment will be a critical skill. Judgment plays itself out in a variety of examples such as when is a model able to be operationalized; how do you validate the output of that model; how do you assess what to do with that output, what is the right use cases; how to make sure that you are targeting the right opportunities with the model and what is the so what?

One concrete business example cited is the use of digital twins in airplane maintenance logs. The interviewee stated:

Reimagine what if I can get real-time information while the airplane is operating and correlate that information to weather patterns by using a real-time digital twin at the same time. For example, managers can ask what the impact on revenue is if I postpone maintenance. Use the technology to reimagine the process. Need to understand the technology.

In this example, getting real-time information on the airplane's operations and doing correlation analysis (with other data such as weather patterns) helps managers have data to exercise fact-based judgment versus relying on their intuition.

Coaching Skills: Another capability was the manager's ability to coach, provide feedback on improvement, and digging for what can be doing differently. One concrete example was managers giving feedback and coaching on the importance of ensuring correct data is collected, and the information is appropriately labeled, especially on the initial point of contact with the data element.

Change Management: When interviewees were asked about managerial skills that managers need, none of the interviewees explicitly mentioned change management as a stand-alone capability category. However, in every AI business case implementation, change-oriented behaviors, actions, and routines were expressed. To a certain extent, change management behaviors are reflected in the other identified capabilities such as coaching employees, communicating via storytelling, influencing the key stakeholders, being authentic and trustworthy. Therefore, some of the additional management behaviors would include building relationships with key partners and stakeholders, anticipating potential employee or workplace issues that impact acceptance of the change, creating a vision of what's possible with the new technology, and applying the specific change levers to support the effort.

Personal Attributes and Traits: Many of the interviewees described the need for managers to display a set of attitudes, attributes, or traits that underlie all these capabilities. To operate effectively in the AI environment across the group of stakeholders, especially in the change-oriented atmosphere, managers need to be trustworthy, need to “walk the talk,” they need to practice “responsible AI,” defined as the ability to understand the possibility of bias in the data and AI recommendations. Also, there is a need to have an imagination, as one interviewer conveyed that sentiment as the need to “reimagine better ways to do things.” Other interviewees stressed the need for managers to be intellectually curious, be authentic, and visionary.

Summary

As a recap, the research study had three going in focus areas to include the following:

- Focus area 1: There will be moderate to a significant change to the manager's role (e.g., their tasks, how they allocate their time and focus due to the utilization and power of AI)
- Focus area 2: Managers will continue to assume an essential role in employee development, engagement, and inspiration because of the potential impact of AI to work design and employee's motivation to embrace AI.
- Focus area 3: Managers at all levels will need to enhance their technical, leadership, and interpersonal knowledge, skills, abilities, and personal attributes to thrive in the AI environment.

Based on the research study, there was evidence that each of these three focus areas has merit; however, there was a greater or lesser degree of validity. Let us take each one in turn.

In focus area one, I identified three major role categories--process and data management, horizontal relationship management, people, workforce, and AI tools management. These three overarching categories are somewhat consistent with the academic literature synthesis. The experts identified a series of managers' roles to include being “designers, innovators, integrators, connectors, guardians, explorers, producers and conductors.” Based on the interviews, most of these roles were evident to a certain degree. I probably heard less about the role of designers or innovators; however, there was an expectation that they will continuously improve their AI systems and continue to find other applications. What is missing from the academic literature on roles present in the research study was the importance of people management. In the construction of focus area one, the intent was to understand the degree of change from a pre-AI state to

the current state. However, based on this set of interviewees, the research study did not add insight into the magnitude of change from the past role to the current position. One potential reason is that the sample of interviewees did not include enough first-line managers in the mix. Out of the twelve individuals, only three interviewees had the current day-to-day operations accountability, which could comment directly on this issue. Another reason is that AI is still in the early stages of being implemented, and the dramatic impact on managers has not been felt yet across a broader swath of companies.

In focus area two that focused on employee development, engagement, and inspiration, based on the interviewees, there was a consensus on the need for employee skill-building and coaching. Also, there was an acknowledgment that employees' roles would change (primarily for their benefit) because they would have new tools, greater autonomy, and an increase in value-added (vs. monotonous, repetitive) activities. However, there was a realization that AI could eliminate the current roles, necessitating employees to be redeployed to another assignment or exited outside the firm. Even though our interviewees did not talk about job loss per se, one of our interviewers was explicit about labor cost savings because they did not have to hire replacement employees due to turnover.

In focus area three, all interviewers talked directly about the need for managers to possess a set of specific capabilities. In one of the interviews, one senior leader went beyond the notion of skills when he stated the following:

Some of it is a mindset. Be willing to take different approaches, including design thinking and experimentation, approaching things differently. Need managers to envision the art of the possibility. Create or do minimum value products, by starting small, perfecting to which necessitates having an agile and experimentation approach.

In comparing what was uncovered in the research study versus the academic literature synthesis, there is overlap in several areas: judgment, technical knowledge, communication and influence skills, relationship management, and several attributes such as imagination, curiosity, and trust. The most significant difference (between the academic literature and the research findings) is in the field of change leadership, which was not explicitly mentioned outright as a critical manager capability. Still, most of the interviewees discussed how they were implementing change elements within their organizations. Change leadership is an organizational capability, and by extension, managers need to possess the skills to lead change.

Based on study 1, the academic literature, and my synthesis, six potentially contributing factors impact managers' success in the AI environment. They include the following:

1. *Firm's AI Maturity Level:* Those firms that are more mature in AI are usually characterized as being data-driven, having robust processes, using AI to drive operational excellence and enhance their customer/marketplace offerings, and having offered a higher degree of skill-building to their associates.
2. *Senior Leader Involvement and Engagement:* In any change effort, the modeling by senior leaders, their use of management practices to keep track of the AI effort, and their coaching to their managers are essential elements to success in an AI environment.
3. *Support and Collaboration by Technologists:* Technologists active support and involvement was cited as a critical success factor in the interviews but rarely mentioned explicitly in the academic literature.

4. *Design of the Manager's Role:* The manager's role is related to the manager's capabilities and the firm's specific culture/operating model. Hackman and Oldham stated that jobs that include variety, autonomy, significance, and identity would enhance motivation, satisfaction and improve meaningfulness, responsibility, and knowledge (Hackman & Oldham, 1976 cited in Grant & Parker, 2009). With that being said, there are certain core elements related to the manager's role that was discovered in the research study to include the following: process and data management, horizontal relationship management, and people, workforce, and AI tools management. Many of those role tasks had variety and were significant consistent with the Hackman and Oldham model.
5. *Existing Manager's Capability Level:* Based on the academic literature and the research studies, managers who are more capable when they possess and demonstrate a higher degree technical managerial, leadership and emotional skills are more successful
6. *Organizational Change Management Approach.* AI represents another continuum of technological, process, and organizational improvement initiatives that have been implemented in organizations. Over the last 25 years, companies have implemented a variety of change initiatives such as Just in Time, Total Quality, Continuous Improvement, Lean Manufacturing, and Agile Methodologies. In each of these examples, the more successful organizations had implemented multi-dimensional approach. Some of these elements that were applied included having a strategy and vision to energize the population, organizing a structure to guide improvement activities and measure success, building individual and

organizational capabilities, and launching communication campaign to ensure continual drumbeat of consistent messages to all levels.

If the organizations are successful in implementing AI, those firms should see a positive ROI, employees would feel more engaged due to enhanced job design & skill acquisition, and teams would become more self-sufficient. This overall model (or individual elements) could form the basis for additional deep-dive exploratory case studies or quantitative studies to measure these various elements' effects.

Discussion

This section will focus on two areas. First, I discuss the practical implications and actions that various audiences can use (e.g., senior leaders, managers, organizational consultants) to implement. Because AI is becoming applied in organizations, any advice is borne from academic research or theory that can help senior leaders focus on improving the cost, quality, and implementation speed while reducing organizational friction. Second, I discuss the opportunities for further research regarding the manager's role in the ecosystem, such as collaboration between technologists and managers, optimal team design as AI matures within organizations, organizational change management elements, and managers' technical skills need going forward.

Practical Implications

The combination of research study findings and the results and analysis of the literature search has generated several practical implications for managers, technologists, and human resource professionals. They are in the following areas to include learning, capability assessments, and talent acquisition processes.

Development Learning Sessions: From my estimation, core knowledge areas could readily form the foundation of a learning curriculum. For example, there could be a series of learning modules that could be part of an introductory “course” called “Leading and Managing in the “Age of the Smart Machine.”⁵¹ Potential topics could include:

- Overview of Emerging Technologies
- Components of AI
- Human + Machine Interface
- Implementation Approach
- Impact of AI on Workforce
- Impact of AI on Leaders and Managers (e.g., Roles and Mindset, Tasks and Capabilities)
- Responsible and Ethical AI

Also, the learning module on the impact of AI on Leaders and Managers can be further developed into a specific manager workshop that takes each of the elements of roles/mindset, tasks, and capabilities and delves deeper into each of these areas. For example, there could be a module on building the skills and attributes, which can be accomplished through various learning modes such as simulations, case studies, short videos, lectures from experts, and real-world applications.

Capability Assessments: From the literature review, I have identified a set of knowledge, skills, and personal attributes that leaders need to possess. Some of them have been affirmed through the research study. One practical implication is utilizing those capabilities in the development of capability assessment processes and tools.

⁵¹ The nomenclature of this potential course is borrowed from the title of Shoshana Zuboff ‘s book titled the Age of the Smart Machine: The Future of Work and Power which was written in 1988. Zuboff’s book was prescient in identifying how technology would impact society and the workplace.

Because these skills focus on AI implementation (and possibly any other emerging technology), they will provide a focused (and future) roadmap of what managers need to develop. The set of capabilities will be invaluable as a starting point, and then leaders can further refine this set of skills for their unique situation and organization. HR professionals can develop 360-degree processes, performance management processes, and organizational health (or employee engagement) surveys can be developed based on the set of capabilities.

Talent Acquisition Process: Effective individual performance is a direct function of several variables, including the organizational culture, the design of the role (including its requirements and tasks), and the individuals' capabilities to perform in the role. One of the first steps in an effective talent management process is attracting and selecting external and internal talent. This research study and academic literature can help various talent acquisition processes. For example, I have identified the critical activities for managers to possess in an AI environment in building job or role profiles. These activities will need to be tailored to the specific industry, organization, or function. Second, another example is creating selection instruments to assess candidates vis-à-vis the capabilities and necessary mindsets that are needed.

Implications for Further Research

Several related future threads could be explored to amplify and extend the understanding manager's role in this new era along several dimensions. Four potential topics are suggested in the following sub-sections:

Collaboration and Trust Building Between Technologists and Managers: There are vital relationships in implementing technology to include the finance person who

signs off on it, the senior leader who supports it, employees who provide input to the design, and ultimately who use the tools. However, several interviewees discussed the importance of technologists in supporting line managers in implementing AI. Line managers' organizations are dependent on the implementation of AI in their respective organizations. There are several questions to be explored further in this topic:

- To what degree is a collaboration among technologists and line managers critical success factors in implementing AI from a technological or change management perspective?
- Which are the highest leverage collaboration and trust building-specific behaviors, actions, processes, and routines among the technology organizations, technologists, line managers' organizations, and individual managers that result in a successful implementation?
- How does the role of technologists and line managers change through the various lifecycle stages of technology implementation (e.g., proof of concept, proposal development, approval, design, development, testing, installation, evaluation, release updates, etc.?)

Technological Capabilities Required of Managers: In most interviews, a key theme was the skilling of employees. Interviewees explicitly stated that those who know AI would have an advantage over those who have not learned AI or possess the thinking skills to operate in this new era. Based on labor economists' forecasts, AI will impact most roles, including administration and management. At the same time, the investment in AI is growing exponentially by firms, and it will begin to permeate critical processes.

Therefore, managers will need to ensure that they enhance their toolkit, especially in the technological domain. There are several questions to be explored further in this topic:

- What technical knowledge domains that managers need to possess and demonstrate in the short term (0-18 months) and medium (18-36 months) timeframes, so they are considered “contemporary”?
- What is the degree of knowledge that they need to possess for the specific technological domains ranging to various levels of expertise: general awareness, working experience, mastery, or expert level?
- Will managers need to possess a third-party certification to prove or validate their expertise if they move from one organization to another, either internally or externally?
- Are there other complementary non-technical skills that will be required to carry out their leadership tasks?

Team Design and Structure: Over the last 50 years or so, self-directed work teams have existed, emanating from “social-technical systems” to current manifestations by companies like Zappos, who implement their ‘holacracy’⁵² model. In some of the interviews, a few individuals mentioned that AI tools would give employees more autonomy; the tools will help them solve work issues independently and free up their time to do higher-level analytical work. There are research questions in the area of team design and structure:

⁵² Holacracy is in a long line of self-management team approaches or evolution over the last 60+ years to include Quality Circles, Continuous improvement Teams in the 1980s and 1990s to agile teams in 2000’s. Parenthetically, Zappos is moving away from holacracy to individual P&L units (Source: <https://qz.com/work/1776841/zappos-has-quietly-backed-away-from-holacracy/>)

- Will AI usher in a wave of self-directed teams?
- What is the optimal team design going forward? For example, can managers increase their span of control and lead several teams?
- Is a need for additional roles on the team? For example, one of the interviews described the need for an evangelist to help pave the way for AI implementation. Is there a need to formalize this type of informal role?
- How do team members create formal and informal networks across teams to share information, best practices, and coordinate work?
- How does the structure of work teams alter and change over time as organizations become more mature in using AI/emerging technologies?

Organizational Change Management Approach: In my interviews, they described the various elements of their implementation approach. There is a need to research the most significant change levers for AI's implementation. Some questions include:

- How significantly different is the implementation of AI than previous technology (e.g., ERP, internet, PCs) installations or other organizational improvements (e.g., reengineering, total quality, lean manufacturing, etc.) efforts? Does AI warrant a different change management approach?
- Are there specific change levers that are more impactful than others?
- Because AI can dramatically impact the scope, tasks, roles, and number of employees, how can organizations generate “genuine commitment” versus “grudgingly compliant” behaviors throughout the lifecycle of AI's implementation.

CHAPTER 4

STUDY TWO PROPOSAL

Introduction

This research study will be a mixed-method approach to understand how the manager's role, tasks, capabilities, and leadership approach is impacted when their teams are in different stages of implementing Artificial Intelligence (AI). Will compare and contrast financial services and non-financial services companies and believe that these findings are generalizable across industries because of the growing ubiquity of AI as a management tool in all organizations. It will go in-depth on one element of the change management elements in implementing AI: the degree of collaboration between technologists and line managers when implementing AI. I believe that these findings will be practical and can be applied to a range of organizational, management, and talent practices, including role design, talent assessment, managerial and leadership development, and potential employee engagement.

Topic and Research Questions

The outcome of the first research study is that the manager's role is still relevant, necessary, and value-added as AI becomes more ubiquitous as a management tool (and as an operating model within organizations). The critical overriding question to be answered in the second research study is the following: *How Will the Manager's Role Change (e.g., activities, capabilities, team and horizontal leadership, key accountabilities, etc.) Due to the Implementation of Artificial Intelligence and Leading in the Digital Age?*

Three focus areas formed the basis for the first research study, qualitative inquiry, and

will be explored in the second research study.

1. There will be a moderate to a significant change to the manager's role (e.g., their tasks, how they allocate their time, and focus) due to the utilization and power of AI.
2. Managers will continue to assume an essential role in employee development, engagement, and inspiration because of the potential impact of AI to work design and employee's motivation to embrace AI.
3. Managers at all levels will need to enhance their technical, leadership, and interpersonal knowledge, skills, abilities, and personal attributes to thrive in the AI environment.

Based on interviews and analysis from the first research study, several findings supported the three focus areas while also uncovering additional insights, “ideas, and puzzles” (Abbott, 1997).

1. The manager's role fell into three categories-- process and data management, horizontal relationship management, people, workforce, and AI tools management—as part of a broader ecosystem (e.g., suppliers, senior leaders, employees, and customers). These roles were consistent with the expert's perspective on the tasks that managers would assume in an AI environment.
2. In terms of capabilities, managers need to possess at least a basic working knowledge of Artificial Intelligence concepts coupled with judgment, influence, communication, and relationship management skills, including imagination, curiosity, and trust. These skills maximize the utilization of AI on their teams and ensure employees embrace this new technology.

3. All the companies had a structure, approach, and process to organize themselves to implement AI successfully. Some of the tactics deployed included change management techniques, such as senior leader involvement, broad-based engagement, and training. One unexpected finding was the strong working relationship between the technologist and the manager as a critical success factor.

Building upon the first research study and the above topics, Figure 4.1 conceptualizes a potential framework for further research. The four elements on the left-side of the group could be characterized as antecedents and input to either organizational change management approach or AI impact on managers. When managers are highly effective in implementing AI, controlling for certain exogenous factors, the result should be positive business results, higher employee engagement, and a well-functioning team.

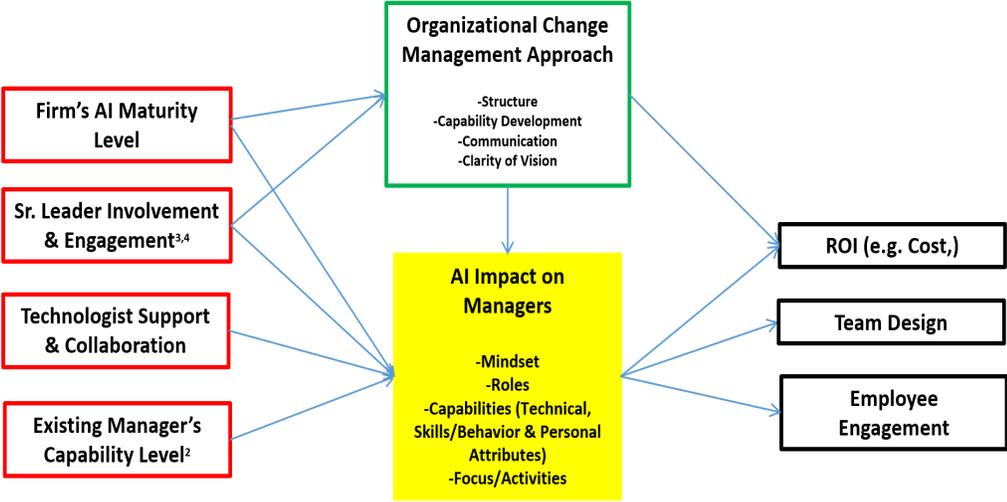


Figure 4.1. AI Impact on Manager's Construct

Using this as the broader context, the second research study will continue to explore the three focus areas and attempt to shed insight into how a manager's role changes or evolves as when teams implement AI tools at varying degrees of complexity. There are various 'ideas and puzzles' worth exploring to understand the impact of AI on the manager's role, as expressed in these questions based on the first research study:

- How does the manager's role change as organizations move from less mature or complex AI to higher AI maturity degrees or complexity? What are the specific areas of accountability for managers?
- What is the degree of technical and non-technical knowledge needed by managers to possess and demonstrate? Does it differ depending on the stages of AI complexity or maturity?
- What are some of the successful change management strategies in implementing AI? Which critical trust-building-specific behaviors, actions, or routines among the technology organizations or technologists with line managers' organizations and individual managers? How does the role of technologists and line managers change through the various software development lifecycle or the multiple stages of AI maturity levels?
- How does the structure of work teams alter and change over time as organizations become more mature in using AI/emerging technologies? What is the role of the manager in the evolution of the team's design? Is there an optimal design or need for additional positions on the team? This question will not be explicitly asked in the second research study. Still, there is a moderate

probability that interviewees would offer a perspective on the operating model of work teams.

Research Method & Approach

For this study, I utilize case study evidence with qualitative and quantitative data (Yin 2006) to form a mixed-methods approach—open-ended structured interviews and a short survey to collect numeric data (Yin 2006). Mixed methods research is considered the third methodological movement, with quantitative and qualitative methods representing the first and second movements (Venkatesh 2013). Although case studies allow for confirmatory (deductive) and explanatory (inductive) findings, the approach will primarily utilize an inductive approach by investigating particular contemporary phenomenon within a real-life context (Baškarada 2012; Yin 1981, Yin 2006), especially when the boundaries between phenomenon and context are not evident (Yin 1981). Although different possible case types are exploratory, descriptive, and explanatory (Yin 1981), the approach will be skewed towards explanatory that builds upon the first research study findings. Case studies are particularly pertinent for answering how and why questions (i.e., explanatory) (Baškarada 2012) (Yin 2006) as well as what questions (i.e., descriptive) (Yin 2006). Case studies collect empirical evidence from one or more organizations to study the subject matter in context (Meyers, 2013) and produce a firsthand understanding of people and events (Yin 2006).

A mixed-method approach is broadly defined as research “in which the investigator collects and analyzes data, integrates the finds, and draws inferences using both qualitative and quantitative approaches” (Tashakkori & Teddlie 2013). There are several purposes for undertaking a mixed-methods approach (e.g., complementarity,

developmental, expansion, compensation, diversity). In this situation, “completeness will be the primary rationale to make sure a complete picture of the phenomenon is obtained” (Tashakkori & Teddlie 2013). The intent is to have a similar mixed design where the information is collected synchronously (Tashakkori & Teddlie 2013), where numeric data will be collected right after the qualitative interview. This approach will be a blend of 'positivism and interpretivism,' which has been one of the "fractal debates between thinking you can and should measure social reality formally and thinking you can't and shouldn't" (Abbott, 2004). I believe that this approach would blend the best of the interpretivist approach as a "way to unravel patterns of subjective understanding" (Roth and Mehta, 2002) along with the elements of the positivist approach, which "generally assume that reality is objectively given and can be described by measurable properties" (Meyers, 2013).

To obtain a multi-dimensional perspective on the critical research questions, I will collect information from three sets of participants:

- The responsible **team manager**, who utilizes the outputs of the AI/algorithms and leads the team of employees working in concert with the AI tool, will be the main target of the research. Getting their direct perspective is essential. However, I expect that they might not be objective; they might provide answers that conform to the corporate PR storyline or accentuate the positive aspects of their contributions.
- The **senior leader** of the group (at least one level up from the manager) responsible for the funding of the AI; can be considered the sponsor of the AI implementation and clears away real or perceived barriers. The senior leader's

perspective is necessary to provide some greater context in terms of the technology implementation and compare or contrast various teams in different stages of implementation.

- The **technologists** (e.g., software engineers, architects, technology infrastructure professionals) who have been supporting the AI implementation are the third population. Because the technologists will usually not be in the chain of command of the manager or the senior leader, they could offer a less self-serving perspective on some of the research questions. Also, they might be able to provide a point of view on this team in comparison to other groups who are implementing AI.

I will identify approximately 8-12 teams drawn from various organizations to include financial services, life sciences, professional services, and industrial firms. The intent is to identify teams/units who have implemented AI and the range of less mature/complex to more mature/complex AI installations. Less complex AI implementations could be characterized as replacing 'mechanistic' (Huang and Rust, 2018) functions; focusing on operational improvements via Robotic Process Automation (RPA) technology; creating 'digital exhaust' through the use of automating processes as well as cleaning up data (e.g., data engineering). At the other end of the spectrum, more complex AI implementations could be characterized as replacing 'intuitive or empathetic' (Huang and Rust, 2018) functions; utilizing both a variety and high degree of unsupervised or unstructured data; deploying machine learning (or deep learning) where

the software learns from experience and adapts; and a high degree of utilizing predictive analytics.⁵³

I will ask individuals to assess AI technology complexity, but there are other types of complexity—strategic complexity, organizational complexity, decision-making, and thinking complexity that AI impacts. Before discussing these areas of complexity and their connection to AI, let's put some parameters on the dimensions of complexity. First, complexity is characterized by diversity, ambiguity, and unpredictability of outcomes relative to inputs or changes in conditions. (Collinson & Jay, 2012). Second, it contains certain properties, including multiplicity (number of potentially interacting elements), interdependence (how connected these items are), and diversity (degree of heterogeneity) (Sargut & McGrath 2011). Third, complex systems produce and use information and signals from both their internal and external environments. Fourth complex systems are adaptable—that is, they change their behavior to improve their chances of survival or success—through learning or evolutionary processes (Mitchell, 2009).

The implementation of Artificial Intelligence in some shape, form, or manner touches upon these strategic, organizational, decision-making, and thinking complexity. For example, strategic complexity is about the positioning of the firm in a changing external competitive environment. Organizations such as Facebook, Netflix, Microsoft use AI technologies, especially machine learning to enhance their strategic competitiveness through their capability to offer more precise and enhanced recommendations (Schrage, 2020) to their customers. In terms of organizational

⁵³ The sources of defining the low end and high end of AI complexity were from a series of one-on-one conversations with senior technologists (Sept-October 2020) and descriptions of AI technologies from the academic literature.

complexity, companies use AI tools to improve their ability to improve business processes, communicate effectively across organizations and ensure data is quickly and efficiently disseminated throughout the organization. Certain AI technologies, such as machine learning, natural language processing, and deep neural networks, utilize large amounts of computing power, deploy advanced algorithms, and draw data from a variety of multiple sources. In order to execute these technologies in organizations, it is a complex endeavor because of the number of interacting elements that need to work in a coordinated fashion. Also, specific processes or tasks are more suited for more advanced AI technologies. This would include those requiring independent judgment, those for which all contingencies could not be predicted in advance, those involving unpredictable interactions with customers or employees (Davenport, 2019), and lastly, where the data is unstructured. Lastly, AI technologies learn from the environment (e.g., reinforcement learning). With multiple feedback loops (e.g., deep neural networks), AI is adaptable when processing information to solve particular business problems.

As stated above, will identify teams that have implemented AI in various stages of maturity, complexity, or sophistication and from various organizations representing a cross-section of industries (e.g., Financial Services, Life Sciences, Industrial Firms, and possibly Professional Services). One of the critical success factors in conducting this study is to undertake a case study screening process to ensure that the selected case studies are viable (Yin 2006) in answering the critical question and related focus areas. The goal is to identify enough of a sample of 4-6 teams drawn along the continuum of high and less maturity.

Table 4.1	
<i>Research Sample Approach</i>	
	Organizations (e.g., Financial Services, Life Sciences, Industrial)
High AI Maturity or Complexity	4-6 teams
Less AI Maturity or Complexity	4-6 teams
	Total: 8-12 teams

Because of the variability of industries and stages of maturity, this approach provides an opportunity to compare, contrast, and analyze along with a variety of dimensions:

- Understand any similarities and differences among organizations in different industries or organizational types (e.g., financial services vs. non-financial services)
- Understand any similarities and differences between high vs. low teams in their AI tool level of maturity/sophistication.
- Determine how managerial roles and capabilities change at different stages of AI tool maturity or business outcomes.
- Identify the key AI change implementation success factors, especially the degree of collaboration between a line of business managers and the technology organization.

The approach to identifying organizations will be primarily "purposive" as a starting point which relies heavily on the expert judgments of the researcher and

potentially leads to a greater depth of information from a smaller number of carefully selected cases (Tashakkori & Teddlie 2013). I have already lined up my current employer and will utilize them for at least two teams, necessitating the need to generate an additional six to ten teams. Out of the ten organizations that participated in the first research study, there is a high degree of probability that two of them would participate, which would leave a gap of two to four organizations or six to eight teams. Therefore, I would go back to the research study 1 participant to re-contact those organizations as participation sources. At the same time, I will contact an extended list of other contacts for referrals or have them act as a broker to other organizations.

Considering the data research approach (8-12 teams with three individuals per team), which will project a sample size of about 24-36 interviews, this should be sufficient to understand the phenomenon. However, focusing on a particular number of interviews simplifies a more nuanced process where the number of interviewees depends on a variety of factors or issues such as saturation, the style or theoretical underpinnings of the study, the breadth, and scope of the research questions, practical considerations of time, resources, and requirements by outside forces (Baker & Edwards, 2012). One researcher did state that “16 or fewer interviews is enough for studies with relatively homogeneous groups” (Hagaman and Wutich, 2017). At the same time, another researcher stated that “15 being the smallest number of participants for a qualitative irrespective of the methodology (Mason, 2010). However, in analyzing the different types of studies (e.g., action research, collaborative research, discourse analysis, hermeneutics, symbolic interactionism, etc.) participants levels, case studies had 36 participants with a median of 33 and a mode of 40 (Mason, 2010). To maximize these interviews and

explore the set of topic areas, I will ask for at least 60 minutes, which sometimes is difficult for individuals to commit to on the onset. However, I would expect that if the conversation is engaging, I should expand the time or get another time slot, especially with the senior leader population. The research findings will apply to a cross-section of companies because organizations will continue to transform themselves to become more digital in all aspects of their business. When this occurs, data collection will increase, and there will be a need to implement analytical and predictive decision-making tools. Thereby various elements of their organization model, including their management practices.

The intent will be to conduct one-on-one semi-structured interviews (see Appendix C for proposed interview protocol and interview questions) to unearth context and insight not only on what was achieved, including the rationale (the why) and method (the how) employed. Besides, these interviews will collect “empirical material on people’s meanings, experiences, or social practices” (Alvesson, 2013). Because the semi-structured interview involves prepared questioning guided by identified themes consistently and systematically interposed with probes designed to elicit more elaborate responses, it is appropriate for this research study (Qu & Dumay, 2011). The semi-structured interview format will also allow the interviewee to expand on a particular topic. The interviewer will go more in-depth on a specific issue, especially when the interviewee has a lot of emotional energy or information on the topic discussed. The interviewer will be attentive to ask follow-up and probing questions to extend the subjects’ answers through the inquiring, persistent, and occasionally having a critical attitude (Qu & Dumay, 2011). Good qualitative

questions are broad but specific enough to focus on the issues most relevant to the individuals under investigation (Venkatesh, 2016). This format will provide enough overall structure for the interview while being able to flex where appropriate. Because many of the interviewees will be considered "elite individuals" (Harvey, 2011), their time is limited, so, therefore, there will be a need to be efficient but ask thought-provoking questions. For efficiency's sake, the plan is to send the topics ahead of time, so the interviewees have a sense of the areas that I would cover in our conversation. I will need to balance--giving the interviewees a sense of what I want to cover so they can think about the topics ahead of time—while simultaneously want the conversation to be spontaneous, authentic, sparking reflection and critical thinking.

The reality of interviewing senior executives is that they usually only really glance at the topics a few minutes ahead of one's conversation, so there will not be any real downside of sending out the topics ahead of time. Besides, to ensure that the interview questions are robust. I will conduct a pilot test with participants like those in the study to determine flaws, limitations, or other weaknesses with the interview design (Turner, 2010). This will allow time to make necessary revisions before implementing the study (Turner, 2010). I will use the individuals who participated in the first research study as the primary pilot group and the experts I consulted when I tested my first research area of inquiry. One last consideration in interviewing managers is that they will communicate their work experiences and the stories. Hence, as an interviewer, “we have a responsibility to create the conditions in which

people can safely tell their stories to someone who is listening and who can be trusted to bring their conversations about the human experience” (Gilligan, 2015). The second element of the mixed-method approach will be constructing and administering a short quantitative questionnaire composed of approximately ten scaled survey items that should take no more than 5-8 minutes. It would be distributed after the interview and will provide an opportunity to probe further with the interviewee on their quantitative responses, if necessary. The intent of collecting quantitative data is to compare and contrast interviewee data across a set of constant metrics; integrate some quantitative information into qualitative data; reinforce or complement what the individual interviewees said in their one-on-one interview. Also, if I determine to sample a larger population⁵⁴, at some point after this research study is completed, this instrument could be a starting point for a broader survey. In constructing the survey items, the overriding objective is to ensure consistency with the qualitative research—how does the manager change as a team/move through various stages of AI implementation and congruent with the qualitative research topic questions. See Appendix E that will be further refined in a pre-survey test. To show the relationship among the four overall research broad set of questions and the specific survey items, see Table 4.2.

I highlighted in yellow where the individual survey items correspond to the specific topical areas. As you will see, I asked survey items that will provide some statistical data to amplify further and illuminate the interviewees' qualitative responses.

⁵⁴ Some potential sources could include the membership of various industry groups such as the Association for the Advancement of Artificial Intelligence (<https://www.aaai.org/home.html>) or university based executive education programs where one might be able to access their students who take technologically oriented offerings.

Lastly, similar to the interview questions, I will pilot test quantitative survey items so that survey items are clear, understandable, and get what I am trying to achieve. If I decide to use the survey broadly, I will add a few more demographic items such as gender, ethnicity, age, and survey items. I will also need to determine if asking the demographic questions will necessitate going back to the IRB for approval. Currently, I was exempt from the process of IRB.

Table 4.2.

Survey Items Relationship To Research Topic Areas

	Topics			
	How does the role of the manager change as organizations move from less maturity of AI (e.g., replacing mechanistic functions; focusing on operational improvement; higher usage of RPAs) to higher degrees of AI maturity (e.g., more human like characteristics; focus on direct machine to customer interaction; higher use of chatbots)? What are the specific areas of accountability?	What is the degree of technical and non-technical knowledge needed by managers to possess and demonstrate? Does it differ depending on the stages of AI maturity?	What are some of the successful change management strategies in implementing AI? Which are the key trust building-specific behaviors, actions, or routines among the technology organizations or technologists with line managers' organizations, and individual managers? How does the role of technologists and line managers change through the various software development lifecycle or the various stages of AI maturity levels?	How does the structure of work teams alter and change over time as organizations become more mature in the use of AI/emerging technologies? What is the role of the manager in the evolution of the team's design? Is their an optimal design or need for additional roles on the team?
Survey Items				
Identify Role in the Organization				
Years Involved in Implementing Advanced Technologies				
Role of the manager to be successful in an AI environment				
Years Involved in Implementing Advanced Technologies				
Capabilities that managers need to possess to succeed in AI environment				
Identify The Maturity Stage of AI Usage on Your Team/Unit				
Types of AI & emerging technology that has been implemented in your team/unit/function				
The technology organization and the line of business work collaboratively in implementing emerging technologies.				
Hours of technologically oriented training or skill building did you participate in the last twelve months				
Hours of management or leadership oriented training or skill building sessions did you complete in the last 12 months				
Critical success factors in implementing AI in your team/unit/organization				
Years of experience working with AI.				
Number of years of work experience				

Data Collection, Analysis, and Approach

As mentioned in the previous section, the qualitative approach will employ a semi-structured approach to interviewing individuals. These interviews will be conducted

via a Zoom platform or person-to-person telephone call. Wherever possible, if not constrained due to privacy and confidentiality concerns by the individual or their respective corporations, will record the interviews and have them transcribed. If they are not transcribed, the interviewer will type notes into a laptop computer, and the data will be stored under a pseudonym file name. A log matches the interviewer's name with the pseudonym file name that will only be accessible by the researcher. It will be kept in a private handwritten notebook only accessible by the researcher. There will not be any identifiable information in the interviewer's notes that can link the individual to their reported data. Also, I will identify the company in the typed-up notes.

The main advantage of face-to-face (albeit via Zoom) semi-structured interviews is that it provides the opportunity to adapt the questions as necessary. Secondly, it ensures that the responses are appropriately understood by repeating or rephrasing the questions and picking up on nonverbal cues from the interviewee (Sekaran & Bougie, 2016). Reading non-verbal cues could be more challenging via a Zoom call, and it will require the interviewer to be attentive, mindful, and quickly establish rapport with the interviewee.

In analyzing the qualitative interviews, the intent will be to use the NVivo software package (QSR, 1999) and, in all likelihood, utilize first and second-cycle coding (Miles et al., 2020). This will help use a constant comparative analytic scheme using two general processes---unitizing and categorizing⁵⁵ (Tashakkori & Teddlie, 2013). The starting point for prescribed coding categories/attributes includes Financial Services

⁵⁵ Unitizing is defined as breaking the text into units of information that will serve as the basis for defining categories. Categorizing is bringing together into provisional categories those units that relate to the same content, devising rules that describe category properties, and rendering each category set internally consistent and the entire set mutually exclusive (Tashakkori & Teddlie, 2013).

Companies, Non-Financial Services Companies, High AI Maturity/Complexity, Low AI Maturity/Complexity, Participants (manager, senior leader, technologists), Managerial Capabilities, Managerial Roles). Also, in terms of second-order coding for managerial skills, will use the capabilities that have been initially identified in the survey (e.g., Computational, Algorithmic and Design Thinking, Artificial Intelligence and Emerging Technologies, Data Management and Analysis, Conceptual Skills, Cognitive Complexity, and Diagnostic Capability, Change Management, Judgment, Interpersonal Orientation and Relationship Building, Social and Creative Intelligence, Curiosity, Questioning, Humility & Trustworthiness, and Passion for Diversity).

In particular, by using NVivo for coding, the intent will be to ensure that the coding scheme is both "objective" (e.g., the codes and the categories require little inference or interpretation from the researcher) as well as mutually exclusive and collectively exhaustive (e.g., categories are mutually exclusive if none of the categories overlap one another to cover a range of possibilities to include events, actions, and behavior (Sekaran & Bougie, 2016).

I will use other features of NVivo, such as utilizing the auto code theme function to check the initial coding versus what NVivo recommends. I will also conduct different data cuts as input to the analysis using NVivo features such as cross-tabbing. One potential output of the investigation might resemble what is illustrated in Table 4.3.

Table 4.3.

Proposed Coding Sequence

	Population			Industry		AI Maturity	
	Manager	Senior Leader	Technologist	Financial Services	Non-Financial Services	Low AI Maturity	High AI Maturity
<i>Illustrative</i>							
Coding Node							
AI Business Problems							
AI Tools and Techniques							
Business Results							
Capabilities: Managers							
Capabilities: IT Professionals							
Change Management							
Conceptual Framework							
Investment Strategy							
Managerial Roles & Activities							
Responsible IT							
Structure for Implementation							
Use Case Examples							
Workforce Implications							

Because of the number of teams and the number of potential companies, the intent is to utilize analytic memoing (Miles et al., 2020) to record ongoing observations, insights, and modifications to the overall approach. At a minimum, the researcher will type in comments about the interviewee in the body of the typed notes as input to more formal analytic memoing and register any ongoing observations. In analyzing the collected data, there will be a series of questions that might help in interpreting the information as noted before, such as:

- Are there any similarities and differences among organizations in different industries or organizational types?
- Do managerial roles and capabilities change at different stages of AI maturity or business outcomes?

- Which are the AI change management implementation success ingredients?
- Do the three interview populations have dramatic or significant differences in their responses to the questions?

Also, it will attempt to utilize analytic generalization as a tool for generalizing from the case studies learnings that can be applied to other concrete situations and not just contribute to abstract theory building (Yin 2013). To ensure that there is ‘interpretive rigor’ needed to ensure it meets several criteria such as interpretive consistency, theoretical consistency, interpretive agreement, interpretive distinctiveness, and integrative efficacy⁵⁶ (Tashakkori & Teddlie 2013). To ensure that there is an interpretive rigor, an antecedent step is to ensure that there is validity in the qualitative study, defined as the extent to which the data is plausible, credible, and trustworthy. Thus, it can be defended when challenged. (Venkatesh, 2013). The quantitative data will be used to augment the qualitative interviews and provide some objective numerical information to aid in the analysis. At a minimal level, I will offer some descriptive analysis based on the survey items. Depending on the number of quality responses, meaning that there are no gaps in the data, and the number of questions asked, this will determine the range of statistical analyses (e.g., one-way ANOVAs,) that can be produced. If there are enough cases to analyze, I could attempt to understand any significant differences among various

⁵⁶ Additional definitions on these five criteria include the following: Interpretive Consistency ensure that the conclusions closely follow the findings meaning that the inference is consistent with the type of evidence. Theoretical Consistency which is also known as explanation credibility meaning is the explanation for the results or relationship consistent with current theories or empirical findings. Interpretive Agreement gets at the notion of would other scholars reach the same conclusions. Interpretive Distinctiveness gets at if the conclusion is clearly different and more defensible than other plausible conclusions that were eliminated by the investigative. Lastly, Integrative Efficacy is the degree which inferences made in each strand of a mixed methods study are effectively integrated into a theoretically consistent meta-inference (Tashakkori & Teddlie 2013).

dimensions--nature of the role (manager, senior leader, technologist), hours of training, # of years of AI experience.

In conducting the qualitative interviews, the researcher will need to be mindful of not succumbing to various cognitive biases, particularly confirmation bias⁵⁷. The interviewer has accumulated quite a bit of knowledge on the topic and will be going into the data collection process with a set of hypotheses and potentially preconceived notions of what might be uncovered. Therefore, there will be a need to keep an open mind instead of listening for information that confirms one's preconceived notions. Simultaneously, having developed as much expertise in the relevant topic areas as possible will increase the probability of asking informed questions (Qu & Dumay, 2011).

Indication of Potential for Meaningful Contribution

In the spirit of attempting to be objective, I will be mindful of displaying the cognitive bias of 'affect heuristic'---defined as falling in love with one's proposal, ideas, or point of view where one cannot see the merits, tradeoffs, or downsides. I believe that my research study could make a meaningful contribution on many dimensions. First, there has been a shortage of academic research on this topic. There has been only one researched-based academic article published to date on the subject of leadership in AI; one book that published by an academic (Professor David De Cremer at the National University of Singapore); a researched-based management practice article/report published by MIT Sloan's Management Review (lead author: Doug Ready) along with many white papers, articles, and statements by consulting firms and academicians. There are two potential reasons for the shortage of academic articles on this particular topic.

⁵⁷ Confirmation bias is defined as looking for information that reinforces one's decisions or actions.

First, the implementation of AI is in its early stages of maturity. It has not reached a critical mass across a swath of industries and companies, so there are not as many use case examples focusing specifically on the manager's role.

A second potential reason is that this research topic crosses several disciplines or knowledge domains such as technology, management/leadership, and change management. Being purely speculative, I believe that a researcher needs to have a working knowledge of these domains, limiting the number of individuals who can tackle the subject. With that being the case, the second contribution exists in understanding a topic that crosses several disciplines. Because managers live in a world of 'complicated systems,' which are "ordered, but that contain many agents and many levels of interchanges" as well as "the work one does usually involve many disciplines, and various kinds of expertise" (Pendleton-Julian and Brown, 2018), research that crosses several disciplines will offer managers a richer perspective on an important emerging issue.

The third potential contribution is the research's practical application. It will provide insight into the manager's role, the capabilities required, the nature of change levers, the degree of collaboration needed with the technology organization, and understanding these elements via being in the early or later stages of AI implementation. These topics could be input to constructing a manager's role and its expected evolution, how managers are selected, assessed, and developed.

Final Dissertation Defense Steps

Below is a list of the significant steps for completing the activities before the final dissertation defense.

Step 1: Revise and finalize the data research proposal. Based on the Dissertation Committee's feedback, I will revise the data research methodology and approach if necessary (but expected). Also, I will recontact those thought leaders who I contacted in preparation for the first research study. The purpose of this contact would be to get their input on the qualitative and quantitative survey items focusing on how they would conceptualize organizations that are low vs. hi maturity levels. Also, I will use them to identify other research sites too. In this step, I will also confirm if there is a need for any modifications to the initial IRB submission. For the first research study, IRB ruled that the research was exempt.

Step 2: Continue to update the literature review section of the dissertation. Over the next five months, I will continue to update the literature review to ensure that recent relevant academic or management journal articles are cited. Also, there have been two books written by academics in the last year or so. For example, Amit Mukherjee (Hult University Business School) wrote a book called *Leading in the Digital World: How to Foster Creativity, Collaboration, and Inclusivity*. George Day (Wharton) and Paul Schoemaker wrote a book called *See Sooner Act Faster: How Vigilant Leaders Thrive in the Era of Digital Turbulence*. I will read both of them and see if they point me to any additional citations or research. I will also continue to mine the various AI think tanks, policy sites, and university research groups for emerging trends.⁵⁸ Besides, as I begin to conduct research, some topical areas will need further exploration (e.g.,

⁵⁸ Some of these include the Future of Life Institute, Stanford University's Human Centered Artificial intelligence, AI Now Institute at NYU, Data & Society Research Institute, Human AI, Partnership for AI, Harvard Kennedy School's Belfer Center for Science and International Affairs, Georgia Tech University's Human-Automation Systems Lab, MIT's Center for Collective Intelligence, MIT's Institute on the Digital Economy, and MIT's Center for Digital Innovation.

technological change management, collaboration & working cross-boundaries, corporate networks, etc.) for inclusion into the literature review. To coincide with the data collection process being completed by the end of the year, setting an end date for the literature review by January 1. Therefore, I can begin the new year, focusing on synthesis and analysis. However, if there are insights from the study, I will embark on a limited academic literature review on a limited number of topics.

Step 3: Identify potential research sites, organizations, and individuals; gain agreement and begin scheduling. (One of the rate-limiting factors in completing the RPI on the original due date was the time and effort ("blood, sweat, and tears") in identifying potential research sites, which, in all honesty, took longer than expected. Identifying research sites will take a shorter amount of time because I already have a group of organizations that I can tap into as a starting point. Also, during this period, I will need to renew my CITI Certification by October 2020 (completed). I will send interviews an email asking them to participate (see Appendix D for a draft email) and contact them individually.

Step 4: Submit the dissertation defense proposal document and defend the dissertation research proposal. Based on initial feedback on research study 2 and input from RPIV, submit an updated dissertation proposal to the committee.

Step 5: Commence, adjust, and complete the data collection process. Ideally, I would like to complete the entire data collection process by January 15th, but realistically, a few conversations will carry over till February 2021. Usually, it is difficult to schedule interviews for the last two weeks in December, so I might need extra time in January to complete the data collection process.

Step 6: Review, synthesize and analyze the data. As the interviews are completed, the information will be loaded into NVivo software utilizing the prescribed coding scheme. Once 50% of the discussions are finished, will identify second-order coding, and when approximately 75% of the interviews have been completed, will start to draft potential findings. Along the way, I would have written analytic memos, which will form inputs to the analysis.

Step 7: Submit a draft of the research study analysis and discussion and obtain feedback from the committee. To ensure that the dissertation and myself are ready for the final defense, discussions, and input from the committee are necessary activities to ensure that the dissertation meets the requirements.

Step 8: Revise Dissertation and Defend Dissertation. Based on the feedback from step 7.

CHAPTER 5

STUDY TWO METHODS, ANALYSIS, AND RESULTS

Methods

As outlined in Chapter 3, Study Two's approach was to conduct mixed-methods research. The overriding purpose of the mixed-methods approach was completeness by obtaining a complete picture of the phenomenon synchronously collecting the information (Tashakkori & Teddlie 2013) right after the qualitative interview. Furthermore, having participants complete the survey during the interview provided an avenue for them to expand on why they scored the item a certain way, which allowed for asking follow-up questions and drawing linkages to their qualitative responses on the open-ended questions. I interviewed three different populations (senior leaders, managers, and technologists) where AI applications have been implemented in their respective organizations as mini-case studies. To cast a large net of potential participants, the researcher utilized the following sources: his current and former employers, Study One participants, and his broader network, either identifying potential participants or act as a referral/broker to other organizations.

Through his multi-prong approach, 150 individuals or organizations were contacted, which netted a pool of about 30 organizations engaged in 'active dialogue.' They all expressed some degree of interest in participating--some either initially committed to participating or at least taking the next step to investigate the possibility of participating within their respective firms. However, over time, many declined primarily

due to other pressing demands⁵⁹. In some cases, they could not get approval from their senior leaders or control functions (e.g., legal, compliance, etc.). In addition, a small percentage of them did not proceed either because their AI implementation was still in its nascent stage, or their AI application focused on RPA tools that did not have the substantial cognitive capability in their application.

One of the positive aspects of these ‘active dialogue’ contacts is that most individuals validated the research topic and piqued their interest. They felt the research was relevant, exciting, and timely. Also, some of these preliminary conversations unearthed additional insights that helped shape the research’s line of inquiry or provided relevant information for the dissertation. Two examples stand out. One of the contacts was a former Google internal consultant (and now McKinsey partner) writing a book on organizational dynamics in the digital age. He had several chapters on leadership and workforce implications. His work unearthed additional research citations that I was able to leverage for this study. Another contact was a senior level partner at a consulting firm and a leading practitioner and thinker in the field of talent and leadership as well. He provided some insights on the humanization of work that is the basis of his next book. Neither one of them are “officially” research participants, but they represent a handful of expert individuals that I identified as part of locating research participants

Drawing from this pool of 30 active dialogue organizations, 11 organizations agreed to participate in the research. Table 5.1, titled Research Sample, identifies the list of industries, number of organizational units or teams, number of interviewees, and gender breakdown of participants.

⁵⁹ There were at least 6 life sciences/pharmaceutical companies that initially expressed interest, but they all pulled out because they were directly or indirectly involved in Covid vaccine research or production.

Table 5.1.*Research Sample*

<i>Industry Groups</i>	<i># of Firms</i>	<i># of Teams or Organizational Units</i>	<i># of Participants</i>	<i>Role</i>	<i>Overall</i>	<i>Gender</i>	
						Male	Female
Manufacturing	1	1	3				
Retail	2	2	6	Senior Leader	14	12 (85.7%)	2 (14.3%)
Consulting (Health Care & Business Technology)	2	2	5	Manager	14	10 (71.4%)	4 (18.6%)
Telecommunications	1	1	3	Technologist	14	9 (64.2%)	5 (35.8%)
Pharmaceuticals	1	1	2				
Technology	1	1	4				
Financial Services	1	4	15				
Health Systems	2	2	4				
Total	8	11	42		42	31 (73.8%)	11 (26.2%)

There was a mixture of eight diverse industries Financial Services, Industrial, Retail, Consulting, Life Sciences/Pharmaceuticals, Health Systems, Telecommunications, and Technology and organized broadly into two categories: Business to Consumer (B2C) (Financial Services, Retail, Telecommunications, Health Systems) or Business to Business (Consulting, Life Sciences/Pharmaceuticals, Industrial and Technology).⁶⁰ Of these 11 companies who participated, 3 were privately held companies (a manufacturing firm, a health care technology consulting firm, and a retail company); 4 substantial leading global companies (a financial services firm, a technology company, a business technology consulting firm, and telecommunications firm) in their respective industries, each with over 100,000 employees; 3 large companies (a retail company and two health

⁶⁰ The Life Sciences/Pharmaceuticals company main product is still in clinical trial, and it has not launched yet. With being said, even though pharma companies do advertise to consumers and ultimately consumed by patients, their products are distributed through retail chains and wholesale drug companies, hence categorized them as B2B. Also, the payment mechanism is mediated through third parties.

care systems firms), with over 10,000 employees and one small publicly traded pharmaceutical/life sciences company. Fourteen teams or organizational units participated in the study, with 42 participants, 31 Males (73.8%) and 11 (26.2%) Females. Of the 42 total participants, I had 14 senior leaders, managers, and technologists. The sample size of 42 participants is acceptable based on other case studies where the average was 36 participants with a median of 33 and a mode of 40 (Mason, 2010).

Based on the quantitative survey, additional demographic information was tabulated on the participant population to include the number of years involved in implementing advanced technologies (Question 8); the number of years of work experience in their careers (Question 9), and how many hours of technologically oriented training they have participated in the last 12 months (Question 10). See Table 5.2 for Participant's Work Experience and Training Information.

Table 5.2.

Participant's Work Experience and Training Information

8. Identify the total number of years involved in implementing advanced technologies such as AI, Cloud Computing, Big Data/Data Modeling, Internet of Things

Role	> than 5 years	3-5 years	1-5 years	< than 1 year
Senior Leader	10	4	1	
Manager	4	5	4	1
Technologist	8	3	1	1
Total	22	12	6	1

9: Please tell us the number of years of work experience in your career.

Role	Over 20 years	16-20 years	11-15 years	0-10 years
Senior Leader	14		1	
Manager	6	3	2	3
Technologist	5	1	3	3
Total	25	4	6	6

10. How many hours of technologically oriented training or skill-building sessions did you complete in the last 12 months? Training could be in-person or virtual; self-directed; webinars; external courses, etc

Role	16 hours +	6-15 hours	3-5 hours	0-2 hours
Senior Leader	11	2	1	
Manager	9	2		2
Technologist	9	1	2	
Total	29	5	3	2

In reviewing the information, I observed that the senior leaders' interview participants had greater seniority and more years implementing advanced technology than managers and technologists. On the other hand, technologists had fewer years of seniority and many years implementing advanced technology. Technologists are usually at lower levels in the organization with less total work experience. For each of these three questions, a large percentage of participants skewed more senior, or the highest in each

category--54% (22 of 41) had five years or greater Implementing advanced technologies; 61% (25 of 41) had more than 20 years of experience in their career, and 74.3% (29 out of 39) had greater than 15 hours or more of technologically oriented training over the last 12 months.

In analyzing the qualitative interviews, I loaded the notes from each of the interviews into NVivo and started with a set of predefined codes (e.g., AI Business Problem, AI tool, Business Outcomes, Complexity, Managerial Capabilities, Manager Role, Mindset, Miscellaneous, and Relationship with Technologist). I added second-order codes primarily in the Managerial Capabilities code which was broken down into ~20 codes. Also, the study utilized the text inquiry feature to search for particular concepts to augment the initial coding. The survey was loaded into Excel and SAS applications to run descriptive statistical analysis and determine if there were any relationships within the data set.

Analysis and Results

This section will analyze the qualitative interviews and the quantitative surveys based on the information collected from the research populations. The analysis and results will be organized into three sections. Figure 5.1 provides an overview in general terms of the content of the sections.

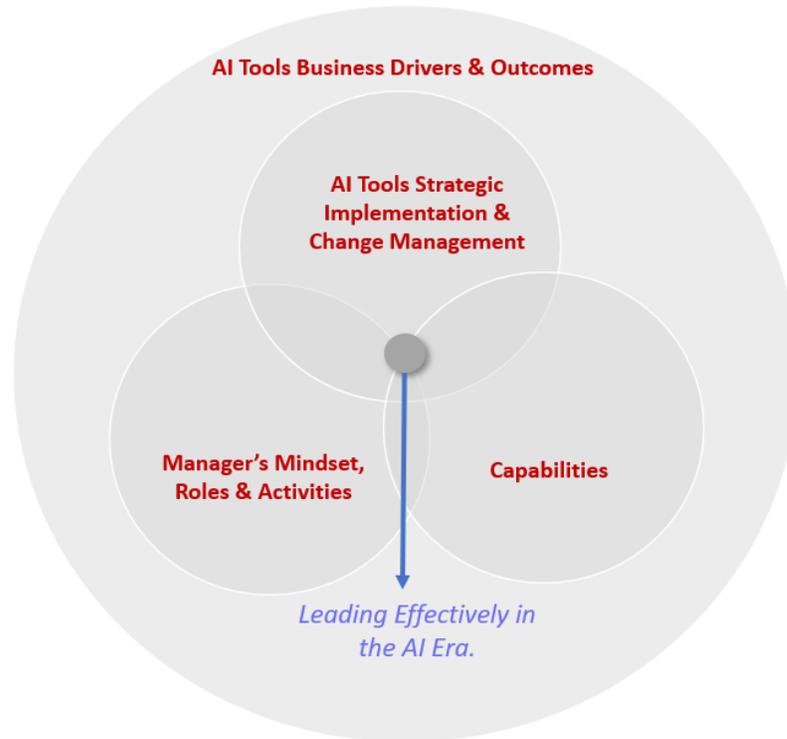


Figure 5.1. Analysis and Results Overview

1. *AI Tools Business Outcomes & Drivers.* This section will discuss the types of AI tools the organizations implement from the mini-case studies, including identifying business drivers and any business results they might have achieved. In Figure 4.1, the AI Tools Business Drivers & Outcomes is the overarching context for understanding how the tools were implemented, the manager's role in their usage, and the capabilities required to succeed in this environment. If there were a different strategic context or milieu, it would change the findings. Because the AI tools that comprise these specific mini-case studies were either at different stages of maturity in terms of implementation or at varying levels of complexity (low, moderate, or high), the range of business outcomes differs. Due to confidentiality concerns, some organizations did not volunteer specific data on this or cite specific tangible results.

2. *AI Tools Implementation & Change Management.* This section will describe the critical success factors in AI implementation, focusing on change management and senior leaders' role & leadership. In particular, how senior leaders personal role modeling and how they created a suitable climate for technology innovation to thrive.
3. *Managerial Mindset, Roles & Tasks:* Considering the first two sections—AI Tools Business Outcomes & Drivers and AI Tools Implementation & Change Management—combined with the qualitative and quantitative data that inquired specifically about the nature of the managers' roles, this section will describe the underlying mindset, tasks, and activities critical for managing in an AI environment.
4. *Capabilities:* This section will describe the technical, functional, leadership, and managerial capabilities that will maximize the probability of succeeding in an AI and digital environment. In addition to the qualitative interviews analysis, this section will report on the results of the survey where I asked individuals to rank order their top three capabilities from the full list (e.g., Computational, Algorithmic Thinking or Design Thinking, AI Knowledge, Data Modeling, Cloud Computing, Data Management Analysis, Conceptual Skills, Diagnostic Capability, Change Management, Judgment Skills, Relationship Building, Emotional Intelligence, Curiosity, and rate each of the capabilities on a scale of 1-5 (1= Not Present/Essential; 5= Critical Success Factor/Very Essential). I will also analyze any significant differences depending on the participant's role (e.g., manager, technologist, or senior leader).

AI Tools Business Outcomes and Drivers

A senior digital leader in a financial services company aptly framed the business context in championing and implementing AI tools when he said, “AI changes nothing, and AI changes everything.” While his paradoxical statement was meant to be provocative, he further explained that pulling together an AI proposal to be funded is no different from any other investment that senior leaders consider. He stated that one needs to build the business case, understand “what is the impact on the P&L,” pitch it and ensure that it meets the financial targets once implemented. This part has not changed. How “AI changes everything,” and the fundamental difference from the past is that AI provides the organization with instantaneous data to dig into where you can see patterns and trends to assess what is happening in the marketplace.

In the companies that participated in the research study, AI tools were built for various business applications at multiple levels of complexity. See Table 5.3 Types & Complexity of AI Business Applications.

Table 5.3.

Types & Complexity of AI Business Applications

Company's Industry	Applications Discussed	Application Complexity	Degree of Complexity			
			Low	Mod.	High	Totals
Manufacturing	• Industrial Sales Customer Quote Pricing	+		2	1	3
Retail	• Customer Sales & Inventory Fulfillment Optimization	+	2		1	3
Retail	• Markdown Pricing Optimization Tool	+		3		3
Consulting: Health Care	• Physician Patient Ambient Listening Tool	+	1	2		3
Consulting: Business Technology	• Consultant Staffing Tool	+		1		1
Telecommunications	• Internal Sales Voice Activation Chatbot	+	2	1		3
Pharmaceuticals	• Drug Candidates Screening	+			1	1
Technology	• Internal Learning Platform	+			4	4
Financial Services	• External Customers Voice Activation Chatbot	+	3	6	4	13
	• Financial Processes Automation	+				
	• Sales Processes Automation	+				
	• Backoffice Financial Operations	+				
Health Systems	• Patient Telemetry Assessment Tool	+			3	3
Health Systems	• Patient Outreach Information Tool	+			1	1
	<i>Total</i>		8	15	15	38

Red=Low Complexity AI Applications Blue=Moderate Complexity AI Applications Green=Higher Complexity AI Applications

As noted in Table 5.3, various business problems or opportunities were being solved at varying degrees of AI tool complexity. For example, at the lower end of the complexity scale, a financial services company built RPA tools to eliminate manual steps where finance and sales operations colleagues manually inputted data from one system. Now, the data automatically flows into information technology systems. One of the driving aspects and benefits of implementing these tools was to improve employees’ day-to-day work experience. One financial services executive described how the RPA effort from an “overarching thematic from an FTE standpoint was to do more with less; our employees felt overworked and did not see career trajectory.” Also, at the lower end of

complexity, a customer service supervisor, working with his internal technology organization, retrofit an external-facing (for residential customers) chatbot to be used by sales representatives when they needed assistance from an internal help desk. The catalyst for building this tool was a cutback in external contractors, as there would be only one full-time individual to handle the volume of calls. As necessity is the mother of invention, this individual took the initiative to meet with the technology team that built the external-facing tool; learned how to code, and single-handedly managed the implementation.

On the higher end of AI tools complexity, four organizations deployed AI tools integral to achieving their strategic objectives. A pharmaceutical organization has built its business model utilizing AI to identify potential drug candidates they can bring to market. This organization scans the medical literature using Natural Language Processing (NLP) to identify potential compounds in clinical trials from other pharmaceutical companies who subsequently did not continue the development process or decided not to bring the drug to market. The Chief Scientific Officer summed their approach when he said:

What we've done here is to look for opportunities and drugs that have been around for a number of years. There are probably 1000-2000 drugs that are parked on the sidelines that failed clinical trials not because they weren't good drugs and not because they did not do what you wanted them to do; they were put aside; big pharma is very reluctant to revive them because they are just full speed ahead on their other compounds.

A technology organization has built an internal learning platform for its hundred thousand-plus employee base. Because of its success, they use it as a revenue-generating product by offering it to their external clients in the marketplace. One of the senior leaders described the driving need for this product when she said:

We were using a learning management system which was not working well. And our folks did not like it. At the same time, they are consuming information outside of the organization in a very user-focused manner that's quick and easy, and there seems to be this divide between what we had internally and then their experience of learning externally. And they preferred that external experience.

In addition, one of the technologists further commented on its success when he provided the following statistics and stated the following, “our NPS (net promoter score)⁶¹ has increased from 23 in 2016 4Q to 64 in 1Q this year; I have 470,000 unique visitors; 98.8 million pageviews and tens of millions of completion records, and 13.7 million learning hours consumed.”

Based on a set of 21 variables, a global consulting organization has internally developed and deployed an AI tool to predict how long it will take to redeploy a person after the person goes off a consulting project. A critical success factor in any business is the efficient use of their fixed capital costs. In a labor-intensive industry, like consulting, it is critical to ensure that their professional staff is fully deployed and generate revenue. The senior leader responsible for deploying this tool characterized how it worked when he stated the following.

Before a consultant goes off a project, we have 90 days to look at multiple options; either we can upskill the individual, or we can think about a different project in which this person can be deployed. What the tool has done is that it has given us a beautiful prediction almost daily for all our employees. And I think it has helped us a lot; the model has reached about 86 to 87% accuracy versus where we started at about 60-65%.

⁶¹ Net Promoter Score was developed by Fred Reichheld when he was at Bain & Co. NPS is a simple but elegant measurement that tracks net promoters—the percentage of customers who are promoters of the item being measured minus the percentage who are detractors. It is calculated by the percentage of customers who respond with nine or ten (promoters) and the percentage who respond with zero through six (detractors). Subtract the percentage of detractors from the percentage of promoters to arrive at the net-promoter score (Reichheld, 2003).

Lastly, a financial services company built a virtual voice assistant, similar to Amazon’s Alexa. Their customers use it to solve their common inquiries (e.g., what is my balance?) or provide proactive alerts when they act. This customer product offering has dramatically increased customer interactions through their omni channels for this financial services company.

See Table 5.4 for a compilation of the responses by participants when they were asked to “Review the below list for the possible AI & emerging technologies that have been implemented in your team/unit/function. Circle all that apply.”

Table 5.4.

AI Tools Implemented

	Question 1: Review the below list for the possible AI & emerging technologies that have been implemented in your team/unit/function. Circle all that apply.						
	RPA	Chatbots	Machine Learning	Predictive Analytics	Productivity Bus Intelligence Tools	NLP	Imaging
Total (126)	14	12	30	21	21	22	6
%	11.1%	9.5%	23.8%	16.7%	16.7%	17.4%	4.8%
Low Complexity	4	2	3	2	6	2	2
Moderate Complexity	6	5	12	9	9	8	1
High Complexity	4	5	15	10	6	12	3

In aggregate, at the lower end of complexity, digital tools such as RPA (Robotic Process Automation), Chatbots, and Productivity Business Intelligence Tools (e.g., Tableau, Workiva) had 47 total mentions of 126 total mentions (37.3%). At the higher end of complexity, I defined it as processing high volumes of unstructured or structured data along with high degrees of computing power to run statistical neural network tools. In aggregate, AI tools such as Machine Learning, Predictive Analytics, and NLP had 76

total mentions out of 126 total mentions (60.3%). Also, in reviewing the differences among research participants who identified the AI tools they implemented as high complexity, they had an aggregate score of 55 with ML, Predictive Analytics, and NLP, totaling 37 (67%).

In terms of business outcomes, I collected information through the quantitative survey and the qualitative conversations. In the quantitative survey, I asked participants to rate how successful or impactful AI has been in 6 areas (e.g., Tangible Quantitative Business Results, Risk Mitigation, Predictive Modeling to Supplement Human Judgment, Customer Satisfaction, Engagement or Loyalty, Employee Satisfaction or Engagement, and Team Self-Management) on a scale of 1-5 (1=no impact and 5=high impact). Table 5.5 summarizes the aggregate totals.

Table 5.5.

AI Impact/Success

	Question 4: Rate how successful or impactful AI has been in the following areas (1=Low Success, 3=Some Success . 5=High)					
	4a. Tangible Quantitative Business Results	4b. Risk Mitigation	4c. Predictive Modeling to Supplement Human Judgment	4d. Customer Satisfaction, Engagement or Loyalty	4e. Employee Satisfaction or Engagement	4f. Team Self-Management
Avg.	3.8	2.8	3.2	3.2	3.6	3.0
SD	1.2668	1.3693	1.2317	1.5237	1.5362	1.6078
Sr. Ldr. Avg.	3.9	2.3	3.1	3.3	3.8	2.9
Mgr. Avg.	3.8	3.1	2.7	2.7	3.3	3.5
Tech. Avg.	3.5	2.9	3.9	3.5	3.7	2.6
Low Complexity	3.5	2.5	2.6	3.3	3.8	3.4
Medium Complexity	3.8	2.3	3.1	2.6	2.9	2.8
High Complexity	3.9	3.8	3.9	3.8	4.4	3.1

The categories with the three highest scores were employee satisfaction (3.6), tangible business results (3.8), and customer satisfaction (3.2). In reviewing the differences among research participants, who identified if the tools they implemented were high complexity, they self-scored themselves higher in every category except in the Team Self-Management category. If the AI tool was primarily internally focused (e.g., pricing tool), this impacted employee satisfaction more than if the tool was more externally focused (e.g., Customer chatbot), moving employee engagement. For example, one of the retail companies implemented a means to better predict the right inventory at the right location to minimize stocks and transportation costs. Due to the implementation of an ML tool that was able to crunch large amounts of different data, it freed up supply chain management professionals to focus on other strategic initiatives (increasing employee satisfaction), and customers were able to get the products they warranted (impacting customer satisfaction)

In terms of business results, certain factors impacted the degree of impact, either at the team level or the broader organizational level, which was achieved by the various teams/administrative units who implemented AI. One variable is the degree of complexity of the tool that was implemented. For example, AI tools in lower levels of complexity usually had more localized impact to the specific unit that implemented them. As mentioned earlier, the organizations whose AI tools had higher degrees of complexity were also the same ones (in most cases) had a more significant strategic impact on the firm, as evidenced by their scores in this category. Another variable is the stage of implementation of the tool. For example, one of the health care system organizations is

implementing an AI tool that will solve several problems over a multi-phase effort. The first (& current) phase predicts which patients are currently on telemetry to monitor their heart rhythms. Because they are costly to operate and hospitals only have a fixed amount of telemetry units allocated, the first phase involves deciding when it will be safe to take a patient off telemetry. The second phase of the project will determine who should be on telemetry. Third, the nature and degree of specificity of the business problem or opportunity that was being targeted. For example, in the retail company mentioned earlier, the organization was able to reduce its costs in the \$10–20-million-dollar range.

AI Tools Strategic Implementation & Change Management

This section outlines the various approaches that the companies described in implementing the AI tools, emphasizing their change management techniques. The degree of change is related to several dimensions, including how significant its impact is, how fast the change needs to be implemented, or the scale of the change. Figure 5.2 shows a visual representation of the model assessment (Heidrick & Struggles, 2016).

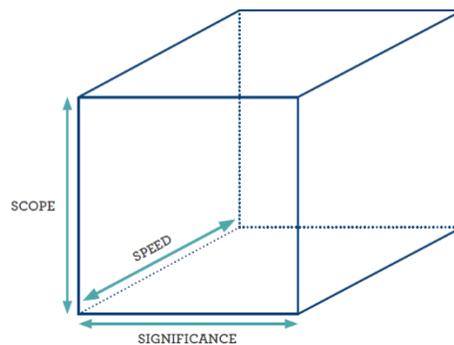


Figure 5.2. Implementation Model Assessment

For the scope factor, the key questions include: Is it contained within a unit or more systemic across the firm or the industry? How big is the scale? (e.g., # of Transactions, External Parties Impacted, Cross Boundaries, etc.). The key questions for the significance factor include: Do the changes influence the business model, strategy, and business operations? Or are the changes more profound at the other end of the continuum, foundational that challenge the firm's mission and core values? Lastly, for the speed factor, the key questions include: Is it evolutionary or continuous improvement change or discontinuous or frame-breaking? In reviewing the organizations that participated in the research study, the applications related to health care were of higher significance because they fundamentally altered patient care directly or the practice of medicine. Also, they were higher on the scale factor because of the number of internal hospital groups that needed to participate in the effort, either as approvers, regulators, or monitors. Those organizations, who were implementing process automation applications, impact were limited within their teams or units; the improvement was incremental and had limited impact to the firm's operating model.

At its basic superficial level, AI is a software implementation. Yet, at the same time, it fundamentally changes the nature of work, impacts decision making; the degree it crosses organizational boundaries (especially data flow); the need for collaboration across organizations, and how it potentially benefits employees, customers, and a firm's position in the marketplace. A manager, a retail company, aptly summarized the importance of change management to AI implementation when he stated the following:

I think the biggest challenge that I've always seen is change management. I'd seen it as the factor that makes or breaks it to implement AI tools. But when you're implementing AI tools, that also means that you're going to have to trust the AI system. So, as you're bringing in new technology, you're changing the way people

work. I will say even more important than actually knowing how the tool's analytics works, and it is change management.

To understand the specific implementation and change management process, plan, and elements, I asked each interview participant about their approach and collected objective data. Next, I asked participants to review a list of critical success factors in implementing AI in their team/unit/organization and to identify all those potential factors that apply. See Table 5.6 Implementation Critical Success Factors that summarizes how the specific participants responded to this question.

Table 5.6.

Implementation Critical Success Factors

	Question 3: Review the list of critical success factors in implementing AI in your team/unit/organization. Circle all that apply.								
	3a. Sr. Leader Engagement & Involvement	3b. Ongoing Communication to Employees	3c. Commitment to Employees Career mobility and Development	3d. Manager's Knowledge of AI, Modeling and Technology	3e. Internal Champion or Evangelist	3f. Training of Employees	3g. Change Management Strategy	3h. Project Management Routines	3i. Governance Processes
Total	36	19	11	18	28	21	20	13	14
%	86%	45%	26%	43%	67%	50%	48%	31%	33%
Sr. Leader	13	7	5	6	11	9	10	4	6
Manager	11	6	4	7	7	7	3	5	5
Technologist	12	6	2	5	10	5	7	4	3
Low Complexity	7	4	2	1	6	2	2	3	3
Moderate Complexity	14	6	4	7	12	10	11	5	5
High Complexity	15	9	5	10	10	9	7	5	6

The number one factor in implementing AI is Senior Leader Engagement and Communication, as cited by 36 of the 38 participants who completed the survey (95%). Followed by Internal Champion or Evangelist (74%), Training of Employees (55%), Change Management Strategy (53%), Ongoing Communication to Employees (50%),

Manager's Knowledge of AI, Modeling and Technology (47%), Governance Processes (37%), Project Management Routines (34%) and Commitment to Employees Career Mobility and Development (29%). In reviewing the scores by population, the critical success factor Change Management Strategy scored a ten by Senior Leaders, which is much higher than the Manager and slightly higher than the Technologist rating. Also, "High Complexity" scored the highest on Sr. Leader Engagement & Communication, Managers Knowledge of AI, Modeling, and Technology.

In general, the qualitative interviews are consistent with the findings from the survey data and fall into the following three overarching categories:

Senior Leader Engagement and Direction: Senior leaders have a profound influence because of certain roles, such as setting direction, monitoring behaviors & metrics, and have the ability to deploy a variety of organizational and cultural levers to drive change. Senior leader engagement is one of the differentiators for successfully implementing digital transformation when comparing leading vs. laggard (or high performing) companies (Brock & von Wangenheim, 2019), as they have engaged and knowledgeable champions at the C-suite (Balakrishnan, 2020). According to upper echelons theory, organizational outcomes, such as AI, are influenced and partially predicted by the beliefs of the top-level management team. (Gfrerer et al., 2021).

Because senior leaders were one of our interview groups, I collected specific ideas to implement the AI tool. First, they acted as provocateurs to challenge the organization to utilize digital tools. For example, a senior leader from a retail company said:

Some of those tasks were very process-heavy. And the answer in the past has always been we need more people to kind of do it. And because we were able to

use automation, the conversation is different. So, if we now run into a task that is overbearing or very repetitive, the question is, well, why can't we automate? It gives people a tool that can solve their problems versus just saying I'm stuck and I'll work harder.

Also, senior leaders ask the right questions to frame the business challenge/objective before embarking on an AI effort. One of the pharmaceutical company senior leaders summed it when he said, “you need to spend a lot of time defining the questions, and defining the question is half the problem.” Secondly, senior leaders create a pull to use AI or other digital tools by providing an overarching challenge that catalyzes the organization to use digital tools to achieve the financial or operations objectives. One of our technologist research participants said the following about her senior leaders:

Four or five years ago, we tried this, and it didn't work, and two years ago, we tried something different, and let me tell you, what is the difference. Our senior leader told his direct managers that they had to find 3% in savings. Until he pushed, until he created the demand, there just wasn't the appetite. His point was to create demand for people to want automation, and he's right, and I can't keep up with the amount of training my team has to do for people right now who have an interest.

Third, the most senior leader usually needs to fund the effort and sets return on investment guidelines. A senior leader from a telecommunications firm said:

We are very financially driven. We are looking for in-year payback and how quickly you can get results and commit to achieving the results. It has to be a cost or efficiency play or a revenue play. The first question that I ask is when's the payback. If it's 12 months, I ask, can you get the payback in 8 months? What I do is pushing a little more on the payback to go faster and do more.

Fourth, they act as a direct sponsor of the activities and act as evangelists for the tool. On the survey, the internal champion or evangelist was the second-highest total in the top three, with 28 mentions. The role of an internal advocate or evangelist was evident in just about all the examples. A good example was when the CIO and

CEO/Board members got behind an initiative at a manufacturing company (owned by a private equity firm) and funded the effort. The organization would not meet its financial plan if the AI pricing effort were not undertaken. The project resulted in more consistent pricing for customer quotes by not leaving money on the table or winning more profitable business because the quotes were priced competitively.

Robust Technology Implementation Approach. One of the other contributing factors cited by many participants was their ability to follow a full technology implementation process. This approach had several elements, including a governance and project oversight process, especially in more regulatory environments, development of prototypes or minimum value products that demonstrate tool functionality, and the utilization of agile software development methodology. A technologist from a financial services company outlined how they utilized the agile software development methodology as they built enhancements to the AI tool:

We believe in the Agile methodology, and we believe in getting something out to customers as fast as possible. If someone wants to implement a new feature, we first asked the person to develop a business case. And then, we call the intake meeting to understand the problem statement. Once the problem statement is understood, we will assign an architect. Then we will talk to the respective teams to figure out where I get this data and put together an architecture design. Depending on the size of the feature or the size of the work, we break it down. Each feature is sized to fit within two to three sprints, each last about two weeks.

Several research participants discussed how initial prototypes of the product were needed to demonstrate enough functionality to gain users' support. A technologist from the technology company said, "AI-generated recommendations still have to pass the sniff test for it to be credible. If you have a critical mass of users that are getting just junk, that's a problem". This company, which implemented a new learning platform, kept track

of what users were clicking on and not clicking on and also utilized A/B testing to test new functionality. The CIO of a retail company reinforced this point when their organization ensured they compared the results using the former methodology to the results generated by the AI machine learning solution. Their application was utilized to process customer orders, and they made a line-by-line comparison from the old system vs. the new system. The tipping point occurred when the new system seemed to make sense compared to their former operating system. These examples assist users in building trust in the tool, which is a prerequisite for believing in its functionality, especially when making predictive recommendations.

Training and Commitment of Employees: The third central element in implementing AI tools is engagement, commitment, and skill-building for employees, which help build momentum for using the tools. Companies with a future-ready workforce deliver 19 percentage points higher revenue growth and 15 percentage points higher net margin than their industry average (Dery et al., 2020). A senior leader from a technology company discussed how the CEO reports on employee training, development, and skill acquisition are one of the “seven or eight different sections that he reviews with all shareholders.” Some of these efforts can be characterized as the use of pull energy (“carrot”), including articulating the WIIFM (What Is In It for Them) vs. push energy (“stick”), ensuring that employee concerns were addressed. A creative WIIFM idea that a technology company deployed was a digital badge for super learners who achieved 120 hours of training. If the person completes the badge, they can post it on LinkedIn.

Managers stated that AI tools would free up employees' time to do more value-added work in several organizations. If employees do more value-added work, it stretches

their abilities, gets them to exercise more independent judgment, and reinforces that there is “no real threat to anybody’s job.” One manager described how he supported this approach with employees when he said,

I would propose talking to the team to say we can do more thoughtful work. Suppose we're not spending time doing this other work. In that case, we can focus on the exceptions and avoid talking about cost savings. If you tee it up that we've got this opportunity to automate mundane things, we can probably free up an hour of everybody's time to think about strategy or think about how we improve processes.

Although AI would not threaten employees employed in certain circumstances, there is always some hesitation to participate in these efforts. Several research participants acknowledged that they had to deal directly with this hesitancy, which is a typical concern by employees. One manager said the following,

There could be concerns that when you bring in this model, it is going to take away my job. So, we have to convince them that this is going to be a hybrid setup. Whatever we are doing will help the human because earlier, there were things there were being missed. It was a nightmare for an efficient person to look through these items, so now we are giving aid to them with AI.

One way to deal with this hesitancy and help build their skills was to offer training for employees. This helped associates with their current role of mastering the AI tools to work on value-added tasks. One technology manager described how a segment of employees became passionate about driving manual processes out of their organization which caused them to show up for learning events. As a result, skilling employees in AI and emerging technology was prevalent in several research studies.

One unique example was when a financial services company developed a skill-based AI/Machine Learning curriculum for the following population: project managers, architects, agile coaches, functional managers, business analysts, and product owners. They categorized their learning efforts into three categories: 1. Root: The roots of the tree

are interconnected disciplines that provide the foundation's data science. This category includes courses in calculus, intro to data structures, intro to data management, and scientific method and reason. 2. Branches: The tree branches represent various topics that can be selected depending on interest and areas of desired expertise. In this category are courses in NLP, cloud computing, and computer vision. 3. Trunk: The trunk of the tree represents topics that require intense dedication and expertise. Courses include advanced optimization, programming in Python or R, machine learning foundations, etc. In this financial services organization, the technology function sponsored hackathons and coding contests where they selected top talent, trained them in AI tools, and then had them work on a real business opportunity.

Involvement of Associates and Users. One of the leading tenets of change management and successful implementations is the participation of those most impacted by the change. If individuals participate in the design of any improvement effort, it increases the probability that they will be genuinely committed vs. grudgingly complying or, at worst, covertly undermining the effort. When employees suggest improvements, tiny tweaks, and changes, this increases trust (Hosanagar, 2019) with the algorithms. Also, the motivation and willingness to change are higher when they get actively involved in the process from the beginning (Gfrerer et al., 2021). Several research participants described how they gain commitment to their AI tool and various approaches they used. Some ensured they started as early as possible, laying the groundwork, especially with functions needed to support the tool and minimize potential blockers. Another person described how he finds one or two champions, gets their feedback on the idea, builds an MVP for them, iterates, and “then start to open it up to a wider audience

whoever wants to use it and that is how you reach critical mass.” Another individual described how in designing the AI tool, they were conscious of not altering the workflow or require extraordinary effort on the part of the users in utilizing the tool. One of the technologists from a health care system described his change management approach used by his senior sponsor when he said:

From a change management perspective, I learned this from one of the physicians I worked with on a project. It is like a political kind of move. You find early adopters, and you approach those first. Get great results. Slowly grow early adopters, especially those that are on the fence. And then, pretty soon, the ones who are very against it become the supporters.

Managerial Mindset, Roles & Tasks

Considering the first two sections—AI Tools Business Outcomes & Drivers and AI Tools Implementation & Change Management—combined with the qualitative and quantitative data on manager’s roles, this section will describe the underlying mindset, roles, and critical tasks for managing in an AI environment. The three elements of mindset, roles, and tasks or activities are interrelated.

Managerial Mindset

Mindset, defined as mental lenses that dictate what information leaders take in and use to make sense of or navigate the situations they encounter (Gottfredson and Reina, 2020) is something individuals need to have as they lead their teams. Their mindset directly impacts their role in the organization and ultimately the tasks, responsibilities, or duties ("what") they undertake. For example, leaders who have a “deliberative and implemental mindset”⁶² are receptive to all types of information as a way to ensure they think and act optimally (Gottfredson and Reina, 2020).

⁶² See footnote 36 for a description for other mindset types.

Based on the qualitative interviews, two related mindsets were identified curiosity and experimentation, especially in AI implementation. Due to the nature of agile software development and how AI models are conceptualized, implemented, and refined within organizations, several participants discussed the need for managers to bring an experimentation attitude to managing their teams. A technologist from the health care consulting firm said:

The management model needs to be able to incorporate experimentation. This is a challenging aspect because our managerial theories are still like Taylorism. Need managers who enable team members to have a bit of that experimentation baked into their workflows. The AI model is probably not going to be right, and it's going to take some iteration.

Curiosity was the second mindset that emerged from the qualitative interviews and the quantitative survey. In the quantitative survey, question 5 focused on managers' critical capabilities to succeed in an AI environment. Curiosity was one of the 13 items that I asked participants to rate on a scale of 1-5 (1=not present/not essential; 5=critical success factor/very essential). Curiosity was the highest rated item with an average score of 4.5 and the lowest standard deviation of .72. It was named one of the top three items by 17 of the 33 individuals who completed surveys. Parenthetically, questioning is a closely related concept that was the second highest-rated item with a score of 4.4 and had the second-lowest standard deviation of .78. One participant felt that there was a close conceptual connection between curiosity and questioning when he said, "because if you're questioning something, then you're acting on your curiosity. But if you're questioning, then hopefully you're turning curiosity into a question that you're trying to see what is the right answer." There were two dimensions where being curious was highlighted by interview participants. First, individuals utilize critical thinking, analyzing

recommendations from the AI model, questioning, probing, and attempting to understand the logic that drove the output from the AI model. A technologist from the technology company said, “if a recommendation comes up, you need to be able to evaluate it effectively. Need to ask yourself what is being recommended to me? Do I think it's going to move something from point A to B?” The second aspect of curiosity is the drive to learn emerging technology concepts consistent with Carol Dweck’s notion of having a growth mindset. A technical manager summed it well when he said the following:

I'm a computer scientist by trade. So, I would tell you that technical managers need to have curiosity. The most important thing that they need to the ability and the time to continue to stay up in the various fields. So, as an example, there's a lot of noise right now around GPT3⁶³. And the question is, how does that apply? So, it's always looking at what is state of the art.

Manager’s Role

Curiosity and an experimentation mindset are critical catalysts in informing or shaping the manager’s role and activities. Managers play a pivotal role in employee engagement, productivity, and motivation. Employees' relationship with management is the top factor in job satisfaction (Allas & Schaninger, 2020), and employees with effective managers give 38% more discretionary effort (CEB's 2017 New Manager Mandate Study). Also, managers impact psychological safety, which is necessary during periods of change, such as AI or technological disruptions, which by its nature will evoke stress, uncertainty, and impact productivity.

At the strategic level, managers in an "AI-powered operating model" assume several roles for operating effectively in this environment (Iansiti & Lakhani 2019; Ready

⁶³ Generative Pre-trained Transformer 3 is an autoregressive language model that uses deep learning to produce human-like text. It is the third-generation language prediction model in the GPT-n series created by Open AI, a San Francisco-based artificial intelligence research laboratory. (Source: Wikipedia)

et al. 2020, De Cremer, 2020), including being designers, innovations, integrators and connectors, guardians, explorers, and conductors. Based on the interviews and analysis, four major categories comprise the manager's role, which includes the following: Human and Technology Resources Manager; Change Agent; Connector, Integrator & Service Provider, and Efficient Continuous Improvement Operator. In addition, in the quantitative survey, I asked participants to rate the duties of a manager to be successful in an AI environment (See Table 5.7).

Of the ten items, seven items scored a four or more, with the top-rated item scoring a 4.3 (with an SD of 1.01), which was 6c (*Exercise Judgment to Evaluate the Use of AI, Quality of the Model and Results*). Two items scored a 3.9, and one item (the lowest-rated item) scored a 3.5 (with an SD of 1.11), which was 6d. (*Empower Employees to Be Self-Directed.*) For each of these ten items, I categorized them into one of the four categories. The following section will detail each of these role areas, including the identification of core activities.

Table 5.7

Successful Manager Duties

Question 6: Rate the following duties of the manager to be successful in an AI environment. 1=Not Present/Not Essential; 3= Somewhat; 5=Critical/Very Essential										
Category	Human & Technology Resources Manager	Human & Technology Resources Manager	Human & Technology Resources Manager	Human & Technology Resources Manager	Human & Technology Resources Manager	Connector, Integrator & Service Provider	Connector, Integrator & Service Provider	Change Agent	Efficient Continuous Improvement Operator	Connector, Integrator & Service Provider
Item	6a. Monitor AI Outputs and Decisions	6b. Ensure Data Integrity	6c. Exercise Judgment to Evaluate the Use of AI, Quality of the Models and Results	6d. Train & Coach Employees	6e. Empower Employees To Be Self Directed	6f. Manage Key Stakeholders	6g. Work Collaboratively with the Technology Organization	6h. Implement a Change Strategy	6i. Looks for Opportunities to Expand the Team's AI Footprint	6j. Ensure all facets of Data Privacy and Security Are Maintained
Average	3.9	3.9	4.3	3.5	4.0	4.1	4.2	4.1	4.0	4.2
SD	1.168897	1.212318	1.016834	1.110416	0.970236	0.930763	0.844714	0.972619	0.924055	1.15737
Senior Leader	4.3	4	4.2	3.7	3.6	3.7	4.3	4.2	3.8	4.7
Manager	4	4.5	4.2	3.5	4	3.9	3.9	4.2	3.9	3.9
Technologist	3.7	3.3	4.6	3.2	4.2	4.5	4.2	4.1	4.1	4
Low Complexity	3.5	4.5	3.6	3.1	3.9	4.4	3.8	3.8	4.1	3.5
Moderate Complexity	4.3	3.9	4.5	3.5	3.7	4.1	4.2	3.9	4.1	4.3
High Complexity	4.0	3.7	4.4	3.6	4.1	4.0	4.3	4.0	4.3	4.0

Human and Technology Resources Manager: Six of ten survey items were categorized into the Human and Technology Resources Manager area. These six items include Monitor AI outputs and decisions; Ensure data integrity; Exercise judgment to evaluate the use of AI, quality of the model(s) and results; Train and coach employees; and Empower employees to be self-directed. Because AI tools will be crucial in improving team and individual productivity, their use will aid decision-making and analysis. AI will provide additional insight (e.g., “augmented intelligence”) to solve problems and be embedded in business workflow or decision-making processes. Managers will need to encourage employees and themselves to utilize augmented intelligence insight and exercise their judgment to evaluate AI outputs.

There won't be a conceptual or practical distinction from managing people or technology, so managers will need to oversee both types of resources simultaneously. One technology manager from a financial services company aptly described the need to manage AI tools and people when he said the following:

In the future, managers will be managing machine learning models and maybe bots which their team members create. Tomorrow it could be a machine learning model developed by one of my team members, and that machine learning model takes decision rights for the organization. Suddenly, as a manager, my risk has increased because I'm not just responsible for the actions of my team member. Still, I'm also responsible for the actions of the models that my team member developed. We ensure that the model is doing what is supposed to do that it is not ethical, it is not biased.

To ensure that employees have the skills to work with AI/digital tools and understand what drives the AI model to make the recommendations, managers play a pivotal role in training and coaching employees. A senior leader from a technology company stated that AI tools would enable employees to move from transactional-based

activities to more client servicing or analytically-based activities. He said that there would be a “significant amount of reskilling will be required, and primarily managers will be the ones who have to lead from the front and take their teams along with them.” In addition, managers will begin “moving from providers of employment to enablers of employment,” therefore managers will see the potential career growth for their teams. They will need to help individuals along their learning journey to get them ready for various roles within the corporation. If implemented successfully, AI can help managers sharpen the focus of their team’s resources and time to meet the demands of their internal or external marketplace. One technologist from a technology company said the following:

AI will allow them to rebalance their resources to focus less on the minutia because the AI tool can provide the list of the five things I recommend. As a manager, I don't have to spend all my time searching or recommending, getting a staffer to do it, or having each of my staff find their path. Rather I can use the AI to say ok, and this is a good path. This is the path that will I push for all my people, and then augment it tailored for each person.

To maximize the power of AI tools to ensure actionable and insightful results requires the manager to grasp the data source, ensure high data integrity that feeds the model, and the relationship of the data to the problem being solved. One of the items on survey deal with data integrity. A senior manager in a pharmaceutical company reinforced this point the importance of data integrity when he said, “we need access to data. Good data is always going to be paramount, and that data can be harmonized, synchronized, and at least normalized, you need to be able to quality control it to make sure that it's usable.” A technologist reinforced this point when they said that the “outcome depends heavily on the data set to train the model. It is also dependent on the

quality of how crisply you can define the outcome. You have to have data to train, so you have to have a well-defined accurate set of data representing that targeted outcome”.

Change Agent: A second essential role that managers assume is one of a change agent. In the quantitative survey, item 6h. *Implement a Change Strategy* scored a 4.1 with a standard deviation of .97. There are three broad dimensions of being a change agent with a corresponding set of managerial activities. The first dimension is setting the stage for the change effort with employees and users, so they readily accept the tool, use it effectively and see its benefit to their day-to-day duties. One way to ensure acceptance of the tool is to create value-added features and minimize any extra effort by users. For example, a health care system developed an ambient patient listening tool. The output (which resulted in a document that captured the patient-doctor interaction) did not require much physician editing. Also, physicians were able to gain insight by seeing patterns in their approach to patient care.

In particular, managers need to deal with employees’ natural unwillingness to participate in activities that could result in job elimination and role diminution. A technologist from a financial services company was mindful of this dynamic when he said:

A manager needs to be aware of the hesitancy for some folks to automate. There's a human aspect, where if you talk about automation, there's this concern that tasks that I do every day will be eliminated due to automation. So sometimes there's a hesitancy on the part, just from a human nature perspective, to offer things up to automate, where it makes sense because folks don't want to minimize their jobs or the work that they do.

One way to deal with this hesitancy and gain commitment is to actively involve associates and users in the tool creation and development and be mindful of how the AI

tool would impact their work. The magnitude of the risk or change to the status quo is directly related to the degree of hesitancy. This is probably felt most acute in health care settings because the tool potentially impacts patient care and health. A senior physician leader in a health care system was tuned in to these concerns when he said the following:

If the process is already established, it is important that you don't want your model to create a new process. You want your model to be able to gain acceptance faster. So, I have had many talks with them on how we will integrate it, so they were ok with that. I took their protocol and put it in where people will continue doing what they are doing. We are just going to augment what they are doing.

The second dimension is the reskilling and upskilling of employees (or users) and crafting communication messages to gain acceptance (or minimize covert resistance) and create enthusiasm for the tool. A manager in a telecommunications company described their efforts in training and communication when rolling out their digital tool. He stated the following, “We made sure that we had education, we did short videos on it, created documentation. Went out and did demos to our end users, so they were aware of it; how to use it and how to access stuff”. The communication strategy ensures that the messages are crafted and customized to the particular audience's needs, hesitancies, and motivations. Some training and communication success factors include having a constant stream of messages, having a formal and structured delivery approach, and ensuring that the statements address the population's breadth and depth. When implementing a new AI tool, a manufacturing company utilized a pilot from one or two European markets before implementing a broader rollout. It kept senior leaders involved in the effort.

Connector, Integrator, and Service Provider: The development, implementation, and refinement of AI models and tools require close integration and connection across several organizational elements—people, functions, hierarchies, data, strategies, and

external suppliers. Managers assume a key integration role among these various elements. Three of these activities were highlighted and rated in the quantitative survey. These items include 6j. *Ensure all facets of data privacy and security are maintained* (4.2 average scores with 1.15 SD); 6f. *Manage key stakeholders* (4.1 average scores with a .93 SD); 6g. *Work collaboratively with the Technology Organization* (4.1 with a .84 SD).

Managers play an essential role in boundary management both within their organization and across external organizations. For example, three research companies purchased their AI solution from third-party external system providers, which necessitated the manager to work with them and their respective internal technology organizations. In some instances, the manager needs to ensure continuous follow-up with the technology teams so that they “do not miss deadlines.” The manager might have to “reach out to them for any clarification and provide data so that we are not delaying the process from our end and the technology team can deliver.” In terms of data integrity, managers should be aware of the “data that gets fed into the system” and “data that comes out of the system that is used downstream.” A senior manager in a pharmaceutical company reinforced this point about data integrity when he said, “we need access to data. Good data is always going to be paramount, and that data can be harmonized, synchronized, and at least normalized, you need to be able to quality control it to make sure that it's usable. Managers are really the connective tissue among the data that is fed to them, transformed by them, and then sent to other parts of the organization.

One dimension to the manager's role as an integrator and connector is within their own team's internal organization structure when they have a versatile set of disciplines or functions represented on their team. This was evident as described by senior line business

manager, who is responsible for their company's external-facing digital tool, when he said:

We have a lot of folks with deep expertise in data analysis, systems development, but also folks who came from product development or a marketing perspective effectively coming together. We have insight development, feature development, product owners, analytics team, performance optimization. We also have a dedicated, experienced design team, which again is a fairly specific skill set.

Lastly, managers can act as 'service providers' to other business users when their AI tools are integral to their service offerings. A technology company built a learning platform powered by AI used by the total employee population and a product offered externally to clients. Therefore, the manager and senior leaders responsible for this tool had to manage and interact with various stakeholders within their ecosystem, ranging from external content providers (e.g., Skillsoft); employees who use the tool and the sales and marketing folks who sell it to external customers. Also, a retail company and a manufacturing firm, the lines of business managers were accountable for providing analytical and pricing support to their merchandisers, supply chain professionals, and the sales organizations. In each of these instances, the AI tool enhanced their organizational reputation and impact on the organization. Still, it requires managers to display a heavy dose of influence, boundary management, analysis, and influence skills. This impact and influence are seen by the below quote from a retail pricing strategy manager when he said the following:

My job is always to provide recommendations. So, my role in advising merchandisers is to see their budget or plans for the year and see how my work aligns with them and how I can help them be more profitable. We tried to explain to them how our recommendations benefit them. And at the same time, we don't want them feeling like they don't have any control over the prices. In addition to all the math and logic behind the recommendation, you still have to stand back

and make sure that the recommendations you're going to provide make sense. There is a logic to it. We're no longer in the back seat.

Efficient Continuous Improvement Operator: The fourth role that managers assume is to manage the entire set of resources under their domain efficiently. They are continuously looking for opportunities to improve their operations, especially their AI and digital tools. If managers possess the mindset of experimentation and curiosity, they will be inclined to continuously improve. One financial service senior manager said, “Projects no longer should exist because a project implies a beginning date and an end date. This is a forever journey, and you will always be improving it. Think of your iPhone; they are up to iOS 12.6.” On the quantitative survey, one of the items dealt with AI continuous improvement: 6i: *Looks for opportunities to expand the team’s AI footprint* (Average score of 4.0, SD of .924). Suppose a manager spends less time on transactional activities. In that case, the manager needs to build the firm’s business or position in the marketplace or create a better employee engagement experience. One financial service senior manager described several examples of questioning the status quo by asking simple questions. He said:

I'm in the third and final act of my career. I want to deliver a business model for my emerging talent that they will want to run, not inherit what we messed up. I've always been described as very creative, whether it be in my business context or this new body of work I'm passionate about. We need people who can ask the what-if question more often than not. I think I'm not unique, but I'm trying to be the sharp end of the spear for my business to be disruptive. I want to be the disruptive guy. I want to ask the question that causes people to think.

With AI tools, managers will need to ensure they are constantly refining and fine-tuning the tool based on input and feedback from their users. This is particularly important in the early phases of a tool’s development when it is still in its learning phase.

In addition, AI tools will cause managers to have more time to dedicate to other business-building activities, and they need to be conscious of how to reinvest this time. Several individuals specifically cited the opportunity to do less non-value-added work like “doing compliance work, crunching numbers, reading policy manuals” and reinvest their time into moving the business ahead. A technology manager from a financial services company highlighted this phenomenon when he said:

Today, a typical business operations team manager spends almost 40-50% of their time in controlling, approving, or monitoring transactions. AI bots or AI-driven tools will do a number of these things going forward. Even the exceptions should be able to manage through automated systems. With that being the case, the manager will certainly have a lot of time in his hands or bandwidth. So that time and bandwidth have to be put in to develop the business. Managers need to figure out a few things. How do I understand the business more rather than just understanding the transactions? How do I know where the revenue is coming from?

Capabilities

This section will describe the capabilities---knowledge, skills, and behaviors---that managers need to deliver on their accountabilities as determined by their roles: Human and Technology Resources Manager; Change Agent; Connector, Integrator & Service Provider, and Efficient Continuous Improvement Operator). This role plays itself in their respective firm’s AI and digital strategy implementation and functions effectively in an AI digitally driven environment.

We asked participants to rate a set of capabilities (e.g., Computational, Algorithmic Thinking or Design Thinking, AI Knowledge, Data Modeling, Cloud Computing, Data Management Analysis, Conceptual Skills, Diagnostic Capability, Change Management, Judgment Skills, Relationship Building, Emotional Intelligence, Curiosity) on a scale of 1-5 (1= Not Present/Essential; 5= Critical Success Factor/Very

Essential). Secondly, participants ranked the other top three capabilities from the list. See Table 5.8 Successful Capabilities Overall Summary, which provides an average for each category, a standard deviation calculation, and a total number identified as the top three.

Table 5.8.

Successful Capabilities Overall Summary

Question 5. Rate the following capabilities (e.g., knowledge and skills) that managers need to possess to succeed in an AI environment. 1=Not Present, 3=Present, 5=Critical Success Factor. Mark an X for your top three													
Item	5a. Computational, Algorithmic and Design Thinking	5b. AI Knowledge	5c. Data Modelling	5d. Cloud Computing	5e. Data Management and Analysis	5f. Conceptual Skills	5g. Diagnostic Capability	5h. Change Mgmt.	5i. Judgment Skills	5j. Relationship Building	5k. Emotional Intelligence	5l. Curiosity	5m. Questioning
Avg.	3.32	3.36	2.97	2.50	3.42	4.20	3.47	3.96	3.99	4.12	3.63	4.53	4.39
SD	1.3200	1.2820	1.4046	1.4096	1.1152	0.8393	1.1695	1.1025	1.0032	0.8960	1.0443	0.7159	0.7793
Top 3	12	8	7	6	6	15	4	7	9	9	4	17	7

The highest scoring items can be characterized as “soft skills” such as Curiosity (4.53), Questioning (4.39), Conceptual Skills (4.20), Relationship Building (4.12), followed by Judgment Skills (3.99), and Change Management (3.96). In addition, Curiosity and Conceptual Skills were #1 and #2 in terms of being in the top three—17 & 15, respectively. Also, Curiosity, Questioning, and Conceptual Skills had the three lowest standard deviation scores ranging from .7159-.8393. At the other end of the spectrum, the lower-scoring items are the one’s that can be characterized as more technical and IT functions such as Cloud Computing (2.5), Data Modeling (2.97), Computational, Algorithmic, and Design Thinking (3.32)⁶⁴, AI Knowledge (3.36) and Data Management and Analysis (3.42). However, Computational, Algorithmic, and Design Thinking’s technical capability was mentioned by 12 individuals as one of their top three items.

⁶⁴ One could make the case that this capability straddles the boundary between softer skills like thinking with technical knowledge of AI and Design Methodologies.

See Table 5.9 Successful Capabilities Role Summary for a data cut by the three roles (senior leaders, managers, and technologists) who participated in the research study.

Table 5.9.

Successful Capabilities Role Summary

Question 5. Rate the following capabilities (e.g., knowledge and skills) that managers need to possess to succeed in an AI environment. 1=Not Present, 3=Present, 5=Critical Success Factor. Mark an X for your top three													
Item	5a. Computational, Algorithmic and Design Thinking	5b. AI Knowledge	5c. Data Modelling	5d. Cloud Computing	5e. Data Management and Analysis	5f. Conceptual Skills	5g. Diagnostic Capability	5h. Change Mgmt.	5i. Judgment Skills	5j. Relationship Building	5k. Emotional Intelligence	5l. Curiosity	5m. Questioning
Sr. Ldr.	3.62	3.69	2.92	2.15	3.31	4.15	3.62	3.85	4.00	3.58	3.60	4.54	4.15
Mgr.	3.46	3.31	3.08	2.46	3.77	4.38	3.54	3.92	3.69	4.23	3.54	4.54	4.46
Tech.	2.83	3.04	2.92	2.92	3.17	4.04	3.25	4.13	4.29	4.54	3.75	4.50	4.58
Avg.	3.32	3.36	2.97	2.50	3.42	4.20	3.47	3.96	3.99	4.12	3.63	4.53	4.39
SD	0.26855	0.21770	0.05842	0.25232	0.20098	0.11107	0.12497	0.09384	0.18965	0.32632	0.06895	0.01424	0.14822

In reviewing the scores by roles, six of the twelve items were standard deviations from .0142 to .1482. Senior Leaders scored the highest in four categories; Managers scored the highest in four categories, and Technologies scored the highest in the remaining six categories. One counterintuitive finding from the quantitative data is that the technologist population had the highest average score in four “soft skills” categories and had the highest average score in just one technical capability--Cloud Computing.

A takeaway from the quantitative survey data supports the idea that managers need to be adept in soft and technical skills to succeed in an AI digitally oriented environment. In the academic literature, Hill (2021) made this point where he described the need for π -shaped individuals who built expertise in several domains, including data science; Smith et al. (2020) made a similar point that managers need to balance analytical

and emotional intelligence. Lastly, a senior business leader in a financial services company stated that a “balance of IQ and EQ is critical.” He further noted that we need individuals who are good at “analyzing data; asking the right questions to get at the data and lastly, translate that data that humans can act upon it.” Based on analysis of the qualitative data, there are three broad categories of capabilities: *Technologically Oriented Skills* (e.g., AI Knowledge, Data Management); *Business Domain Knowledge*, and *Soft Skills* (e.g., Curiosity, Judgment, Communication Skills, Change Management/Continuous Improvement, Questioning, Problem-Solving, Visioning, and Teamwork). Each of these categories is essential and interrelated. For example, an individual needs to understand the business context to understand the potential benefits of building the AI solution. At the same time, the managers need to have a working knowledge of AI to ask probing questions to the software engineers as they recommend potential solutions. Below is a further elaboration of each of these categories.

Technologically Oriented Capabilities: There are two primary technologically oriented capabilities to lead in a digitally oriented environment. The first is a working knowledge of AI. On the survey, 5b. AI knowledge scored 3.36, with Senior Leader having an average of 3.69. There was an overriding consensus that managers do not really need to know the underpinnings of the underlying system or what goes on in the black box. However, they need to understand how AI can be applied to their business problem, application, or “day-to-day work.” One participant stated that this general understanding needs to proliferate within organizations to identify and maximize the potential opportunities that AI or ML could bring to their respective businesses. A senior leader in a pharmaceutical company pointed out that managers “stay away from AI because there

is complexity fear, especially for regular people who don't have engineering or computer science backgrounds to understand or comprehend. AI is not very complex." Also, in certain circumstances, managers need to have enough understanding to evaluate vendor AI tools presented to them. One future development that will impact the degree of knowledge of managers (or other users) is how these tools might become commoditized and as accessible as Excel someday.

In terms of having a working knowledge, there were specific dimensions as described by several research participants. First, managers need to "understand at a high level how results are calculated", which variables should be inputs into the model and understand how the system weighs certain variables or analyzes specific scenarios. A technologist from a health care consulting firm said:

I don't think (managers) need much knowledge. If you manage it (AI tools), you need to know enough to manage it and deploy the tool appropriately. You need to know enough that it is not going to be a silver bullet. You need to know enough about it to understand where you can gain a lot of leverage---narrowly focused problems or questions that you will answer.

Second, managers need to understand the limitations of AI or Machine Learning and understand which problems can be solved by AI, ML, or other digital tools. A technologist from a financial services company reinforced this point and said:

Need a more general understanding of what makes sense to automate and what doesn't. It is logical decision-making and being aware of where I am going to get value from doing automation. If I do this activity once a month and it takes five minutes to do it, maybe I can automate it, but is that as much value as automating something that I do multiple times a day.

Third, managers need to have enough awareness to ask the right question and tie the specific technical AI tools (e.g., NLP, Machine Learning) to the particular business contexts. Fourth, managers need to have enough AI knowledge to ensure that their model

has been deployed in compliance with their respective corporation's policies, requirements, and processes for AI tools. Technology organizations cannot assume the compliance task. Fifth, managers need to have enough understanding to explain how the AI tool came to its conclusions or outputs. A senior leader from a retail company reinforced this point when he said:

I think it broadly knows how these things are employed and enough about how they work. They need to understand that this happens on the outputs when they manipulate the inputs or the dials. Being able to recognize and say I see this in the output. If we miss classifying or if we're too reactive or if I'm not reactive enough in my approach across time, I might see this in the outputs and if my results seem reasonable.

The second technologically oriented capability was data management. In the quantitative survey, two questions focused on data modeling data management. On the survey, 5c. Data Modeling had a 2.97 average with a low SD of .06 and Item 5e. on the other hand, Data Management and Analysis had a 3.42 average with an SD of .20 with Manager, so I asked participants to rank their top three capabilities. In combining the two items related to data, the number of mentions in the top three would total 13 which would be the second-highest rated capability behind Artificial Intelligence.

One of the critical success factors in deploying AI models is their complete dependency on the underlying data that feeds the model to fit the particular problem that the organization is looking to solve. There are specific dimensions that managers need to know as it relates to data management. First, they need to understand "good data is always going to be paramount;" know which databases are compiling the data; and understand the difference between structured and unstructured data. Second, managers need to appreciate that the data is dynamic, especially in models which utilize a

continuous data feed. A senior leader from a financial services company made this point when he said:

Production data keeps changing every day, every minute, every hour, right. If the production volume is too high, outdated data may tweak the model's accuracy. What we are looking at here is a very continuous connection between the actual data and the model. If there is a disconnect between the model and the data, your model may fail. And in fact, the worst part is, it may give you wrong decisions.

Third, managers must understand where the data element stands with the AI model's overall development and implementation. Before any tool is determined, the initial steps are problem statement identification, cost identification, and then selecting the ROI related to the potential benefits, followed closely by data analysis. A technologist made this point, relating a discussion he had with a potential manager.

So, we started with a solution that was the wrong thing to do. So, then we had to tell the client that that's not the right thing to do. First, you have to do something called the analysis of the data. You have to spend a lot of time staring at the data. You have to understand the data and identify the data privacy concerns.

Fourth, managers need to understand the upstream and downstream implications of the data they use and assess their respective models' information. In large complex organizations, data is “interconnected between multiple businesses.” For example, data generated by one part of the business could potentially be used for “cross-selling and upselling” in other business units.

Business Domain Knowledge: This category is defined as the contextual knowledge and skills relevant and necessary for AI and digital tools to be conceived, developed, implemented, and refined within the firm. This knowledge encompasses, but is not limited to, organizational strategy, business processes, regulatory/governmental rules, regulations and requirements, administrative procedures/policies/rules, and to a lesser extent, one’s professional discipline’s subject matter. In each mini-case study, the

various AI or digital tools solve a unique and specific problem embedded in the specific organizational construct even though the underlying tools such as recommendation engines, chatbots, and NLP are general tools that can be applied across industries. There are four dimensions for business domain knowledge.

First, the manager needs to be versatile in the various disciplines that are represented on his team. This notion was particularly true of several companies implementing highly complex tools that had a strategic impact. For example, two pharmaceuticals company executives stated the need to understand pharmacology, clinical trials, and data science, primarily to assess the utilization of the AI outputs to ensure that they are clinically relevant. Second, managers need to understand the firm's overall business strategy and realities, and how the tool is built to support the operational and strategic goals. A business consulting firm's business leader said, "At the end of the day, we know what our company's realities are. If you look at our firm, there are three or four big needs the business is supporting: a customer or a sales revenue priority, a margin or profit priority, social governance priority, and an employee satisfaction priority". Third, the manager needs to understand the financial, economic, or operational thresholds to sell or implement the AI tool/model. One senior telecommunications leader described their firm's payback as less than one year when recommending IT solutions. A technologist from a technology firm made a similar point when he said:

The manager needs to understand the use case better. AI has a terrible habit of solving problems that don't need to be solved. So, it's about understanding business value. We run tons of experiments, and we do influence business priorities. We can't be afraid to see an opportunity here, but we better make sure that we've got that interlock with the business. If we build this and we invest the time because it's non-trivial time. These are costly resources--data scientists are not cheap, machine learning engineers are not expensive.

Fourth, managers should understand how similar tools have been adopted in other parts of the organization or the industry. One senior financial services business leader described how he and another manager went out to Silicon Valley to meet VC or start-up firms investing or building technological capabilities in their respective space within the financial sector.

Soft Skills: Several capabilities have been organized into the soft skills category to include Curiosity & Questioning; Judgment; Change Management & Continuous Improvement, Problem Solving, Conceptual Skills & Diagnostic Capability, Communication Skills and Emotional Intelligence. Several recent research studies supported the importance of soft skills in leading in the digital environment. First, IBM surveyed senior executives in 2018 (LaPrade et al. 2020) where the five of the top seven skills can be considered soft skills—willingness to be flexible, agile, and adaptable to change, time management skills and ability to prioritize, ability to work effectively in team environments, ability to communicate effectively in a business context, capacity for innovation and creativity, and ethics and integrity. Second, there is a need to create a high involvement organization or empowerment, inspire and motivate employees, tolerate ambiguity, process, or analyze high amounts of data for decision-making, and manage change and connectivity (Corellazzo et al., 2019). Third, DeCremer (2020) identified eight critical skills: critical thinking, curiosity, agility, imagination, creativity, emotional intelligence, empathy, and ethical judgment.

Even though these soft skills will be discussed as separate entities, the reality is that they are used in unison by leaders. For example, several research participants discussed how they needed to work collaboratively (teamwork and relationship building)

with their internal technology partners or external suppliers in implementing the AI tool (change management), which entails ensuring that they frame the need (judgment) and communicate it effectively (communication skills).

The first capability is Curiosity & Questioning. Curiosity was the highest rated item for a 4.53 score, with 17 individuals rating it as being in the top three. The Questioning item was the second-highest-rated for a 4.39 score, with seven votes in the top three. When research participants completed the survey, they felt that each of these concepts was closely related, as noted by one of the participants when he said, “because if you're questioning something, then you're acting on your curiosity. But if you're questioning, then hopefully you're turning curiosity into a question that you're trying to see what is the right answer.” As mentioned earlier, curiosity can be considered a mindset or attitude that managers bring to all aspects of their work. In addition, there were a series of behaviors that demonstrate both curiosity and questioning. First, leaders need to have a healthy skepticism, especially when the AI tool makes a recommendation/prediction or generates an output. One health care technology consultant said, “you need to be able to trust the model that is doing what it has been properly trained to do but have enough skepticism, to recognize that model only has narrow intelligence, not broad intelligence to work on problems.” Second, managers need to frame and ask the right question. Having a healthy skepticism goes a long way to maximize the probability that the AI tool would generate actionable outputs and ensure that the technicalities of the respective AI technology (e.g., NLP, Machine Learning) tie back to the specific business issue or context. Third, managers need to constantly learn, especially new technologies (e.g., GPT3) or newer technologies applied in their industries.

The second soft skills capability is Judgment, with an overall score of 3.9, with nine individuals rating this item as one of their top three. Artificial Intelligence is an aid in judging and productivity. In most cases, it “helps to inform, educate and speed up the decision-making process or speed up a workflow process” versus replacing humans. Hybrid roles that combine humans and machines working together will depend on judgment (Siegelman et al., 2019), and better judgment will result in more accurate predictions (Agrawal et al., 2018). Also, judgment is the process of determining payoffs and requires determining the relative value of difficult to quantify factors and thus compare (Agrawal et al., 2018). First, managers need to display a discerning ability to analyze the output or prediction from the tool and provide additional contextual factors in their discernment. A senior leader from a specialty retailer described this phenomenon when he said:

We have tremendously high turnover in terms of the actual product in upwards of 40%. This year is not the same as last year. Do the demand patterns make sense, or is the optimization picking up an anomaly based on our previous 16-18 months?

The second element related to judgment is to assess when a manager finds a technology solution to ensure that it is the right solution for the problem. In addition, managers need to assess if the investment in the tool would make a material difference to the “way we operate” and bring enough value. The third element has less to do with technical judgment than the social, organizational, and interpersonal aspects of implementing the tool. This aspect of judgment relates to discerning the stakeholders, identifying potential roadblocks, and determining the right moment to bring forward proposed AI solutions. For example, employees should have the ability to discern the contextual factors relevant to accepting an AI recommendation or prediction. Second is

the ability to determine the data elements that are most necessary for the problem that AI will potentially solve or understanding the various weighting on the variables that the AI tool will utilize in coming up with its recommendation.

The third soft skills capability is Change Management (which scored 3.96 on the survey (SD=. 09) & Continuous Improvement. Both of these capabilities are a critical lever in managers achieving two of their core roles as a “Change Agent” and “Efficient Continuous Operator” as well as operationalize the mindset of “Experimentation.” To be effective in Change Management and Continuous Improvement, managers need to have a threshold competence in the other technical and soft skills. For example, managers need to build trusting relationships with key stakeholders, communicate effectively on the rationale (or benefits of the tool), and have a working knowledge of the application to outline how the tool will be operationalized and improved in this particular setting. As outlined in the previous role’s section, managers need to know and do the following concerning Change Management and Continuous Improvement: understand how the AI tool impacts employees; deal with employees natural reticence when there is a perception that the AI tool could eliminate their role; lay the foundation with functions who need to support the tool; gain financial or operational support to other organization; continue to question the status quo; constantly refine and update the device or find other potential applications, and act as a provocateur to challenge the organization to utilize digital tools. In this capability, several elements stand out. First, managers, who are especially driving and leading the implementation of the tool within their teams, need to understand those impacted by the application. A senior leader from a telecommunications company made this point as she was talking about her manager when he rolled out the internal chatbot:

He did not throw the tool out there. He wanted to get feedback from the community. He took the time with sales reps for them to give feedback, to make changes, and be able to speak their language. The whole thing about change management is understanding from the user perspective what they need.

A second element is the ability to frame the AI tool as a value-added inspiring element for employees. A senior leader from a telecommunications person said:

When you hear automation or AI, it harkens back to factory workers in the 1990s. Where it is going to take my job away. Need all levels of individuals to understand that automation is our friend because a computer will handle routine and mundane tasks. It frees us as human beings to do creative work and do more higher-level thinking.

A third element is this capability to understand and apply a methodology to manage change or implement technology. Several participants discussed various approaches, such as agile software development or other tailored strategies. For example, one individual described their effort called ADKAR, which stands for “awareness, desire, knowledge, ability, and reinforcement.” Another senior technology manager discussed how he reads external reports on how there will be AI-driven “software-driven lifecycle” methodology and “how in the future coding or architecture will be done by bots.” The fourth element is setting compelling vision and strategy to maximize the opportunity to improve their work with AI tools or digitization. One technology manager described how he and his team are “trying to position us to where we need to be three years from now, and nobody else is seeing it yet.” Another technology manager stated a need for “entrepreneurial leadership” because we want to stay at the forefront of this space; we come up with new features and new functions, and then we have to sell it to the business.”

The fourth soft skills capability is Problem Solving, Conceptual Skills, and Diagnostic Capability. To be effective in this capability, you also need a working

knowledge of the Technologically Oriented capabilities and demonstrate effective the soft skills of Curiosity and Questioning capabilities. On the survey, I asked participants to rate both Conceptual Skills and Diagnostic Capability. Conceptual skills had a 4.20 average (SD=.893), the fourth highest-rated item, and Diagnostic Capability had a 3.47 average (SD=1.1695). There are several elements associated with this capability. First, to be effective in this capability, managers need to demonstrate “logical, reasonable thinking” that is data driven. Second, managers need to demonstrate conceptual and visioning skills by visualizing how the tool would be implemented. A financial services technology manager reinforced this point when he said:

As a manager, you should visualize what the end tool should like in your mind as a basis. It might not turn out eventually the same. If you take that approach, you can provide continuous feedback on your business requirements to the technology or digital team to get you as close as possible to what you have had in mind.

Third, individuals need to ensure they follow a structured approach starting with a well-defined, measurable problem and data that can be analyzed. These are necessary prerequisites followed by identifying potentials risks and benefits before “thinking about technologies.” The last crucial element is demonstrating diagnosis skills to ensure an adequate understanding of the problem’s complexity and the underlying data (e.g., structured, or unstructured) required for the relevant technology.

The fifth soft skills capability is Communication Skills and Emotional Intelligence. On the survey, Emotional Intelligence had a 3.63 average score with an SD of 1.04). In unpacking this set of capabilities, specific elements include the ability to: build relationships⁶⁵ across one’s ecosystem (e.g., suppliers, other functional peers,

⁶⁵ In terms of relationship building, we asked participants to rate this capability as one of the managers need to possess to succeed in an AI environment which scored a 4.12 average (4th highest rated item on the survey.)

subordinates, and senior leaders); create teamwork among one's vertical and horizontal stakeholders; display calmness during periods of stress especially during the implementation process for technology tools; have the ability to present the features and benefits of proposed AI solutions to senior leaders for funding or support as well as have employees see the benefits to their day to day jobs.

Summary

For Study 2, three focus areas guided the research inquiry--- there will be a moderate to a significant change to the manager's role due to AI; managers are essential to employee development, engagement and inspiration because of AI's impact, and managers need to enhance their technical, leadership, and interpersonal capabilities---via a mixed-methods survey. The process entailed interviewing 42 individuals accompanied by a quantitative ten-item study that was analyzed using Nvivo along with some basic descriptive statistical analysis generated the survey's quantitative data. The research participants were drawn from 11 organizations that spanned various industries comprised of private and public companies. Figure 5.3 synthesizes the overall results.

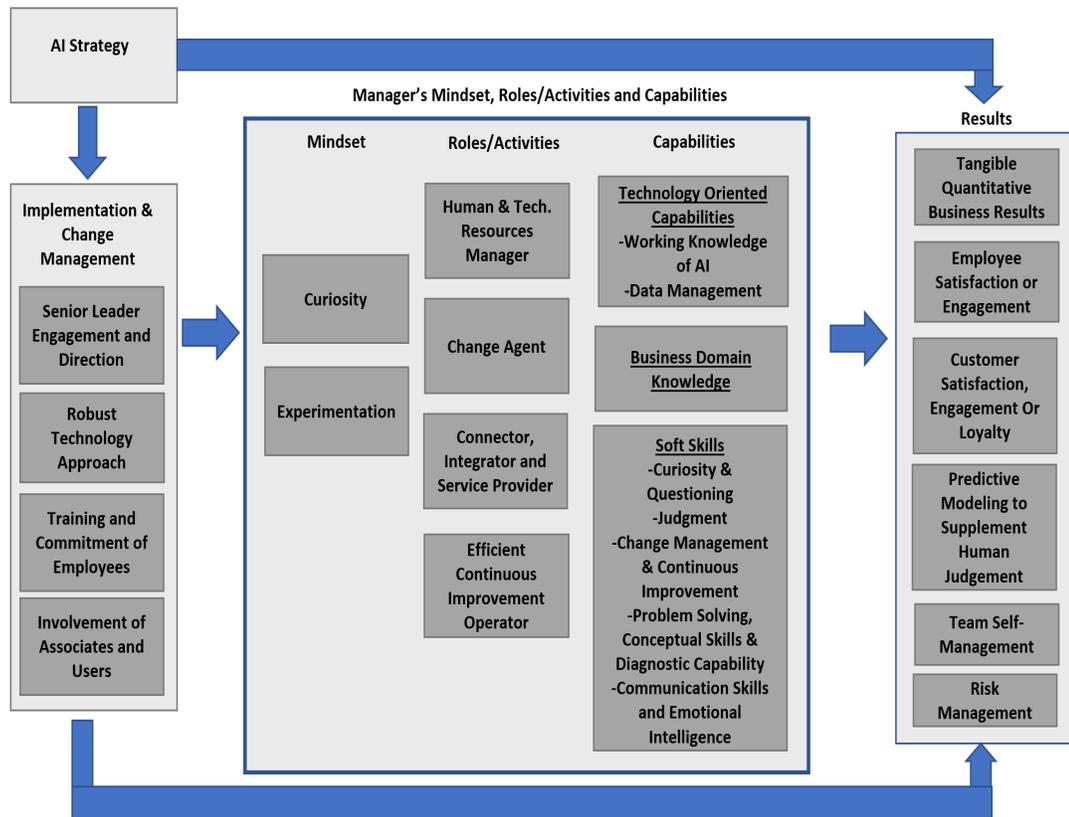


Figure 5.3. Research Results Summary Overview

The box labeled AI Strategy is the firm's strategic approach to implementing AI tools. Depending on the AI tool's complexity and business application, some organizations utilized AI in a variety of ways: as a strategic component of their overall business strategy (e.g., a pharmaceutical company); a tool to improve their external customer-facing services (e.g., financial services; retail; health systems); better serve internal customer needs (e.g., telecommunications); a tool ensure their employees are fully deployed (e.g., consulting firm); or used AI to improve internal processes (e.g., financial services). When implemented successfully, it will achieve a set of business outcomes as listed in the Results box. However, these results are achieved through successful implementation and change management approach directly impacted by the activities and capabilities of middle and senior-level managers. The next chapter will outline the synthesis of the key findings from both research studies, a description of the practical implication, and other areas for potential research.

CHAPTER 6

CONCLUSIONS

This chapter contains three sections. First, it provides a synthesis of the findings from both research studies. Second, it outlines the practical implications of the results to managers and organizations. Last, it describes additional areas for further study and research that could further the scholarship in this area. Because the rate of digitization by companies has increased since the beginning of the pandemic, and given the project rate of AI spending by corporations, AI will continue to impact organizations, teams, leaders, and employees. As such, the findings, implications, and further research suggestions are timely and necessary to add to the dialogue, scholarship, and management practices facing the public, private, not-for-profits organizations, teams, leaders, and employees.

Findings

There are four overall summary findings based on the academic literature review and the two research studies.

Finding 1: Managers need a working knowledge of AI & business domain knowledge, supplemented by soft skills, to lead humans & machines in a digitally oriented environment effectively.

One key question was the degree of technical knowledge that managers would need to lead in an AI digitally oriented environment. For example, one scholar stated that managers need to have "a competent understanding of AI tools, concepts such as machine learning, natural language processing, deep learning, artificial neural networks, intelligent robotic process automation, and their potential/possible applications" (Reinhardt 2018).

At the same time, my assumption was that managers would need to have a deep understanding of AI and possibly understand how to code.

In study 1, research participants stated that managers need to develop technologically oriented knowledge of software development lifecycle, blockchain, AI, basic statistical algorithms, data management fundamentals, design thinking, and experimentation. In study 2, I asked about the capabilities needed to operate in an AI environment and specifically probed about the degree of required mastery. The quantitative survey that participants completed listed several technical topics, including Computational, Algorithmic and Design Thinking, AI Knowledge, Data Modeling, Cloud Computing, Data Management, and Data Analysis. By possessing a working knowledge of these topic areas, managers will be able to interact with data scientists and software developers; evaluate AI tools; understand how AI can be applied in their business problems; and understand the critical role that data plays in model development, deployment, and refinement. But to use this knowledge, managers need contextual business domain knowledge about how AI tools meet their strategic or operational goals.

Both technologically oriented skills and business domain knowledge are the required threshold set of capabilities. However, soft skills are the differentiating set of capabilities to succeed in an AI environment. The first study identified several soft skills such as communication and influence skills, judgment, coaching, and personal attributes such as trustworthiness, "walk the talk," and practicing "responsible AI. In study 2, I had several soft skills listed on the objective survey: conceptual skills, diagnostic capability, change management, judgment, relationship building, emotional intelligence, and questioning. Based on the qualitative and quantitative information, I identified the

following 'soft skills' categories: curiosity & questioning, judgment, change management & continuous improvement, problem-solving, conceptual skills & diagnostic capability, communication skills, and emotional intelligence. This set of skills will provide the necessary cognitive and emotional bandwidth for managers to meet their role accountabilities especially managing humans and machines simultaneously.

Finding 2: Managers are critical to realizing the potential power of AI in their organizations. However, AI will augment and take on more managerial duties.

This finding is a potential paradox. On the one hand, there are examples of organizations using AI tools to augment or assume managerial duties. For example, Amazon's 125,000 warehouse employees receive their targets from algorithms (Cappelli, 2020). Amazon also tracks each associate's productivity rates and automatically generates warnings or terminations regarding quality or productivity without input from supervisors. (Mukherjee, 2020). Likewise, supervisors no longer not fire bad drivers at Uber; they are deactivated by an algorithmic scoring tool (Pasquale, 2020). MetLife uses Cogito, an app-based AI coach, to provide call center employees with real-time feedback. If the call center person is talking too fast, then a window flashes a speedometer; if the call center person sounds sleepy, then the app flashes a coffee-cup icon. (Roose, 2021). At the extreme, by 2024, new technologies can replace as much as 69% of the tasks historically done by managers, such as assigning work, approving expenses, onboarding employees, and nudging productivity (Kropp et al., 2021). Several applications freed up managers' time to expect that they would reinvest this time into more excellent business value-added activities in both of my research studies.

The other half of the story is that corporate AI spending and US Federal AI spending are multiplying. According to the International Data Corporation, corporate AI

will grow from \$50.1 billion in 2020 to more than \$110 billion in 2024. At the US Federal level, departments and agencies spent a combined \$1.8 billion on unclassified AI-related contracts in FY2020, representing more than six times higher than what it was just five years ago—about \$300 million in FY 2015 (Stanford University Human-Centered Artificial Intelligence, Artificial Intelligence Index Report 2021). This spending might be higher considering that many firms are rethinking their investment rate due to the pandemic and the need to increase their digitization blueprint.

With this rate of spending and increased expectations to deliver on AI, managers will need to successfully execute their critical accountabilities in the following areas: Human and Technology Resources Manager; Change Agent; Connector, Integrator & Service Provider, and Efficient Continuous Improvement Operator. Although AI will take over the transactional part of the role, mastering these activities will ensure that their role is value-added and not disintermediated to oblivion. However, what will be disintermediated will be those purely administrative tasks.

Finding 3: A robust strategic implementation and change plan is necessary but not sufficient unless senior leaders display public and private leadership.

At a superficial level, AI is a software implementation. At the same time, it is a culture change effort that alters the nature of work and impacts decision making. It crosses organizational boundaries (especially data flows), thereby necessitating collaboration across organizational units. When firms fully implement an AI application, it can benefit employees, customers, and a firm's position in the marketplace.

Across both research studies in this dissertation, survey participants discussed the importance of a purposeful multi-dimensional change strategy and tactics. When organizations successfully implement AI, there is a palpable excitement about the tool's

potential problems, increased employee capabilities, fewer concerns about job reductions and achieve tangible business results. Survey participants identified a set of successful change elements, such as active involvement of associates and users who will be directly or indirectly impacted; the delivery of training (be it upskilling or reskilling), which helps to generate commitment by employees; the execution of a structured technology implementation approach including the building of beta or minimum value products; the support of capable technologists who work collaboratively with the line of business users; and a communication campaign to thwart employees concerns about job diminution or elimination which gets them excited about the possibilities of the technology to their day to day work.

The lynchpin of the change effort is senior leader engagement and communication. Their engagement sets apart successful digital transformation (Brock & von Wangenheim, 2019). Senior leader engagement was identified by 36 of the 38 participants (95%) as one of the top three critical success factors in implementing AI. What do they do, and how do they behave or act? First, they are knowledgeable champions (Balakrishnan, 2020). Second, they are direct sponsors of the activities and act as evangelists for the tool. Third, they ask the right questions to frame the business challenge/objective before embarking on an AI effort. Fourth, they challenge the organization to utilize digital tools. Fifth, they fund the effort and set return on investment guidelines at a practical level. Sixth, they monitor progress and eliminate roadblocks.

Finding 4: In organizations implementing more complex AI applications, managers will lead either formally or informally multi-functional units or cross-discipline individuals. In addition, they will need to demonstrate a higher degree of decision-making and thinking complexity.

As stated earlier, complex systems are characterized by a specific set of characteristics, including diversity, the unpredictability of outcomes, many independent items, and a high degree of interactive elements. AI tools and technologies are called upon to solve business complexity, whether strategic, organizational, or decision-making. Also, by its nature, AI is a complex set of tools and technologies too. Managers will need to operate effectively in this challenging environment. Two dimensions were evident from this research.

First, as organizations implement more complex AI tools, the structure of those teams might begin to migrate to include formally (or minimally informally) various disciplines needed to implement or oversee the specific AI application. This phenomenon was evident in three case studies in research study 2. First, a financial services manager was responsible for overseeing the firm's external-facing digital tool, where he had marketing, data analysis, and user interface disciplines on his team. Second, a pharmaceutical line of the business executive had to coordinate pharmacologists, clinical trials professionals, and data scientists to assess AI outputs to ensure they are clinically relevant. Third, a chief learning officer had software developers, data scientists, and learning content professionals on his extended team. In each of these cases, the deployment of the AI tool is a critical component of the organization's achieving its business strategy or serving its customer base. Figure 6.1 characterizes the various applications into four quadrants. The three examples aforementioned would be in quadrant 1 where the tools that are implemented are highly complex, strategic, and externally focused.

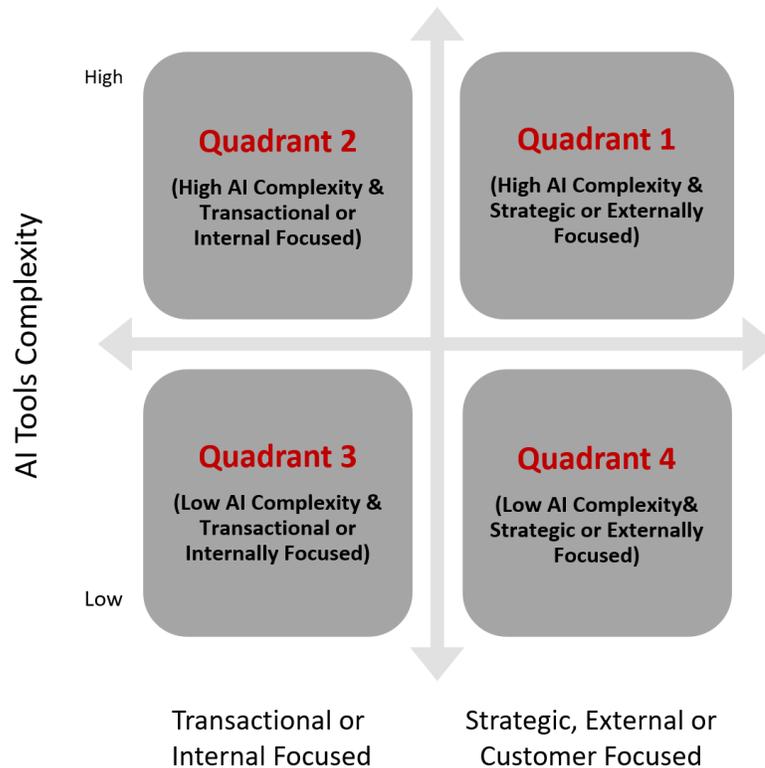


Figure 6.1. AI Tool Framework

An emerging finding is that managers will be called up to lead more cross-functional disciplined teams, especially when the tools are more complex, whether internal or external-facing. Thus, quadrant one is the likely candidate where managers will have cross-functional teams that they need to lead.

Second, managers will need to enhance their decision-making and thinking complexity skills because their organizations will be more complex. The complexity of the AI tools will require higher-order capabilities. Leaders will need to understand their thought processes better, including their cognitive or decision-making biases. For example, do managers know if they use more inductive or deductive reasoning? Are they more of a systems thinker that can see the whole picture and understand how the various

elements interact? Are they more of a reductionist thinker to reduce complex problems to their core elements? Do they know their decision-making biases? For example, are they overconfident when they perceive a similar situation or pattern they are currently facing? Also, managers will be utilizing more complex AI tools, so they need to ensure that they are more discerning to ensure that the specific tool meets the business problem they face. Therefore, the judgment, questioning, and curiosity aspects identified in the research findings will be essential capabilities for managers to possess to operate in a more complex environment.

Practical Implications

As stated before, these practical implications have timely applications due to the growing use of AI and ubiquity within organizations and the rate of spending by corporations and nation-states. There are three areas that will be affected by AI: Capability Development, Capability Assessment, Implementation Checklists, Role & Team Structure, and Talent Acquisition.

Capability Development: A series of learning products or solutions can be created based on the academic literature review and dissertation research. First, organizations can use major elements of this dissertation content in a virtual or in-person learning program. For example, there could be a stand-alone workshop as an introductory “course” called “Leading and Managing in the “Age of the Smart Machine.”⁶⁶ Focusing on AI technical components; human & machine interface; decision making (both generally and within an AI context); impact of AI on the workforce; managers role, mindset, and capabilities;

⁶⁶ The nomenclature of this potential course is borrowed from the title of Shoshana Zuboff ‘s book titled the Age of the Smart Machine: The Future of Work and Power which was written in 1988. Zuboff’s book was prescient in identifying how technology would impact society and the workplace.

implementing AI, and AI ethics. Responsible and Ethical AI. Second, organizations can create learning pathways, especially for managers, a combination of learning content (drawn from the learning modules mentioned earlier), assessments, short videos, lectures from experts, case studies, and real-world case studies drawn from the research participants. These capability development offerings can be implemented in organizations at different stages of their AI implementation lifecycle. Companies that are just starting out with implementing AI could offer introductory sessions describing the history of AI history, an overview of its technical components in layperson's language, and AI's impact on the workforce. Those beginning to embark on AI pilots can leverage research on change management to help senior leaders understand their role and orient managers to their role and capability expectations. Lastly, organizations beginning to implement AI across their organization broadly can offer skill-based managerial learning programs. There are several benefits to this approach. First, it would create a shared language across the leadership population. Second, it would make a more significant strategic alignment. Lastly, it would increase the probability of the pilots succeeding because managers would have the requisite skills to lead in this environment.

Capability Assessment: A second practical implication is turning the specific managerial capabilities into a stand-alone capability assessment instrument, especially for those organizations embarking or in the middle of AI implementation. For example, the assessment approach could be a low-tech paper version or loaded into a software-based 360 tool that can generate automated reports. One of the benefits of these assessments is that organizations can have measured outcomes over the lifecycle of implementing AI, thereby observing results at different periods. These capability assessments could be used

during the performance review process as inputs for evaluating the behavioral aspect of performance. In addition, some elements of the managerial roles and capabilities could be integrated into an overall organization's leadership capability model. This step is usually taken when organizations have decided that a specific strategy necessitates reinforcing a new set of knowledge, skills, attitudes, and behaviors. The research findings on capabilities can be a 'copy and paste' especially for organizations at a later stage in their AI

AI Implementation Assessment Toolkit. Based on the research findings and academic literature review, organizations will create an AI organization readiness and implementation assessment toolkit. This toolkit could include an assessment checklist that could be administered electronically and some of the best practices that have been identified through this research. If the organization is recently embarking on AI implementation, it can utilize the findings to understand the potential gaps in the change plan or managerial capabilities. If the organizations have already embarked on AI, this assessment would provide some insight into potential gaps in their implementation approach.

Talent Acquisition Process: Effective individual performance is a direct function of several variables, including the organizational culture, the design of the role (including its requirements and tasks), and the individuals' capabilities to perform in the role. One of the first steps in an effective talent management process is attracting and selecting external and internal talent. This research study and academic literature can help inform the talent acquisition process. For example, talent acquisition professionals can build managerial role profiles based on the outputs from this research. If the hiring organization

is in lower complexity AI applications, they can minimize the needed technical knowledge. Conversely, if the hiring organization is in the throes of implementing more complex AI, then the assessment would emphasize more of the technology capabilities. The role profiles will need to be tailored to the specific industry, organization, or function. Second, another example is the creation of selection instruments to assess candidates vis-à-vis the mindsets, knowledge, skills, and personal attributes identified.

Implications for Further Research

There are several potential avenues for further research that amplify and continue what was uncovered in this dissertation.

Manager's Role in Highly Complex AI Environments: As noted in Figure 6.1, a research opportunity can explore how the role and capabilities of managers change, morph, or amplify in quadrants 1 and 2 versus when managers operate in an environment where AI tools are less complex. In addition, if one can collect data on each quadrant, it will give researchers and practitioners a more nuanced view of what it takes to succeed as they move across these various quadrants or dimensions.

Team Design and Structure: As mentioned in finding 4, one potential thread is how teams will be structured when AI tools are implemented in high or even moderate or low complexity applications. Will teams become more cross-disciplined? Will managers need to have breadth and depth of skills looking more pi shaped? Secondly, would employees be more autonomous and self-directed when data democratization and AI tools are broadly disseminated within the corporation. If this occurs, can managers increase their span of control because employees would need less day-to-day direction? Third, would new roles be created on the team, such as “evangelists” who help in AI

implementations? Fourth, will there be a need to create communities of practice and networks where organizational units can share best practices as they implement AI tools?

Research Summary Quantitative Study: Figure 5.3 shows my conceptual model with specific antecedents and outputs. One potential avenue of inquiry is conducting quantitative analysis to understand the moderating and mediating forces that impact business results. Some questions include: what is the impact of the firm's AI strategy on implementation and change management approach and results? How much does the manager impact business results? Which elements of the manager's role, tasks, and capabilities have the most significant impact? Which aspects of the change implementation approach (e.g., employee involvement) have the most impact?

Responsible AI: Over the last 18 months, there have been several academic and management studies on the ethics of AI. One potential future avenue of research is going deeper into the role of senior leaders by ensuring they act responsibly understand the ramifications to their stakeholder ecosystem. In addition, how do senior leaders create the right culture, infrastructure, governance process, and procedures to ensure that their AI implementation stays within their respective corporate or society guidelines?

Personality Profiles of Managers Who Implement AI. Building upon the manager's capabilities, one thread of further investigation is understanding personality profiles for those driving AI. Is their personality assessment different from other senior executives? For example, have line of business managers or technology managers who are implementing AI take off-the-shelf personality assessments (e.g., Five-Factor Model; Hogan Inventories) to see if a personality profile is more successful in implementing AI than another?

Longitudinal Study of AI implementation. One research approach is to follow a company as they begin implementing AI across their portfolio of businesses or within their organization. This research study would provide insight into the challenges, pitfalls, and good practices as organizations move through the life cycle of implementing AI tools.

Limitations & Generalizability

This section will discuss limitations as well as the generalizability of the research study approach and findings.

The limitations will discuss two aspects—first, a discussion of those individuals who would be considered AI skeptics, and second, the limitations inherent in the study design and execution based on the design choices made by the researcher. In terms of the first aspect, there are skeptics at the macroeconomic level and the micro-organizational or individual level.

At the macro level, some skeptics believe that the benefits of AI to increasing total employment will be offset by the loss of jobs within the economy. There will be a dislocation of individuals in specific job categories who cannot be reskilled or upskilled fast enough to take advantage of the new roles that AI will create. There is another set of skeptics that have to do with the ethical dimension of AI. They believe that AI will offer consumers more superb choices, as evidenced by internet platforms' rise in recommendation engines and services. Still, there will be a cost to data privacy as well as the power will be shifted to these large platforms. It is a Faustian deal that consumers are striking. On the one hand, consumers have free instantaneous search, but they give up their rights to the data they generate due to their clicks on a website, ordering a book

from Amazon, or downloading a Netflix movie. Even though this study does not deal directly with these macro-level issues, they form the backdrop and context where organizations are implementing AI, or their employees are experiencing AI in their day-to-day activities.

At the micro-level, whether at the organizational or individual level, the skeptics revolve around several issues. First, some senior leaders are concerned that AI applications don't unintentionally cause unforeseen reputation or information risks in the marketplace. Therefore, argue for the need to put adequate checks and balances to prevent these risks from surfacing. Second, the information technology organization is skeptical about allowing business users to utilize AI tools in the spirit of 'citizen developers' without understanding AI's potential ramifications. Third, AI will impact employees on several dimensions. First, academicians and management theorists describe how employees' roles will, in all likelihood, be eliminated or at least certain aspects of their jobs. Second, AI implementation will involve a reskilling of employees' capabilities to perform future functions necessitated by AI tools or technology. Third, employees naturally lack the willingness to embrace AI or participate in AI implementations when they realize that new technologies could eliminate or diminish their roles.

Organizations that implement AI must be aware that skepticism in several areas is overtly or covertly present. Therefore, the change and communication strategy must purposely target skeptics' concerns, especially those of employees and their managers. Senior leaders ultimately bear accountability for any change effort, especially AI, and must understand at a detailed role level how it will impact specific individuals. For example, suppose there is a strategy to increase automation or the use of AI prediction

algorithms. In that case, managers need to anticipate the impact and mitigate actions to dampen the impact. This could include but is not limited to:

1. providing the opportunity for increased training especially for those individuals who have the greatest need.
2. guaranteeing (at least for a certain time period) that employees will not lose their jobs due to implementation of AI.
3. ensuring that 'citizen developers' who are implementing AI have a technology third party review before they put AI tools into production.
4. engaging in a group or one-on-one dialogue to understand the concerns at the employee population level (e.g., Account Payable clerks; paralegals) or at the specific employee level (e.g., Jane Doe who manages the Chicago call center).
5. creating individualized, customized plans for a population of employees or at the individual level.

Like any change effort, there will always be skeptics who need to be engaged in an authentic two-way dialogue where leaders employ a communication style of co-creating solutions instead of a selling and telling style that does not engender long-term commitment.

In terms of the study design limitations, I collected data from three populations: senior leaders who were optimistic about AI and sponsored relatively successful implementations. Also, technologists and managers worked collaboratively and were responsible for implementing the tool in their respective teams or units. Inherent in this study design are certain limitations. First, the sample population of AI installations was in

corporate settings, and I did not draw examples from the not-for-profit sector. Second, even though the AI installations were at various stages of maturity, all case studies had positive outcomes or were on a positive trajectory. I did not study unsuccessful AI implementations either within these organizations or from other organizations. Third, I did not survey employees as one of the sample populations, which was purposeful because of the potentially lengthy process that would extend the study's timeline. For example, I would have needed HR and Legal organizations to approve employee involvement, and managers would have been required to have introductory conversations to explain the purpose of the study, which would have added extra steps. Fourth, I did not purposefully talk to individuals within the case studies organizations who were the skeptics, providing an alternative or potentially contrasting perspective. Therefore, our research findings are not directly applicable to non-corporate settings, organizations that were unsuccessful in AI implementations, or faced resistance by skeptics. Lastly, the study design did not capture the voice of employees. However, even with these limitations, there are lessons that can be gleaned that could apply to those situations.

Based on the study design, limitations, and findings, the research is most applicable and generalizable in the following contexts. First, organizations in which senior leaders play an active role in the shepherding and sponsoring of the change effort versus middle managers who are main the initiators of change.⁶⁷ Second, where the underlying AI technology is more in the realm of augmented intelligence, AI is utilized to assist in decision-making and problem solving by employees and managers. In contrast to

⁶⁷ Jon Katzenbach (along with a team from McKinsey) published a book in 1996 called *Real Change Leaders: How You Can Growth and High Performance at Your Company* where they studied middle managers who were ushering in change in their respective organizations at their level. Katzenbach and his McKinsey consultants make the case that effective change could happen at the middle of organizations. The theme of changing happening by middle managers was also present in his 2018 book called *The Critical Few* where he coined the term of 'authentic informal leaders'.

digitization (or AI-enabled technology) via robotic process automation to improve data flow or gain labor savings. In these cases, human intervention will not be required. Third, even though the list of managerial mindset, roles, activities, and capabilities identified in the context of AI implementation, I would postulate that these capabilities apply and are generalizable to other future technologies. Because AI is fundamentally a change effort, these findings will apply to other change efforts that organizations will face, whether they are ushered in by technology or other organizational forces. Fourth, one of the study design limitations has been the non-involvement of employees who are individual contributors or individuals identified as AI' skeptics'⁶⁸. With this being case, the findings will need to be reality tested with this in mind. For example, if a practitioner were going to utilize the research findings, especially in organizations with a higher degree of skepticism, leaders would need to place a greater emphasis on the change and communication elements. In addition, organizations will need to ensure that managers who are initially selected to participate in initial AI use case examples possess more of the capabilities required as a starting point.

⁶⁸ Even though there might be practical and methodological issues associated with identifying skeptics, one potential idea is to insert a series of questions on the objective survey that was administered. For example, could ask the degree of confidence that they have that AI will be transformative in their organizations or ask them to comment on when they thought AI will achieve net benefits minus the total costs of implementation. If individuals answered less than positive in these items, it might be a proxy for their level of skepticism.

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APPENDIX A

RESEARCH STUDY 1 INTERVIEW PROTOCOL

Part I: AI Business Case & Problem: I first want to start with understanding the overall AI ecosystem before delving deeper into the manager's role:

1. What business problem are you trying to solve with AI?
 - What has been the specific process that you are trying to change? How is AI changing your work processes?
 - Which AI tool or application are you using?
2. Is this the first foray into implementing AI?
 - Have you used other process improvement methodologies or other technologies before embarking on AI?

Part II: Impact on Managers: As the manager, what to probe how it has changed the manager's role to date and will examine how it might alter your role in the future?

1. Before AI was fully implemented on your team/organization, where did you allocate most of your time? Now, please contrast with the current state or post-implementation?
 - Areas to probe including resolving unforeseen problems, reducing bottlenecks in workflows, producing status reports; project management; coaching your employees, holding staff meetings, etc.
2. What capabilities or skills are you currently utilizing and/or developing to function in this new environment? Do you foresee any additional capabilities that you might need?
3. What are you doing as a manager to build the capabilities of your employees to succeed in this "age of the smart machine"?
 - Areas to probe: Are employees going to workshops, utilizing web-based tools, capturing best practices, etc.
4. Has AI eliminated less transactional work and freed up time for more analytical/value-added work? If you have freed up additional capacity, what other activities have you utilized?

Part III: Impact on Employees. In this section, I want to understand how AI has impacted your employees:

1. Can you provide some specific examples of how your employee's day to day activities changed with AI being implemented?
 - Has AI eliminated less transactional work and freed up time for more analytical/ value-added work? If you have additional capacity, how are you using that capacity?
2. What new skills or capabilities are being required for associates to thrive in this new environment? Please comment on technical and non-technical skills that are important.
3. Have you used AI or other emerging technologies in training your employees?
4. Are you recruiting employees with different sets of skills now that you are implementing AI?

Part IV: Implementation Process & Enablers. In this section, I want to probe on the change management approach to implementing AI.

1. What activities, processes, and mechanisms do you employ to ensure the successful adoption of AI?
 - Probe for one way and two-way communication; training/capability building, use of pilots before large scale implementation; management routines, etc.
2. As the manager, what was your involvement in the implementation process/change management plan?
 - Probe to the degree that the manager help shapes the plan

Part V: Outcomes and Results

1. How are you measuring the impact and outcomes of your AI efforts?
 - Probe for tangible or quantitative outcomes primarily to process changes.
2. Has there been any changes to the organizational climate/health of your team?

APPENDIX B

RESEARCH STUDY 1 DRAFT EMAIL TO PARTICIPANTS

Dear _____,

As you well know, emerging technologies such as Artificial Intelligence, is beginning to have an impact on how work is structured; the impact on decision making and data analysis as well as the skills required of all employees to operate in the "age of the smart machine". Like any change effort, managers will assume a pivotal role in the successful adoption of AI to ensure the workforce is "willing and able" to maximize the economic & strategic benefits of these new tools.

Because AI is in the early stages of adoption, there has not been in-depth research on the role of the manager especially how it impacts their role such as their day-to-day activities; how they lead, engage, and train their team as well as the necessary capabilities to succeed in an AI environment.

As a doctoral student, my intended research is to focus on this topic and my intent is to interview individuals from a variety of organizations who are implementing AI. Because of your expertise and involvement, I would like to invite you to participate in an interview.

Rest assured, that I will not be identifying individuals or the organizations by name when I write up my research which eventually will become part of my doctoral dissertation.

However, I will be willing to share my whole doctoral thesis as well as pull together a PPT presentation to share my results with you or anyone else in your organization.

As part of the process, I will need you to review the attached consent form that you agree to participate that provides additional information pertinent to our conversation. Will send you the set of questions in advance to give you some time to prepare and if you can block one hour that would be ideal.

I appreciate your help and look forward to our conversation.

APPENDIX C

RESEARCH STUDY 2 INTERVIEW PROTOCOL

Part I: AI Implementation: Application and Business Case

- What business problem are you trying to solve with AI?
 - Probe on the specific process?
- What AI tool did you implement?

Part II: Impact on the Manager: Role and Capabilities

- Since AI has been implemented on your team, can you describe how your daily, weekly, and monthly activities? How has that changed over the time of the AI being fully operationalized?
 - Probe on areas of accountability
- What are the critical capabilities that are required for managers in an AI environment?
 - Probe on judgment and decision-making skills (e.g., which decisions do you get involved in now; decisions that you delegate and decisions that the team makes on their own?)
- Can you describe the nature of your routines and interactions with your team?
 - Probe how that has changed over time.

Part III: Change Management Tactics & Relationship with the Technology Organization

- Can you describe how you; your team works with the technology organization?
 - Probe for the depth and breadth of relationships with the technologists?
 - Probe to understand what types of support the technology organization provides and what is the role of the technologist.
 - Probe if the role changes over time.
- What are some additional change management tactics that were used by you or your team in implementing AI?
 - Probe for one way and two-way communication; training/capability building, use of pilots before broad-scale implementation; management routines, etc.
- What is your role during the implementation process?

Part IV: Outcomes and Results of the AI Effort

- What have been the outcomes or results to date since you have implemented AI?
 - Probe for tangible business results, customer satisfaction, employee engagement, and the degree of team self-sufficiency or autonomy.

Distribute the quantitative survey; collect answers, and probe for any reactions.

APPENDIX D

RESEARCH STUDY 2 DRAFT EMAIL TO PARTICIPANTS

Dear _____,

As you well know, emerging technologies such as artificial intelligence (AI) are beginning to have an impact on how work is structured; on decision-making and data analysis; as well as the skills required of all employees to operate in the age of smart machines. Like any change effort, managers will assume a pivotal role in the successful adoption of AI to ensure the workforce is willing and able to maximize the economic and strategic benefits of these new tools.

Because AI is in the early stages of adoption, there has not been in-depth research on the role of the managers, especially how AI impacts their day-to-day activities; how they lead, engage, and train their teams; and how they develop the necessary capabilities to succeed in an AI environment.

As a doctoral student, my research focuses on this topic and my intent is to interview individuals from a variety of organizations who are various stages of implementing AI. Because of your expertise and involvement, I would like to invite you to participate in an interview.

Rest assured that I will not be identifying individuals or the organizations by name when I write up my research which eventually will become part of my doctoral dissertation. Your participation will be confidential and any quotes or information from you will be untraceable to you. My research has been approved by Temple University's research ethics board and it follows strict protocols to safeguard your identity.

At the end of this process, I will be willing to together a PowerPoint presentation to share the findings and results with you or anyone else in your organization.

As part of the process, I will need you to review the attached consent form that you agree to participate that provides additional information pertinent to our conversation. Will send you the topical areas in advance to give you some time to prepare and if you can block one hour that would be ideal.

I appreciate your help and look forward to our conversation.

Sincerely,
Joseph Bonito

APPENDIX E

RESEARCH STUDY 2 QUANTITATIVE SURVEY

1. Review the below list for the possible AI & emerging technologies that have been implemented in your team/unit/function. Circle all that apply.
 - a) Robotic Process Automation
 - b) Chatbots
 - c) Machine Learning
 - d) Predictive Analytics
 - e) Productivity Business Intelligence Tools (Tableau, Workiva, etc.)
 - f) Natural Language Processing
 - g) Imaging
 - h) Other: _____

2. Rate the complexity or maturity level of AI tool usage or implementation. Circle one item.
 - a) **Low Complexity/Maturity:** Utilizing Robotic Process Automation; Use of Data Visualization to Make Decisions/Highlight Problems.
 - b) **Moderate Complexity or Maturity**
 - c) **High Complexity/Maturity:** Utilizing Predictive Analytics; Utilizes a Large Amount of Different Types of Structured & Unstructured Data; Deploying Machine Learning or Deep Learning

3. Review the list of critical success factors in implementing AI in your team/unit/organization. Circle all that apply.
 - a) Senior leader engagement & involvement
 - b) Ongoing communication to employees
 - c) Commitment to employees' career mobility and development
 - d) Manager's knowledge of AI, modelling, and technology
 - e) Internal champion or evangelist
 - f) Training of employees
 - g) Change management strategy
 - h) Project management routines
 - i) Governance processes

4. Rate how successful or impactful AI has been in the following areas:	1=low success or minimal impact. 3=some success or impact, 5=high degree of success and meaningful impact)
a) Tangible quantitative business results (e.g., cost, revenue, etc.)	
b) Risk mitigation	
c) Predictive modeling to supplement human judgment	

d) Customer satisfaction, engagement, or loyalty		
e) Employee satisfaction or engagement		
f) Team self-management		
g) Other:		

5. Rate the following capabilities (e.g., knowledge and skills) that managers need to possess to succeed in an AI environment.	1=not present/not essential, 3= somewhat present/essential, 5=critical success factor/very essential	Mark an X for your top three picks
a) Computational, algorithmic and design thinking		
b) Artificial Intelligence knowledge		
c) Data modelling		
d) Cloud computing		
e) Data management and analysis		
f) Conceptual skills		
g) Diagnostic capability		
h) Change management		
i) Judgment skills		
j) Relationship building		
k) Emotional intelligence		
l) Curiosity		
m) Questioning		

6. Rate the following duties of the manager to be successful in an AI environment:	1=not present/not essential, 3= somewhat present/essential, 5=critical success factor/very essential
a) Monitor AI outputs and decisions	
b) Ensure data integrity	
c) Exercise judgment to evaluate the use of AI, quality of the model(s) and results	
d) Train and coach employees	
e) Empower employees to be self-directed	
f) Manage key stakeholders	
g) Work collaboratively with the technology organization	
h) Implement a change strategy	

i)	Looks for opportunities to expand the team's AI footprint		
j)	Ensure all facets of data privacy and security are maintained (i.e., responsible AI)		

The following demographics will be used to explore differences among survey respondents and used only for research purposes.

7. Identify your role in the organization. Circle one item.
 - a) Senior Leader/Sponsor of the AI Effort
 - b) Manager of the Team/Unit
 - c) Technologist/Software Engineer/Data Scientist/Data Modeler
 - d) Other

8. Identify the total number of years involved in implementing advanced technologies such as AI, Cloud Computing, Big Data/Data Modeling, Internet of Things. Circle one item.
 - a) Less than 1 year
 - b) 1 year to 3 years
 - c) 3 years to 5 years
 - d) Greater than 5 years

9. Please tell us the number of years of work experience in your career. Circle one item.
 - a) 0-10 year
 - b) 11-15 years
 - c) 16-20 years
 - d) Over 20 years

10. How many hours of technologically oriented training or skill-building sessions did you complete in the last 12 months? Training could be in-person or virtual; self-directed; webinars; external courses, etc. Circle one item.
 - a) 0-2 hours
 - b) 3-5 hours
 - c) 6-15 hours
 - d) 16 hours and above