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Understanding the Complex Ethical Landscape of Artificial Intelligence Adoptions

Chrissann R. Ruehle
University of South Florida

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Understanding the Complex Ethical Landscape of Artificial Intelligence Adoptions

by

Chrissann R. Ruehle

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Business Administration
Muma College of Business
University of South Florida

Co-Major Professor: Dejun Kong, Ph.D.
Co-Major Professor: T. Grandon Gill, D.B.A.
Priya Dozier, D.B.A.
Robyn Lord, D.B.A.
Tianxia Yang, Ph.D.

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AI Ethical Decision-Making, Grounded Theory

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DEDICATION

I dedicate this dissertation to God, my husband, my parents, my family, and my friends that have offered encouragement and support throughout this endeavor. I so appreciate that you joined me on this journey towards achieving a lifelong dream. Thank you for checking in and asking how things are going which helped me to stay on track. The spring and summer of 2020 was certainly a challenging time with Covid-19, and yet you stood by me and cheered me towards the finish line. Thank you!

Further, I wish to dedicate this dissertation to my grandmother, Janice Sparks, and my mother-in-law, Cari Pennington, that passed away during the spring of 2020. Both family members asked when I would be finished. I am pleased to report that I have kept my word and finished strong.

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ABSTRACT

Although Artificial Intelligence (AI) has existed since the 1950's, it has experienced a series of expansions and declines over the years. Currently, AI is on an upward trajectory and has prompted the fourth industrial revolution as many scientists have noted. Some firms have rapidly embraced this technology and experienced growth while others have been slow to adopt. Naturally, this expansion often has societal impacts. The aim of this study is to explore ethical considerations that arise during the adoption of this technology. This research addressed three questions: 1. *How do market and regulatory forces reportedly shape Artificial Intelligence adoptions?* 2. *What ethical principles/perspectives do managers follow when adopting Artificial Intelligence and Machine Learning systems?* and 3. *What ethical issues exist within the firms that adopt Artificial Intelligence and Machine Learning systems?*

Since the research in this area was limited, I decided to use a qualitative exploratory approach. This dissertation contained three primary components: an industry analysis, a discussion case study along with a supporting instructor's manual, and a grounded theory study. Through the industry analysis, I identified key actors operating within this market, determined power dynamics, and prepared an AI Stakeholder Power/Interest Matrix. This tool provided managers with strategies they can use to prioritize their internal resources and manage relationships with these stakeholders. The discussion case study and instructor's manual focused on a company, Vectra Digital, that designed its own AI in-house and explored the ethical and operational aspects of this decision. Faculty can use this package – discussion case study and instructor's manual – to prepare a highly engaging learning experience for business students.

Finally, the grounded theory study included industry expert interviews and proposed a new approach, an Ethics Integrated AI Adoption Framework with AI Trust functioning as an antecedent to these leader behaviors. From a theoretical standpoint, this study served as a bridge between AI trust and ethics, as well as AI trust and AI-Human job design, along with ethics and AI-Human job design.

CHAPTER ONE: INTRODUCTION

Background

There has been a revolution in Artificial Intelligence (AI) and Machine Learning (ML) in recent years in response to the explosion of pervasive data, increased availability of open source software, mainstream use of cognitive technologies, and amplified computing capacities (Davenport & Harris, 2017). McKinsey Global Institute anticipates that advanced cognitive technologies such as AI and ML have the capacity to generate new business value ranging from \$3.5 trillion to \$5.8 trillion within nineteen industries by 2020 (Chui et al., 2018). This technology is being used in a variety of industries including insurance, automotive, banking, and retail as conveyed by Chui et al. (2018). Further, the McKinsey study revealed that cognitive technologies are most frequently deployed in sales and marketing functions as well as supply chain management and manufacturing (Chui et al., 2018).

AI Use Cases

The researchers at McKinsey examined over four hundred use cases (Chui et al., 2018) to identify the types of problems that AI and ML were being deployed to solve. The researchers described a use case as “a targeted application of digital technologies to a specific business challenge, with a measurable outcome” (Chui et al., 2018, p. 11). Their study revealed eight categories of problems which could be solved by various AI and ML techniques. Some of the highest value applications related to the sales and marketing functions included classification or image recognition, forecasting of sales, and cluster analysis which was used for market

segmentation. In terms of operations management, preventive maintenance prediction, logistics/routing optimization, and customer service were identified as high value areas (Chui et al., 2018). For purposes of this dissertation, my research predominantly focused on the sales forecasting and marketing segmentation functions for one case study, and the predictive capabilities in marketing and sales along with operations within the grounded theory study.

Technology Adoption

The extant technology adoption (TA) literature offers some insights that may prove valuable upon investigating the introduction of AI. The established models in this mature research area draw on concepts from the information systems, psychology, and sociology disciplines. The Technology Acceptance Model (TAM) as developed by Davis (1989), along with the TAM-2, which was an extension credited to Venkatesh and Davis (2000), served as the Information Technology lens for the case study investigation. Based on his research, Davis (1989) identified two variables that impact users' inclination to utilize technology in their daily work to improve productivity and performance. Those variables include "perceived ease of use and perceived usefulness" (Davis, 1989, p. 319; Lee, Kozar & Larson, 2003, p. 751).

As a result of Davis' work, he learned that many computer and software firms were applying end user surveys to develop innovative information technology product offerings, however, the surveys were not validated. The firms did not appear to utilize a scientific approach to correlate the survey measures with user behavior and Davis subsequently responded by developing scientifically validated scales which could be used to estimate user intentions. Several years later, Venkatesh and Davis (2000) determined there were socialization and cognitive elements to the technology adoption process. Effectively, the authors estimated that "social influence processes...including subjective norm[s], voluntariness, and image" in addition

to “cognitive instrumental processes...such as job relevance, output quality, result demonstrability, and perceived ease of use” impacted adoption behaviors (Venkatesh & Davis, 2000, p.187). The socialization space within this model is an interesting avenue to explore regarding ethical behavior.

The TAM and TAM-2 models focus primarily on adoption behavior of the individual and functioned well as the ethical lens for the discussion case study. These models held a dominant position within the information technology discipline. The decision to provide management students with exposure to these models was a solid pedagogical approach for the discussion case. For the grounded theory study, I wanted to examine both firm and individual level factors. TAM and TAM-2 concentrated on individual level factors whereas the Diffusion of Innovation theory (DOI) provided both firm and individual level perspectives. Therefore, I selected DOI as the technology adoption lens for the grounded theory study.

Ethical Considerations

For this investigation, it was important to begin by defining the term “ethics”. As described by Collins (2019, p.5), “ethics are the principles a person uses to determine whether an action is good or bad. Every stakeholder interaction can be interpreted through an ethical lens”. Prior to selecting the ethical lens, I explored six ethical theories including egoism, social group relativism, cultural relativism, utilitarianism, deontology, and virtue ethics. Egoism prioritized self-interest over other interests, social group relativism emphasized group norms functioning as a reference, and relativism stressed maintaining legal standards (Collins, 2019). Utilitarianism highlighted comparing the needs of the majority versus needs of the few, deontology underscored the importance of treating every person with respect, and virtue ethics accentuated

moral character (Collins, 2019). Government entities as well as businesses often used utilitarianism in their decision making and this approach was the foundation for capitalism.

For purposes of this investigation, the primary ethical theory to be used was utilitarianism. As discussed in the Stanford Encyclopedia of Philosophy, utilitarianism entailed selecting the moral course of action that would achieve the greatest good for the maximum quantity of people (Driver, 2014). When applying this ethics approach, one typically evaluated the consequences of a course of action and applied a formula to calculate the action that would lead to the greatest good. Within the course of business, managers and employees were often tasked with performing a cost-benefit analysis, especially in the context of technology adoptions, which was grounded in utilitarianism. This ethical theory may become particularly problematic when managers must weigh and prioritize the interests of different stakeholders during the AI/ML adoption process which makes for an interesting study.

One of the key challenges that resulted from studying ethical decision making in the workplace is related to employees having different perceptions of a situation, values, and ethical frameworks. It is likely that most managers and associates had a standard ethical framework on which they rely (or fail to rely on) when making decisions with an ethical element. The difficulty arose when several workers relied on different frameworks (i.e. one worker subscribed to utilitarianism while another relies on deontology/moral rights). Collins (2019) proposed a multi-step process whereby workers shared their position along with their ethical reasoning on an issue, reflected on the other side's ethical perspective, identified the other parties' ethical theory, and restated their position using the other parties' approach. This ethical decision-making approach was an interesting perspective to bring to the analysis of this research.

Given this newly found power and potential source of competitive advantage driven by AI, firms recognized there were risks and potential landmines that needed to be evaluated and addressed. This information was being used in hiring and promotion, consumer loan approvals, medical treatment diagnosis, and even criminal sentencing hearings, in addition to other areas. As such, this technology was a powerful fulcrum with societal implications. As Milton Friedman stated, “The power to do good is also the power to do harm; those who control the power today may not tomorrow; and, more important, what one man regards as good, another may regard as harm.” (Friedman, 2002, p. 3).

Consequently, organizations needed to proactively plan to address the introduction of AI, particularly from an ethics standpoint. Krishna et al. (2017) from Deloitte provided action steps that firms took to manage algorithmic risk which was a vital component of AI adoptions. The team provided recommendations targeted towards training data quality control, algorithmic design, and output usage pitfalls (Krishna et al., 2017). While this was a start, it was important for managers to fully understand the complex ethics landscape involved in AI projects so they can make informed decisions about adopting these cognitive technologies. The proliferation of data being captured should prompt society, firms, and individuals to consider its use and the inherent ethical risks.

Attitude Towards AI

Furthermore, it was important to consider the attitudes and perceptions of individuals towards this emerging technology. As conveyed by Zhang and Dafoe (2019), many Americans have mixed attitudes towards AI/ML and the governance of this technology. The University of Oxford’s Center for Governance of AI conducted a survey of more than two thousand American adults. Survey participants that were college graduates, male, and earned higher incomes

expressed a higher degree of support for this technology as compared to individuals with a high school education or less, female, and possessed lower income levels. It was interesting to note that “the overwhelming majority of Americans (82%) believe that robots and/or AI should be carefully managed” (Zhang & Dafoe, 2019, p. 3). Moreover, the survey results suggested that safeguarding privacy and civil liberties, controlling the spread of fake news and misinformation, preventing cyberattacks, and protecting personal data were the highest priorities of Americans concerning applications of AI (Zhang & Dafoe, 2019). Notable was participants’ perceptions of which organizations should have accountability for developing and managing this emerging technology. Respondents appeared to trust military and universities to design AI/ML while they believed technology firms and non-governmental organizations should be responsible for overseeing the technology.

Purpose Statement

The objective for this research was to develop an understanding of market or regulatory pressures driving organizations to follow certain ethical perspectives/principles and determine how ethics plays a role in shaping manager decisions for adopting AI inside the organization. Since limited research has been conducted in this area, this study can serve as a springboard for management scholars to continue investigating ethical concerns, as well as inform leaders that wish to enumerate ethical considerations in their decision-making processes.

Research Questions

There were three research questions that were guiding this investigation. The first research question was: *How do market and regulatory forces reportedly shape Artificial Intelligence adoptions?* The intention was to review academic and practitioner-focused literature to assess how environmental forces were impacting the decision to adopt this technology. The

second research question included: *What ethical principles/perspectives do managers follow when adopting Artificial Intelligence and Machine Learning systems?* There has been considerable discussion in the literature about a variety of ethical issues and it was important to learn how managers were addressing these issues within the workplace. The third research question was: *What ethical issues exist within the firms that adopt Artificial Intelligence and Machine Learning systems?* Although the literature does point to a range of ethical issues, it was important to develop an inventory of the types of ethical issues that firms are facing.

Selecting the appropriate unit of analysis was an important component in designing this investigation. Overall, this dissertation was comprised of three studies that utilized a multilevel approach. This dissertation was carefully crafted with an eye towards publishing these manuscripts soon. Ethics in AI is a very resonant topic currently and I wanted to ensure this valuable information can be shared with stakeholders. The industry analysis, discussion case study, and instructor's manual concentrated on firm-level considerations. Whereas the constructivist grounded theory investigation focused on both firm and individual (manager)-level perspectives. By combining the firm and individual level explorations, it provided a deeper understanding of how ethical issues are shaping AI adoptions.

Philosophy of the Researcher

As recommended by Creswell (2018), I began planning this research by examining my motives, background, and assumptions. As a faculty member that teaches organizational ethics, I was interested in learning more about the intersection of ethics and technology in the business environment, particularly the introduction of AI. Prior to entering academia, I worked in a management consulting capacity implementing materials management systems in healthcare settings, so I recognized the business value of this technology. My previous experiences in

consulting with clients on adopting and implementing new technologies informed my research. Given the social nature of technology adoptions and ethics, I decided to apply a constructivist approach. This entailed having an open mindset towards the data, interpreting data gathered through interviews, and applying that approach to construct new knowledge (Creswell, 2018). As a means of maintaining self-awareness and identifying potential biases along with keeping them in check, I maintained a journal to reflect on my experiences throughout this research process.

Dissertation Structure

This research project followed a traditional dissertation format. It began with an introduction, then proceeded to an industry analysis, a discussion case study, an instructor’s manual, and a grounded theory study, then progressed to a conclusion. The industry analysis addressed research question 1, while the discussion case study, instructor’s manual and grounded theory study addressed research questions 2 and 3. This approach was selected to provide a holistic perspective on external as well as internal, firm-centric forces impacting AI adoptions. Please see Figure 1 for an illustration.

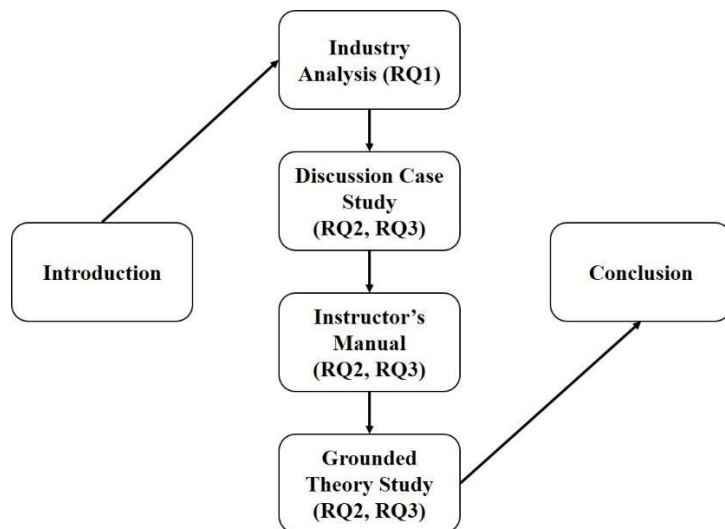


Figure 1. Dissertation Structure

Ethical Theoretical Foundation

Utilitarianism

The ethical lens that was applied in this study was Utilitarianism. Individuals that utilize this approach focus on extending the amount of good that is achieved for the highest quantity of individuals (Driver, 2014). Early classical philosophers Jeremy Bentham and John Stuart Mill associated “good” with “pleasure” (Driver, 2014). Bentham asserted that individuals were either motivated to conduct actions that would result in pleasure or to prevent pain (Driver, 2014). The case study and grounded theory investigation enabled me to explore the motivations for adopting this technology. Was the AI adopted in order to derive economic benefits or “pleasure” for the firm as well as the individual, or was it adopted to address pain points within the firm such as staffing issues, quality concerns, client service, management issues? Interestingly, Bentham considered assigning the moral quality of an action based on the effects of that action, not necessarily on the essence or characteristics of that activity. This approach allowed for changes or evolution in a technology. Given that AI technology is rapidly evolving, this flexibility provides an interesting space to examine the ethical issues related to AI adoption.

Moral responsibility emerged as another research opportunity. Jago (2019) provided intriguing research that explored differences in perceptions of authenticity related to work provided by humans as compared to items produced by ML. Through a series of four experiments, Jago demonstrated that individuals perceive some categories of work provided by humans as being more authentic than the same caliber work provided by ML. He proposed that perceptions of some types of work developed by ML can be strengthened by making explicit the work of the ML designers. Further research is needed to clarify which domains were applicable and identify the relationship between moral authenticity and human judgments, decisions, and behaviors.

Evaluating and Validating Qualitative Studies

While reviewing this research, it was important to assess the validity of this work. Creswell (2018) emphasized the following evaluation criteria for the discussion case study and instructor's manual: describing a specific time period and scope of a decision, listing the site selection criteria, providing sufficient background information and details of the case, communicating themes, sharing applicable learnings, and discussing the author's role in preparing the case. The grounded theory study has a different set of standards as discussed by Creswell (2018): emphasizing processes, leveraging a coding process that lifts the data from concepts to themes, diagramming a theoretical model, connecting with future research recommendations, using analytic memos for data processing, and demonstrating evidence that the researcher engaged with the data. Both studies met these criteria for validity.

References

- Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., Malholtra, S. (2018). Notes from the AI frontier, insights from hundreds of use cases. Retrieved from <https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20AI%20frontier%20Applications%20and%20value%20of%20deep%20learning/Notes-from-the-AI-frontier-Insights-from-hundreds-of-use-cases-Discussion-paper.ashx>
- Collins, D. (2019). *Business ethics: Best practices for designing and managing ethical organizations*. 2nd edition. Thousand Oaks, CA. Sage Publications, Inc.
- Creswell, J.W., Poth, C.N. (2018). *Qualitative inquiry & research design*. 4th ed. Thousand Oaks, CA. Sage Publications, Inc.

- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340. <https://doi-org.ezproxy.lib.usf.edu/10.2307/249008>
- Driver, J. (2014). "The History of Utilitarianism", *The Stanford Encyclopedia of Philosophy* (Winter 2014 Edition), Edward N. Zalta (ed.), URL = [<https://plato.stanford.edu/archives/win2014/entries/utilitarianism-history/>](https://plato.stanford.edu/archives/win2014/entries/utilitarianism-history/).
- Friedman, M. (2002). *Capitalism and freedom*. Chicago, IL. University of Chicago Press.
- Jago, A. S. (2017). Algorithms and Authenticity. *Academy of Management Proceedings*, 2017(1), 10853. doi:10.5465/AMBPP.2017.10853abstract
- Krishna, D., Albinson, N., Chu, T. (2017). *Managing algorithmic risks: Safeguarding the use of complex algorithms and machine learning*. Retrieved from <https://www2.deloitte.com/content/dam/Deloitte/us/Documents/risk/us-risk-algorithmic-machine-learning-risk-management.pdf>
- Lee, Y., Kozar, K., & Larsen, K. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, 12, pp-pp. <https://doi.org/10.17705/1CAIS.01250>
- Vectra Digital (2019). *Get to Know Ada*. Retrieved from <https://www.vectradigital.com/service/ada/>
- Venkatesh, V. (2006), Where to Go From Here? Thoughts on Future Directions for Research on Individual-Level Technology Adoption with a Focus on Decision Making. *Decision Sciences*, 37: 497-518. doi:10.1111/j.1540-5414.2006.00136.x

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 46(2), 186-204.

doi:10.1287/mnsc.46.2.186.11926

Yin, R.K. (2018). *Case Study Research and Applications: Design and Methods*. Sage Publications, Thousand Oaks, California.

Zhang, B. & Dafoe, A. "Artificial Intelligence: American Attitudes and Trends." Oxford, UK: *Center for the Governance of AI, Future of Humanity Institute*, University of Oxford, 2019. <https://ssrn.com/abstract=3312874>

CHAPTER TWO: INVESTIGATING MARKET AND REGULATORY FORCES SHAPING ARTIFICIAL INTELLIGENCE ADOPTIONS

Please note that portions of this industry analysis have been accepted for publication in an upcoming issue of the Muma Business Review. Through a creative commons license, these excerpts have been approved for publication by the author as part of this dissertation.

Tagline

Utilizing the stakeholder analysis framework, this article elucidates the market structure, competitive and regulatory forces influencing AI adoption decisions within firms, and subsequent profitability.

Keywords

Artificial Intelligence, Machine Learning, Organizational Ethics, Stakeholder Analysis

Executive Summary

The Artificial Intelligence (AI) industry has experienced tremendous growth in recent years. Consequently, there has been considerable interest in the media regarding this emergent technology. Practitioners and academics are interested in learning how this market functions to make evidence-based decisions regarding its adoption. The purpose of this manuscript is to perform a systematic examination of the current market dynamics as well as identify future growth opportunities for the benefit of incumbents in addition to firms seeking to enter the AI market. The primary research question is: *How do market and governmental forces reportedly shape AI adoptions?* Drawing on predominantly practitioner focused literature, along with several seminal academic sources, the article examines and maps stakeholders in the market

using the AI Industry Stakeholder Power/Interest Matrix. This approach allows for the identification and analysis of key stakeholders as well as power and influence within the industry. Semiconductor and cloud computing firms play a substantive role in the industry and wield substantial power, as revealed by this analysis.

The Industry

Practitioners and academics similarly have a vested interest in understanding the structure as well as broad competitive and regulatory forces that shape the Artificial Intelligence (AI) market and its subsequent profitability. In recent years, AI has garnered considerable hype and misinformation in local and national media. The primary question arises as to how market and regulatory forces reportedly shape AI adoptions in firms. This article intends to discurtain the hype and provide an evidence-based assessment of this market. Knowing how these forces operate within the market, practitioners and academics are empowered to formulate strategy and harness these market forces to maximize profitability.

It is interesting to note that AI has a generalized definition, yet the definition is somewhat ambiguous. Examining some of the AI definitions from key actors that have been provided in the public space is an insightful exercise. There are some interesting similarities and differences contained in these definitions. Multiple designations emphasize the pattern recognition and prediction functions of AI. Some definitions emphasize “human-like” advanced cognitive abilities such as decision-making, learning, and problem solving, whereas others underscore processing and automation functions which are low to mid-range cognitive abilities.

Table 1. Selected Definitions of Artificial Intelligence

Definition	Source
Artificial Intelligence is a branch of computer science dealing with the simulation of intelligent behavior in computers, and the capability of a machine to imitate intelligent human behavior.	(Artificial Intelligence a, 2020, p.1)
the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from experience.	(Artificial Intelligence b, 2020, p.1)
Artificial Intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.	(Nilson, 2010, p.13)
a programmed ability to process information.	(Launchbury, 2019, p.1)
The theory and development of computer systems that can perform tasks that normally require human intelligence, such as visual perception, speech recognition, learning, decision-making, and natural language processing.	(IEEE-USA, 2019, p.1)
the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, and even exercising creativity.	(Chui, Kamalnath, & McCarthy, 2019, p.1)
AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.	(Ransbotham, Khodabandeh, Fehling, Fountain & Kiron, 2019, p. 3)

Table 1. Selected Definitions of Artificial Intelligence (Continued)

Definition	Source
a collective term for computer systems that can sense their environment, think, learn, and act in response to what they are sensing and their objectives.	(Rao, Verweij, & Cameron, 2016, p.1)
AI is the general study of making intelligent machines.	(Introduction to AI, 2020, p.1)
AI is the field of computer science dedicated to solving cognitive problems commonly associated with human intelligence, such as learning, problem-solving, and pattern recognition...may connote robotics or futuristic scenes.	(<i>What is Artificial Intelligence?</i> , n.d., p.1)
an umbrella term for a family of techniques that allow machines to learn from data and to act on what they have learned rather than simply following rote instructions created by a program and emphasizes the characteristics of prediction, automation and optimization.	(Thomas, 2019, p.2)

Global strategic planning

This article focuses predominantly on the United States' marketplace. International Data Corporation estimates that worldwide spending on AI Systems will flourish to \$98 billion by 2023, with over half of this investment derived from U.S. firms (*Worldwide*, 2019). However, it is important to note that globalization plays an important role in today's business environment, especially in the AI market. Technological developments, such as AI, function as macro environmental forces that are driving globalization (Hill & Hult, 2019). Nearly all the dominant actors in this space, including multinational firms Amazon, Facebook, Microsoft, IBM, Apple, and Google, have a global presence.

After recognizing the significance of this technology, the United States' government established a strategic plan for the development and promotion of AI. As stated in the 2019 strategic plan, "Artificial intelligence enables computers and other automated systems to perform tasks that have historically required human cognition and what we typically consider human decision-making abilities" (Select Committee on Artificial Intelligence, 2019, p. 1). Priority areas contained within the plan include research and development funding, approaches for human-machine interactions, frameworks to address ethical, legal, and social concerns , security initiatives, open-source data sets, performance benchmarking for AI, and workforce requirements to support these initiatives (Select Committee on Artificial Intelligence, 2019).

As well, the European Commission has been working to create standards and operating guidelines to bring some structure to the AI field. The European Commission offers the following definition, "a generic term that refers to any machine or algorithm that is capable of observing its environment, learning, and based on the knowledge and experience gained, take intelligent actions or propose decisions. Autonomy of decision processes and interaction with other machines and humans are other dimensions that need to be considered" (Artificial Intelligence: A European Perspective, 2018, p. 2).

Another AI powerhouse, the Chinese government, has invested considerable resources in designing an AI ecosystem that has helped them to become a world leader in this field. In a recent strategic plan, The People's Republic of China offers the following perspective on AI (State Council, 2017, p.2):

Artificial intelligence is thought to be the strategic technology leading the future, the world's major developed countries regard the development of artificial intelligence as the major strategy to increase national competitiveness and enhance national security, therefore they intensify the introduction of plans and policies and the deployment of the core technology, top talent, standards etc. trying to grasp the initiative in the new round of international science and technology competition.

One such technological development, the Internet, has created many opportunities for consumers around the world to gather information about firms as well as the products and services they are producing in other countries (Hill & Hult, 2019). This development has created many options for buyers that are exploring different products. Furthermore, the Internet has created a low-cost marketing channel whereby firms can easily access customers on a global scale. This platform has enabled small firms to establish a large-firm online presence and achieve economies of scale related to their production.

Economic perspectives

Economists categorize AI as being a transformative General Purpose Technology (GPT). Like the steam engine and electricity, AI has the power and functional characteristics to positively impact virtually every sector of the economy (Bresnahan & Trajtenberg, 1992). Productivity gains in AI are positively related to productivity gains in complementary technologies (See Rosenberg, 1979) which, in turn, spurs additional innovation and investment in research and development. General Purpose Technologies, as defined by Bresnahan & Trajtenberg (1992), possess the following three characteristics: 1. pervasiveness, 2. advancement over time, and 3. proliferation of innovation. Pervasiveness implies that this technology is widely distributed across industries and market sectors.

Rosenberg (1979) stresses the important role that complementary technologies play in activating productivity levels related to a single technology advancement. Essentially, technological innovations such as AI need to be viewed utilizing a systems lens. Innovations located throughout the value chain function as gates and subsequently prompt AI related productivity improvements (Rosenberg, 1979). Further, the author asserts that the inventor of an AI innovation may have to wait on another innovation to be developed prior to implementing the

AI. A second characteristic of this technological interdependence is derived from the process of bringing a new technology product to market. Initially, the product is introduced to the market and consumers rapidly purchase the product. Over time, the technology product is gradually refined and modified to meet dynamic needs of end users. It may take considerable time for large productivity gains to be observed as many of the changes are additive. This requires patience on the part of the inventors, developers, and investors (Rosenberg, 1979).

The consulting firm, Accenture, recently surveyed 6,672 business leaders and technology executives to learn about their perceptions of digital transformation within their respective firms (Daugherty & Wilson, 2019). The 2019 Technology Vision report revealed a group of complementary technologies, labelled DARQ, that propel companies forward in their digital transformation journey. DARQ includes “Distributed Ledger Technology (DLT), Artificial Intelligence (AI), Extended Reality (XR), and Quantum Computing (QC)” (Daugherty & Carrell-Billard, 2019, p. 17). DLT, which includes Blockchain, consists of a decentralized virtual network that allows for the dissemination of information across companies, networks, and geographic boundaries and collaboration in real time in order to build trust (Daugherty & Carrell-Billard, 2019; Dozier & Saunders, 2020). AI aids in rapidly examining data sets, identifying patterns and trends, and providing guidance to help foster evidence-based decision making. Further, AI is used in concert with other technologies like robotics and voice activated applications to automate tasks that are normally performed by humans. XR encompasses virtual reality and augmented reality which allows humans to have a lifelike experience with a brand or company while improving productivity and performance in the workplace (Daugherty, 2019). Quantum Computing is an advanced processing system in which computers estimate the

characteristics of data based on mathematical formulas and develop sophisticated models rather than relying on simple zeros and ones as used in traditional computing.

For perspective, it is helpful to review SMAC which facilitated the first digital revolution. SMAC consists of Social (S), Mobile (M), Analytics (A), and Cloud (C) (Olenski, 2016). Social includes all the social media applications that a firm uses to communicate with its customers such as Twitter, Facebook, LinkedIn, and Instagram, in addition to other channels. Mobile encompasses technologies such as smartphones and tablets which allow consumers to access a firm on-the-go. Analytics packages allow a firm to make sense of the data provided by its customers and suppliers, as well as formulate appropriate marketing programs and offerings tailored to those needs. In his Forbes article (2016), Olenski claims that firms utilizing these four technologies jointly developed a thorough understanding of their customers and business partners, even to the point of being able to anticipate their needs and motivations. Many CIOs were tasked with making the decision to implement these tools and sometimes they did not have considerable experience with them. Yet, these leaders ended up using them for budgeting and prioritization decisions within the organization.

Firms operating in this space understood the true competitive advantage that could be achieved by utilizing all four technologies in concert (Olenski, 2016). As discussed by Olenski (2016), looking at these technologies from an alternative perspective revealed that firms that chose not to embrace these assets were left behind. Firms that plan to utilize DARQ recognize that they need to be fully utilizing SMAC as a foundation. Otherwise, they will not have the capabilities to take full advantage of these advanced technologies.

McKinsey surveyed 2,360 business leaders from a broad range of organizations about their experience in deploying AI within their respective firms. The survey focused on “33 AI use

cases across eight business functions” (Cam, Chui, & Hall, 2019, p. 2). The results revealed that AI’s predictive modeling capabilities enable firms to capture additional revenues in the customer service, marketing, channel management, churn management, and promotion functions of the business (Cam et al., 2019). Whereas preventive maintenance prediction models provided by AI allows firms to achieve significant cost reductions in the manufacturing areas of the business (Cam et al., 2019).

Further, McKinsey’s study confirmed that AI is distributed across virtually all industry sectors, however, this technology has penetrated some market sectors to a higher degree than others. The top three sectors include High Tech, Automotive and Assembly, and Telecom, whereas the lowest three sectors include Pharmaceuticals, Professional Services, and Infrastructure. The High Tech, Automotive and Assembly, and Telecom sectors displayed heavy use of machine learning, virtual agents, and robotic process automation. Notably, physical robotics, machine learning, and natural language text understanding were the dominant AI applications in the lowest three sectors. Machine learning appears to be the dominant application across all sectors (Cam et al., 2019).

AI applications

For context and setting the stage for the remainder of this manuscript, it is helpful to review the types of AI applications that are currently being deployed. Machine Learning has been the most visible AI application and has served as a key contributor to the expansion of AI (Bringsjord & Govindarajulu, 2019). The field of Machine Learning (ML) consists of computer systems that generate statistical models and algorithms independently, solve complex problems, and predict results using either training data sets or historical performance records (Bringsjord & Govindarajulu, 2019). It is important to note that the quality of the data that is used for the

training data set and entered into the system plays an important role in the quality of the output or prediction that is generated. If the data that is entered is inferior in quality, then the information that is generated from the ML will reflect that poor quality.

Within the ML domain, there are three primary categories which include Supervised Learning, Unsupervised Learning, and Reinforcement Learning. In a Supervised Learning application, the user provides a set of data that has been labelled or identified to the system; subsequently, the system studies and learns the characteristics of that data set. When a new data set is introduced, the system applies those characteristics to the data to predict the results of a proposed calculation or formula (Rebala, Ravi, & Churiwala, 2019). In an Unsupervised Learning application, the user provides a large dataset, but does not provide an answer key or labels per se. Instead, the system studies the data set, identifies patterns in the data, and assigns groups of items that have similar characteristics based on its analysis which is subsequently used for predictions (Rebala, Ravi, & Churiwala, 2019). The computer system studies its external environment for signals and responding with an appropriate action in Reinforcement Learning. The system “learns” based on responses to modify its actions in response to those external signals (Rebala, Ravi & Churiwala, 2019). This learning method is used in dynamic problem-solving situations and situations with large solution sets such as computerized games and autonomous driving scenarios (Rebala, Ravi, & Churiwala, 2019).

The McKinsey study referenced previously identifies Robotic Process Automation (RPA) as being a high growth technology used in the High Tech, Automotive and Assembly, and Telecom sectors. Boulton, in CIO Magazine (2018, p.1), describes RPA as:

an application of technology, governed by business logic and structured inputs, aimed at automating business processes. Using RPA tools, a company can configure software, or a “robot,” to capture and interpret applications for processing a transaction, manipulating data, triggering responses, and communicating with other digital systems.

Examples of RPA include deploying bots to field human resources-related questions from employees, or automated customer invoicing.

Computer vision is another subset AI field that has gained momentum in recent years. Analytics market leader, SAS, defines computer vision as “a field of AI that trains computers to interpret and understand the visual world. Using digital measures from cameras and videos and deep learning models, machines can accurately identify and classify objects, and then react to what they see” (Halper, 2017, p.6). The use of mobile technologies like smartphones and tablets makes it easy for users to upload images to the Internet and software applications for review. In recent years, computer vision programs have become remarkably more accurate in assembling photos, creating images, and identifying images based on a large database.

Natural Language Understanding (NLU) has gained traction as indicated by systems like Amazon Alexa. Amazon defines NLU as a system in which “computers can deduce what a speaker actually means, and not just the words they say. In short, it is what enables voice technology, like Alexa to infer you are probably asking for a local weather forecast when you ask ‘Alexa, what’s it like outside?’” (*What is Artificial Intelligence?*, n.d., p.1). Relatedly, National Language Processing (NLP) is another technology within the AI domain. SAS defines NLP (Halper, 2017, p. 6) as:

NLP involves analyzing, understanding, and generating responses ultimately to enable interfacing with systems using human rather than computer languages. For text, NLP often uses semantics to parse sentences for entities (people, places, things), concepts (words and phrases that indicate an idea), themes (groups of co-occurring concepts), or sentiments (positive, negative, neutral).

Recently, Facial Recognition Technology has garnered both positive and negative attention. U.S. law enforcement agencies have used Amazon’s Rekognition facial recognition technology for criminal investigations (*What is Artificial Intelligence?*, n.d.). Examples of

business use cases include using this technology to identify defective parts or products on an assembly line, study diseased crops in a field, or even identify passengers via digital passports for airport security. Despite the benefits of this technology, there are some documented issues and problems. The Wall Street Journal reported on recent empirical evidence from the National Institute of Standards and Technology that Facial Recognition programs contain racial and gender bias (National Institute of Standards and Technology, 2019). IBM offers a definition of Facial Recognition Technology to include: “face detection, facial authentication, and facial matching” (Montgomery & Hagemann, 2019, p.1).

The use of virtual agents is another sub field of AI. Companies such as Microsoft offer virtual agents that can easily be deployed with limited knowledge and skills in coding and AI (Microsoft AI School, 2019). These virtual agents can assist with routing customer service calls to the appropriate department, or even fielding frequently asked questions from customers such as providing store operating hours, directions, and customer account balances or inquiries. The value in utilizing these programs is that the firm can provide customer service 24/7 while allowing for flexibility in handling dynamic call volumes in a cost-effective manner.

Some people perceive robotics and AI to be interchangeable. However, robotics and AI are not necessarily the same. According to Dell Technologies, “some robots may be programmed to perform the same tasks over and over without any ‘intelligence’ built in”, whereas “smart robots may be programmed to carry out complex tasks that require more thought and adaptation” (Dell Technologies, 2019, p.1). For instance, a firm that manufactures fire hoses, Task Force Tips Inc., uses vision guided robots throughout the valve production process and employees that formerly worked in production now serve as technicians servicing the robots which has bolstered overall firm productivity (Dell Technologies, 2019).

Finding the right balance of human workers and robots is an important consideration for firms. Introducing AI robots into the manufacturing process often stems from a need for increased speed and efficiency. In his article in *The Verge*, Hawkins reported that Elon Musk admitted that the production delays of Tesla's Model 3 sedans were a result of "over-reliance on automation and too few human assembly line workers building the model 3" (2018, p. 1).

Finally, the topic of autonomous vehicles needs to be considered. Firms exploring this technology emphasize the safety aspect of autonomous vehicles. Semiconductor manufacturer, Nvidia (2020, p.1), describes the relationship between AI and autonomous vehicles as:

AI gives cars the ability to see, think, learn, and navigate a nearly infinite range of driving scenarios. Nvidia uses the power of AI and deep learning to deliver a breakthrough end-to-end solution for autonomous driving – from data collection, model training, and testing in simulation to the deployment of smart, safe, self-driving cars” .

Stakeholders

Upon reviewing this industry analysis, it is helpful to apply a stakeholder analysis approach as a lens to understand the dynamics of key stakeholders within the AI ecosystem. Beyond shareholders, there are many other actors that have a vested interest in this market space, and it is important for firms to consider their diverse needs.

Cloud computing providers

One group of stakeholders includes cloud computing providers. The explosion of cloud computing in recent years has spurred growth in the AI field. For companies to store and process the massive volumes of data they are accruing, they need to obtain storage capacity and advanced computing technology like graphic processing units. Cloud technology provides companies with the scalability and flexibility to handle these complex requirements. According to MarketLine's U.S. Cloud Computing Industry Profile (2019), cloud computing in the U.S. generated revenues of \$85.4 billion in 2018 with an accelerating compound annual growth rate

(CAGR) of 29.5%. MarketLine estimates that cloud computing's growth will slow to 27.15% between 2018 and 2023 and achieve a market value of \$287.2 billion by 2023 (2019). The introduction of 5G technology and the Internet of Things (IoT) along with improved internet quality is contributing to the acceleration of cloud computing (MarketLine, 2019), Four firms lead the industry including: AWS (Amazon Web Services), Microsoft Azure and Office 365, Google Cloud and IBM Cloud. A fifth firm, Salesforce, is rapidly gaining a foothold in this space (MarketLine, 2019).

Semiconductor manufacturing firms

Semiconductor manufacturers comprise another significant group of stakeholders. McKinsey studied the semiconductor industry and estimates that growth in AI will create opportunities for firms that manufacture high efficiency semiconductors. The firm's study projects that semiconductors supporting AI applications will increase by 18 percent annually over the next few years (Batra, Jacobson, Madhav, Queirolo, Santhanam, 2018). MarketLine reports that the semiconductor industry earned \$79.8 billion in revenues in 2018 and had a CAGR of 13.2% between 2014 and 2018 (2018). For the five-year period, 2018-2023, MarketLine projects the semiconductor industry will grow by 13.4% and generate \$149.8 billion by 2023 (2018). Market leading firms that operate in this space include Intel, Texas Instruments, Qualcomm, and Micron Technology (MarketLine, 2018).

Relatedly, manufacturers of graphic processing units (GPU's) represent another segment of stakeholders that have a strong relationship with the AI market. Nvidia is a market leader in this group as the firm produces GPU's for the gaming, data centers, automotive and virtual reality markets (MarketLine Nvidia, 2019). MarketLine's Nvidia Company Profile (2019) reports that the data center market achieved \$71 billion in revenues in 2018 and anticipates

annual revenue of \$99 billion by 2022 with a CAGR of 8.4%. In addition to Nvidia, firms such as Advanced Micro Devices, Intel, and AMD have established a foothold in this market space.

Computer manufacturing firms

Computer manufacturers are key stakeholders within the AI market space. According to Dun and Bradstreet's First Research Computer Manufacturing Profile (2019), this industry within the United States contains three primary clusters including computer products (approximately 41% of revenues), storage devices (28% of revenues), and peripheral equipment (31% of revenues). In recent years, computer manufacturers have lost market share due to availability of computing capacities available through smart phones and tablets. In response, computer manufacturers have entered the AI space to capture production efficiencies as well as new revenue streams. For instance, IBM is a dominant player in this industry, and the firm's research lab introduced its well-known IBM Watson offering in 2010. IBM Watson stepped into the spotlight through its impressive performance on the television show, Jeopardy, which highlighted the competencies of this technology (*A Computer called Watson*, 2011; Best, 2013). Rival computer manufacturer, Hewlett Packard, launched its AI offerings in 2017. Hewlett Packard Enterprises (HPE) recognized that many firms did not possess the hardware and software infrastructure along with the expertise to manage AI adoptions. Consequently, HPE developed a "Deep Learning Cookbook" and wrap around support services to facilitate and manage AI adoptions (HPE Introduces, 2017).

Internet publishers and broadcasters

Another pivotal group of stakeholders consists of Internet publishing and broadcasting firms which includes firms with a NAICS code of 51913B (Holcomb, 2019). This group of companies provides internet-based information and entertainment services such as "news, music

and video” and mainly derives revenue from online advertising and sales of customer data (Holcomb, 2019). Some firms that comprise this category include Facebook, Google/Alphabet, Apple, and Netflix (Holcomb, 2019). IBIS World estimates this industry generated \$141.1 billion in 2019 with an annual growth of 13.6% between 2014 and 2019 and expected growth of 9.9% between 2019 and 2024. This industry includes social media advertising which has experienced explosive growth in recent years. The growth in smart phone usage has facilitated much of the growth in this market as more people have access to the Internet and are spending more time visiting social media sites which provides increased opportunities for online advertising.

U.S. search engine firms

Like Internet publishers, U.S. Search Engine companies are another group of stakeholders that play a vital role in the AI landscape. IBIS World indicates this group includes firms like Google/Alphabet and Microsoft which operate search engines and generate income from advertisers that pay to post advertisements on the search pages. Consumers search for websites and content on the search engines for free, and in return, they receive wrap around value added services such as email, social networking sites, blogging platforms, in addition to other functions. IBIS World estimates the 2019 revenue for this industry as \$89.7 billion with a 13.5% annual growth rate from 2014-2019, and a projected annual growth rate of 10.1% during this time (Holcomb, 2019). This growth can be attributed to increasing consumer demand for Internet access and increased use of mobile devices to gather information on products and services (Holcomb, 2019).

Ecommerce and online auctions

The industry comprised of Ecommerce and online auctions is another key stakeholder that has embraced the power of AI. Online retailers such as Amazon sell products and services

primarily through the Internet (Terdiman, 2018). These firms sell a wide variety of products including media items, clothing, electronics and even groceries. This is a recent development (Spitzer, 2019). MarketLine indicates that the online retail industry earned \$297.8 billion in revenues during 2017 and is projected to reach \$447.4 billion by 2022 which is more than a 50% increase over 2017 revenues (MarketLine Online Retail, 2018). Consumers have developed a comfort level with online retailers, and resultingly, they are shopping using their smart phones and tablets which is a key driver of revenue growth.

Higher educational institutions

Historically, educational institutions have played a critical role in gathering research, disseminating findings, and designing innovative AI products and services. Stanford University, Carnegie Mellon University, University of California - Berkeley, Harvard, MIT, Wharton School of the University of Pennsylvania, New York University have active innovation labs and have been instrumental in guiding companies, military, and government entities within the AI space. In 2019, Stanford University introduced the Institute for Human-Centered Artificial Intelligence, named HAI, to facilitate cross-disciplinary research, education, policy consulting, and communication to ensure government entities as well as companies are focused on designing AI that benefits humanity (Stanford University launches, 2019). AI pioneers, Herb Simon and Allen Newell, were faculty researchers at Carnegie Mellon University, so it is fitting that Carnegie Mellon has established a cross disciplinary research initiative which includes a department dedicated to Machine Learning research and development (Linder, 2017). University of California-Berkeley has created the Berkeley Artificial Intelligence Research (BAIR) Lab which includes faculty, graduate students, and doctoral researchers that study the effects of AI on humanity. BAIR is focused on creating transparency around research collaborations and developed an open source area for researchers to store and share datasets.

In 1998, Harvard University established the Berkman Klein Center for Internet and Society to investigate diverse topics ranging from algorithm use in the legal system, governance issues related to autonomous vehicles, AI transparency and accountability, AI in relation to media information quality, and finally global governance issues, in addition to other projects (Berkman Klein Projects and Tools, 2020). The Berkman Klein Center encourages collaboration among researchers and publishes research findings to a wide range of audiences to educate and inform stakeholders. MIT's Computer Science and Artificial Intelligence Lab, CSAIL, has a long and eventful history in the AI field. Since its inception in 1963, CSAIL has focused on inventing new technologies and approaches for human-machine interactions that influence the daily lives of people throughout the world (CSAIL Mission, 2020).

The Wharton School at the University of Pennsylvania established the Mack Institute for Innovation Management to oversee research on emerging technologies. Faculty seek to establish collaborations between the institution and the business community to identify research and educational funding opportunities (Mack Institute About, 2020). New York University has created the AI Now Institute which studies the effects of AI on our daily lives and provides research on ethical issues including bias, safety, and labor implications (AI Now, 2020).

Clearly, higher education institutions recognize that further research and public education is needed. Hence, some of the nation's premier educational institutions have established organizational structures to channel institutional resources as well as promote research and industry alliances to further these efforts. Moreover, these entities have developed communication channels to educate and inform the public of these important initiatives.

Strategic partnerships

Another important development in the AI stakeholder space is the formation of strategic partnerships between business, academia, and government. The Partnership on AI is a strategic partnership that was formed in 2016 to foster cooperation, research, and education among key stakeholders in addition to the public (PAI, 2020). The organization's focus includes the following six themes: "1. safety-critical AI, 2. fair, transparent, and accountable AI, 3. AI, labor and the economy, 4. collaborations between people and AI systems, 5. social and societal influences of AI, and 6. AI and social good" (PAI, 2020). Founding members include Apple, Google, Deepmind, Amazon, Facebook, Microsoft, and IBM (PAI, 2020), and current membership includes over fifty organizations.

Trade associations

The trade association, Association for the Advancement of Artificial Intelligence (AAAI), plays a key role in fostering information sharing, research collaboration, and education among stakeholders in the AI market space. This association organizes AAAI conferences, publishes AI Magazine, and provides funding opportunities to promote education and research. Researchers need a dedicated space to share findings and connect with like-minded professionals; a need that is served by AAAI.

U.S. government

Another stakeholder is the U.S. government. In 2019, the federal administration developed the American AI Initiative and organized a summit to obtain input on policy (The White House, 2019). A review of the Federal Government's proposed 2020 budget reveals this program is "receiving \$850 million for funding" (The White House, 2019, p. 3) A key strategy entails providing funding resources to areas that the private sector does not typically support like

early stage research. The goal is to foster technology transfer for early stage research projects, streamline funding administration, and provide tax benefits for firms that invest in these projects. For coordination purposes, the National Science and Technology Council's Select Committee on AI was formed.

Customers

Customers are also important stakeholders. Some consumers use AI to purchase goods or obtain services as well as information. They often utilize a personal assistant application such as Siri or a virtual assistant like Alexa to perform a supportive task such as providing directions or dimming a light in the house. Throughout the application, consumers are focused on the experience and expect the device or application to enhance it (Brill, Munoz & Miller, 2019). The consumer expects accuracy, timeliness, and dependability of the service provided by the AI.

Another important aspect of the customer experience entails the disclosure and use of personal identity and the benefits of that transaction. Consumers provide their name, address, email, and age in addition to other critical aspects of their identity with the objective of receiving something of value in return. Consumers signing up for a Facebook account, for instance, is an example of this privacy transaction. To obtain a personal Facebook account, consumers must disclose their first and last names, email address, password, gender, and age.

Tucker identifies the following three concerns in relation to privacy: "data persistence, data repurposing, and data spillover" (2019, p.2). Given today's cloud storage technology, companies can easily store data over a long period of time which emphasizes the characteristic of data persistence. Once a consumer establishes a Facebook account, the data will remain stored on the Facebook server indefinitely. If Facebook is notified of a person's death, the organization will create a memorial of the individual's page (Managing a Deceased Person's Account, 2020).

Data repurposing entails the long-term storage, potential sale, and unanticipated future use of the data that an individual provides. The issue concerning Facebook and Cambridge Analytica is an example of data being repurposed in unanticipated and unauthorized ways. In 2016 the United Kingdom's *The Observer* reported that Cambridge Analytica acquired user profiles and Facebook "likes" based on an app survey that users had completed through a research project (Facebook & Cambridge Analytica, 2018; Golbeck & Aral, 2018). The firm used this information for marketing purposes during the 2016 Presidential election campaign without Facebook user consent specifically for that purpose.

The final concern is data spillover and subsequent privacy violations that occur during data collection. Using the Facebook and Cambridge Analytica situation to illustrate this concern, when Facebook users completed the app survey, the system captured user profiles of respondents as well as the user profiles of their network connections. These individuals that were part of the survey participant networks did not have knowledge of, nor did they provide consent for their data being captured and utilized in this manner.

Senior leadership (including Boards of Directors)

It is also important to consider the roles and expectations of internal stakeholders in the AI market. Executives at the firms that are adopting AI, whether the technology is designed in-house or purchased from an outside company, routinely utilize a cost leadership strategy. As a result, Executives tend to maximize the use of AI in operational areas of the company including supply chain management and manufacturing. Preventive maintenance programs are frequent candidates for AI deployments (Cam, Chui, & Hall, 2019).

Another area emphasizes the labor shortage and subsequent skills deficiency created by a flourishing U.S. economy (Forrester, 2019). Leaders recognize the challenges with attracting and

retaining highly skilled and qualified workers. In response to this talent war, leaders have searched for opportunities to automate certain jobs or even tasks within jobs to offset this talent gap. Cognitive technologies such as AI provide companies with the flexibility to adapt to the changing competitive environment (Forrester, 2019).

Non-management associates

Non-management employees need to be included in this analysis. Bughin & Manyika (2019, p.4) report that “Stress, work safety, and fears about jobs are often cited as the largest sources affecting organizations’ productivity today.” Workers may experience stress due to repetitive mundane tasks and heavy workloads that are time sensitive (Bughin & Manyika, 2019). Further, hazardous tasks may be required for a job which can add to the worker’s stress. NIOSH (Bughin & Manyika, 2019) advocates for companies making enhancements to working conditions to improve worker stress levels and productivity. Firms can deploy AI to handle repetitive tasks and jobs which pose hazards to humans as an approach for reducing employee stress levels and improving working conditions.

Further, workers express some concerns and potential fears about their jobs being displaced by AI. A recent study by Northeastern University and Gallup revealed that employees do not have a detailed understanding of AI technology (Northeastern-Gallup, 2019) which may contribute to the fear of the unknown. Education on AI technology is needed, especially among workers with jobs that are risk of being replaced or have the potential for being supplemented with AI (Northeastern-Gallup, 2019). This analysis leads to the question of which organization should provide training and education on these new cognitive technologies. The Northeastern/Gallup study revealed that most workers expected employers to provide this training as compared to higher educational institutions (Northeastern-Gallup, 2019).

As provided in the evidence presented here, external, and internal stakeholders have a wide range of perspectives and expectations that must be addressed. AI poses both benefits and challenges to an organization and it is imperative that a firm develops a thoughtful adoption strategy that takes these diverse perspectives into account.

Method

This industry analysis represents a component of a traditional dissertation that is being submitted to meet the requirements of the Doctor of Business Administration degree at the University of South Florida. This investigation includes the following seven stages: 1. practitioner-focused review journals, 2. academic research institutions, 3. management consulting firms, 4. trade associations and industry alliances, 5. company white papers and case studies, 6. government agencies and institutions, and 7. academic journals (See Table 2).

Table 2. Literature Review Methodology for Artificial Intelligence Analysis

1. Practitioner-focused Review Journals	2. Academic Research Institutions	3. Management Consulting firms	4. Trade Associations and Industry Alliances	5. Company white papers and case studies	6. Government Institutions/ Agencies and private research groups	7. Academic databases and journals
12	9	21	5	9	8	6

I began reviewing practitioner-focused review journals such as Harvard Business Review, MIT Sloan Management Review, and the Wall Street Journal for the time period 2018 - 2020 since these publications appeared to have the most current information on the AI industry. The next step consisted of using a snowball approach and expanding the search to include working and white papers, e-newsletters, and articles published by premier academic research institutions such as Harvard's Berkman Klein Center, Stanford University, Carnegie Mellon

University, and Massachusetts Institute of Technology. These organizations regularly publish research articles and disseminate their findings to the research community quickly, as compared to working through the traditional publishing channels with long time frames.

While reviewing the work of these institutions, it became apparent they had cultivated cooperative relationships with many consulting firms such as Boston Consulting Group, Deloitte, McKinsey, PWC, KPMG, CapGemini, and Gartner. These consulting organizations had websites containing detailed results from their research studies as well as strategy papers, use cases, and case studies for the AI industry. After completing my review of the extensive consulting firm resources, I searched for trade associations (AAAI, IEEE) and trade publications (Tech Republic, CIO Magazine) that were mentioned in the consulting firm papers which yielded several articles. Through this research, I learned that some market leaders in this space had their own in-house research teams and published company white papers and case studies that provided industry insights.

The next phase of my research focused on government institutions/agencies in addition to private research organizations. The government entities are developing strategies and policies to support the industry within the U.S. The National Bureau of Economic Research (NBER) was categorized in the private research entities group and appeared to have an expanding research stream. After analyzing the articles collected to date, I noted there was some missing information. The final step in this research process was to examine academic databases and journals to fill in these gaps. I searched the IBIS World database by NCAICS codes to identify industry profiles. It was interesting to note that Artificial Intelligence was spread across multiple industry profiles including retail, food service, and automotive sectors. The academic databases that I searched included Google Scholar and JSTOR.

Analysis

Since this manuscript has a practitioner-scholar focus, I began by reviewing Mendelow's seminal framework- The Power-Dynamism Matrix (Mendelow, 1981). This researcher argued it is important for managers to align environmental scanning activities and scarce resources with stakeholder power levels and environmental dynamics (Mendelow, 1981). In 1999 Johnson & Scholes expanded this model, dubbed the Power/Interest Matrix, to focus on evaluating stakeholder interests as compared to power rather than environmental scanning and power (See Figure 2). This matrix, appearing in Figure 2, displays the strategies that can be used to manage relations with these stakeholders.

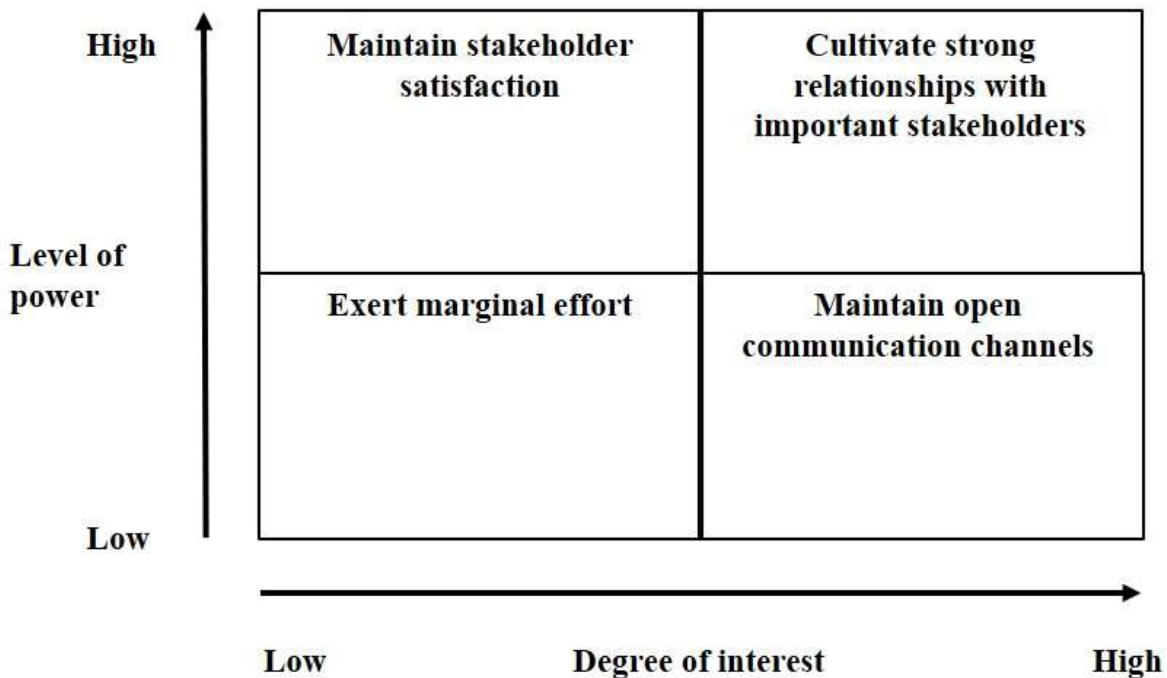


Figure 2. Adapted Stakeholder Power/Interest Matrix

(Adapted from Johnson & Scholes, 1999; Mendelow, 1981)

Mendelow provided a list of four steps to aid users in preparing this analysis including:

“1. determine who the stakeholders are, 2. rate the power of each stakeholder, 3. rate the

dynamism of each stakeholder, and 4. allocate responsibility for scanning developments related to each group” (1981, p. 415). For this assessment, I substituted the term “interest” for dynamism and used a ratings scale of 1 to 5 with 1 being low and 5 being high for each respective item. The “interest” score includes: “frequency of being included in decision-making and frequency of influence by technology and economic shifts” from Mendelow’s matrix (1981, p.415). In simple terms, what is the impact on the stakeholder if the AI is adopted? What gain or loss will the stakeholder experience when the AI is adopted? The “power” score reflects the following four dimensions: “possession of resources, ability to dictate alternatives, authority level, and influence level” (Mendelow, 1981, p. 415). Power can be derived from a variety of sources. Examples of power sources include the position within the organization, level of AI expertise, budgetary resources, organizational structure, and experience deploying AI.

This is prepared from the perspective of a company that is interacting with these stakeholders. This approach includes firms currently operating within the market or new firms that are considering entering the AI marketplace. The basis for this analysis included industry profiles obtained from IBIS World, MarketLine and the other industry resources referenced in this report, and assigned scores based on the profiles as listed below in Table 3.

Table 3. Interest and Power Scores for AI Industry Stakeholders

Stakeholder	Interest Score	Power Score	Selected References
Cloud Computing provider	4.5	4.5	(MarketLine Cloud Computing, 2019)
Semi-conductor firms	2.8	4.5	(MarketLine Nvidia, 2019)
Computer manufacturers	2.5	3.5	(First Research, 2019)
Ecommerce and Online auctions	4.0	4.8	(Terdiman, 2018)
Search engines	3.5	4.0	(Holcomb, 2019)
Internet publishers	2.5	3.5	(Holcomb, 2019)
Consulting firms	4.0	4.5	(Cam, Chui & Hall, 2019)
Academic institutions	4.0	2.5	(Berkman Klein, 2020; Stanford University, 2019)
Trade associations	4.0	2.8	(IEEE, 2019)
Government agencies	2.0	4.0	(The White House, 2019)
Customers	4.0	2.8	(Tucker, 2017)
Senior executives	4.5	4.0	(Forrester, 2019)
Non-management employees	4.0	2.0	(Bughin & Manyika, 2019)

Subsequently, each stakeholder had an interest and a power score which translated into an x and a y coordinate, respectively. The next step was to plot these stakeholders on a two by two grid based on the x and y coordinates (See Figure 3 listed below).

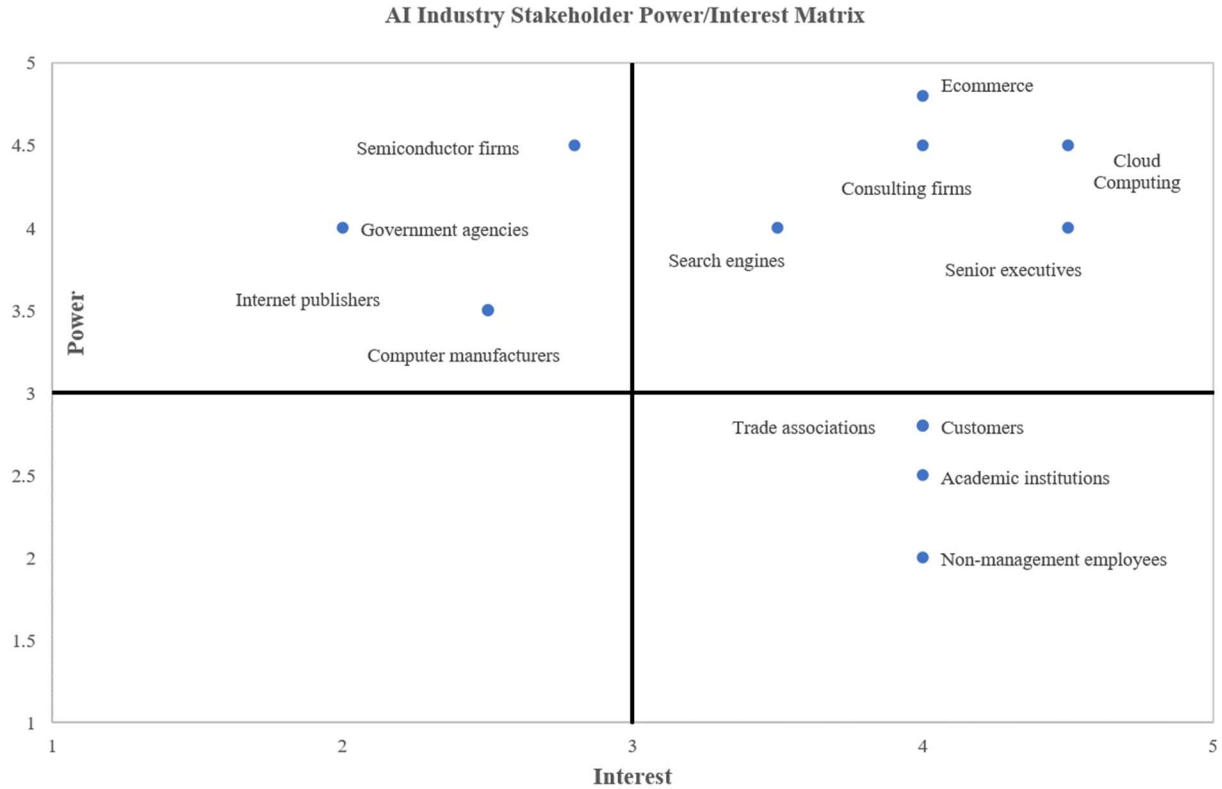


Figure 3. Artificial Intelligence Stakeholder Power/Interest Matrix

(Matrix was adapted from Johnson & Scholes, 1999; Mendelow, 1981. Data was generated by author.)

Discussion

The Stakeholder Power/Interest Matrix (Johnson & Scholes, 1999; Mendelow, 1981) served as a powerful tool for exploring the AI industry stakeholder relationships. Organizations that resided in the top left quadrant (See Figure 3) possessed a high degree of power, yet their interests in individual businesses was mainly a distant one (low to moderate level). The stakeholders residing in this category included government agencies, semiconductor firms, Internet publishers, and computer manufacturers. Since these stakeholders were powerful, it was important for these firms to search for opportunities to maintain a position of good standing and maintain regular communications.

Interestingly, my analysis revealed there were no organizations positioned within the lower left quadrant with low power and low interest. My sense from reviewing the literature was that most firms in the AI industry were fairly engaged. According to the literature, government agencies seemed to have the lowest activity levels, but I expect an increase in the future as big technology firms begin to call for the government to step in and develop governance measures.

Organizations positioned within the lower right quadrant (See Figure 3) had a high degree of interest, yet their power was limited. This group included non-management employees, customers, academic institutions, and trade associations. The approach for interacting with this group included maintaining open and frequent communications. Many of the higher education institutions were publishing regular newsletters, podcasting, and blogging to disseminate their research findings to the public. Some non-management employees perceived AI as potentially taking their jobs, so they certainly had a vested interest.

The top right quadrant (See Figure 3) represented the key players and important stakeholders. This group included cloud computing providers, consulting firms, ecommerce organizations, search engine firms, and senior executives. These stakeholders were very engaged in the industry and represented potential partners and collaborators. Firms should seek opportunities to collaborate with these organizations and stakeholders for mutual benefit.

As a follow-up to this study, a future research opportunity would be to survey technology executives either within a single company or from multiple firms to capture their perspectives on this matrix. This analysis was derived from the industry reports that were included in this study. Interviewing executives at firms that are working in this environment would yield valuable insights.

Another potential future research area is to apply the Technology-Organization-Environment (TOE) framework to this industry analysis to develop a deeper understanding of how these external contexts and environmental forces shape the adoption process. A third research area would be to take a deep dive and explore how a company is using their own proprietary AI in the form of a case study.

Conclusion

Through this study, my focus was on developing an understanding of how the AI market is structured as well as the resulting market forces and subsequent profitability. By evaluating the practitioner literature, this analysis contributes to the extant literature in a variety of ways. This article contains a summary of key industry definitions which is valuable for establishing a baseline understanding of the technology. The AI Industry Stakeholder Power/Interest Matrix illuminates the power and influence dynamics between stakeholders within this dynamic industry. Since the pool of literature focusing on this topic was limited within the academic sphere, I expanded my research to include practitioner and governmental sources. As a result, these findings effectively addressed the primary research question: *How do market and governmental forces reportedly shape AI adoptions?*

Semiconductor and cloud computing firms possess a great deal of market power and have established dominant market positions as a result. Smaller and medium sized firms will struggle to gain market share if they are competing for the same customers in that market space. From a customer perspective, cloud computing technology allows resource-strapped firms to access AI technologies without having to invest in massive data storage and server capabilities. Further, cloud computing firms can provide massive data sets that are needed to run AI which brings the technology closer to smaller firms.

References

*References marked with an asterisk were included within the systematic review.

**A Computer called Watson*. (2011, February 14). IBM History. Retrieved August 07, 2020, from <https://www.ibm.com/ibm/history/ibm100/us/en/icons/watson/>

*AI Now Institute. (2020). In *NYU Tandon School of Engineering*. Retrieved from <https://engineering.nyu.edu/research-innovation/centers-and-institutes/ai-now>

*Artificial Intelligence: A European Perspective. In *EU Science Hub*. Retrieved from <https://publications.jrc.ec.europa.eu/repository/bitstream/JRC113826/ai-flagship-report-online.pdf>

Artificial intelligence a. In *The Merriam-Webster.com Dictionary*. Retrieved from <https://www.merriam-webster.com/dictionary/artificial%20intelligence>

Artificial intelligence b. In *Encyclopedia Britannica*. Retrieved from <https://www.britannica.com/technology/artificial-intelligence>

*Batra, G., Jacobson, Z., Madhav, S., Queirolo, A. Santhanam, N. (2018). In *Artificial-intelligence hardware: New opportunities for semiconductor companies*. Retrieved from <https://www.mckinsey.com/~media/McKinsey/Industries/Semiconductors/Our%20Insights/Artificial%20intelligence%20hardware%20New%20opportunities%20for%20semiconductor%20companies/Artificial-intelligence-hardware.ashx>

*Berkman Klein Projects & Tools. (2020). *Berkman Klein Center at Harvard University*. Retrieved from <https://cyber.harvard.edu/projects-tools>

*Best, J. (2013). IBM Watson: The inside story of how the Jeopardy-winning supercomputer was born, and what it wants to do next. In *Tech Republic*. Retrieved from

<https://www.techrepublic.com/article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer-was-born-and-what-it-wants-to-do-next/>

- *Boulton, C. (2019). What is RPA? A revolution in business process automation. In *CIO Magazine*. Retrieved from <https://www.cio.com/article/3236451/what-is-rpa-robotic-process-automation-explained.html>
- *Bresnahan, T.F., & Trajtenberg, M. (1992). General purpose technologies: Engines of growth. *NBER Working Paper No. 4148*. Retrieved from <https://www.nber.org/papers/w4148.pdf>
- *Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management*, 35(15/16), 1401–1436. <https://doi-org.ezproxy.lib.usf.edu/10.1080/0267257X.2019.1687571>
- *Bringsjord, S. & Govindarajulu, N. S. (2019). "Artificial Intelligence", *The Stanford Encyclopedia of Philosophy* (Winter 2019 Edition), Edward N. Zalta (ed.), URL = <https://plato.stanford.edu/archives/win2019/entries/artificial-intelligence/>.
- *Bughin, J. & Manyika, J. (2019). Your AI efforts won't succeed unless they benefit employees. *Harvard Business Review*. Retrieved from <https://hbr.org/2019/07/your-ai-efforts-wont-succeed-unless-they-benefit-employees>
- *Cam, A., Chui, M., & Hall, B. (2019). Global AI survey: AI proves its worth, but few scale impact. *McKinsey & Co*. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact>
- *CSAIL Mission and history. (2020). In *CSAIL About*. Retrieved from <https://www.csail.mit.edu/about/mission-history>

- *Chui, M., Kamalnath V., & McCarthy, B. (n.d.) *An Executive's Guide to AI*. Retrieved from <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/an-executives-guide-to-ai>
- *Daugherty, P. (2019). Managing technology for the post-digital era. *MIT Sloan Management Review*. Retrieved from <https://sloanreview.mit.edu/article/managing-technology-for-the-post-digital-era/>
- *Daugherty, P. & Carrell-Billard, M. (2019). Accenture technology vision 2019: Full report. *Accenture*. Retrieved from https://www.accenture.com/_acnmedia/PDF-94/Accenture-TechVision-2019-Tech-Trends-Report.pdf
- *Daugherty, P., & Wilson, J. (2019). Human + Machine: Reimagining work in the age of AI. *Accenture*. Retrieved from <https://www.accenture.com/us-en/insight-human-machine-ai>
- *Dell Technologies. (2019). Artificial Intelligence solutions. *Dell Co*. Retrieved from <https://www.delltechnologies.com/en-us/solutions/artificial-intelligence/index.htm>
- *Dozier, P.D., & Saunders. (2020). The inter-organizational perspective on blockchain adoption within an ecosystem. *Twenty-Eighth European Conference on Information Systems (ECIS2020)*, Marrakesh, Morocco.
- *Facebook and Cambridge Analytica: What you need to know as fallout widens. (2018, March 19). In Technology. In *New York Times*. Retrieved from <https://www.nytimes.com/2018/03/19/technology/facebook-cambridge-analytica-explained.html>
- *Forrester. (2019). The Future of Work. *Forrester Research*. Retrieved from <https://go.forrester.com/wp-content/uploads/2019/07/Forrester-Future-Of-Work.pdf>

- *European Commission. (2020). What does the General Data Protection Regulation govern? In *Europa.eu*. Retrieved from https://ec.europa.eu/info/law/law-topic/data-protection/reform/what-does-general-data-protection-regulation-gdpr-govern_en
- *First Research Industry Profile (2017). Computer Manufacturing. *Dun and Bradstreet*.
- *Golbeck, J. & Sinan, S. (2018). Why the Cambridge Analytica scandal is a watershed moment for social media. In *Knowledge@Wharton*. Retrieved from <https://knowledge.wharton.upenn.edu/article/fallout-cambridge-analytica/>
- *Halper, F. (2017). Advanced Analytics: Moving toward AI, Machine Learning, and Natural Language Processing. *SAS Best Practices Report*.
- *Hawkins, A.J. (2018, Apr. 13). Tesla relied on too many robots to build the model 3, Elon Musk says. In *The Verge*. Retrieved from <https://www.theverge.com/2018/4/13/17234296/tesla-model-3-robots-production-hell-elon-musk>
- *Hill, C. & Hult, T.M. (2019). *Global Business Today*. 11th edition. McGraw Hill. New York, NY.
- *Holcomb, G. (2019). Industry report 51913b: Internet publishing and broadcasting in the US. In *IBIS World*.
- *HPE Introduces new set of artificial intelligence platforms and services. In *HPE Newsroom*. Retrieved from <https://www.hpe.com/us/en/newsroom/press-release/2017/10/hpe-introduces-new-set-of-artificial-intelligence-platforms-and-services.html>
- *IEEE-USA Position statement. (2019). *Artificial Intelligence*. Retrieved from <https://globalpolicy.ieee.org/wp-content/uploads/2019/06/IEEE18029.pdf>

- *Introduction to AI and Machine Learning. In *Using AI for Social Good*. Retrieved from <https://ai.google/education/social-good-guide/>
- Johnson, G. and Scholes, K. (1999). *Exploring corporate strategy*. Prentice Hall, London.
- *Launchbury, J. (2019). A DARPA perspective on Artificial Intelligence. *DARPA*. Retrieved from <https://www.darpa.mil/attachments/AIFull.pdf>
- *Linder, C. (2017). CMU creates new initiative to become world leader in artificial intelligence. In *Pittsburgh Post-Gazette*. Retrieved from post-gazette.com/business/tech-news/2017/06/27/CMU-artificial-intelligence-AI-new-interdisciplinary-department-Pittsburgh/stories/201806270124
- *Mack Institute of Innovation. (2020). In *Mack Institute About*. Retrieved from <https://mackinstitute.wharton.upenn.edu/about/>
- *Managing a Deceased Person's Account. (2020). In *Facebook Help Center*. Retrieved from https://www.facebook.com/help/275013292838654?helpref=hc_global_nav
- *MarketLine Industry Profile: Cloud Computing in United States. (2019). *Cloud Computing Industry Profile: United States*, N.PAG. Retrieved from <http://search.ebscohost.com.ezproxy.lib.usf.edu/login.aspx?direct=true&db=buh&AN=139772108&site=ehost-live>
- *MarketLine Industry Profile: Mobile Apps in the United States. (2017). *Mobile Apps Industry Profile: United States*, 1–44. Retrieved from <http://search.ebscohost.com.ezproxy.lib.usf.edu/login.aspx?direct=true&db=buh&AN=127463752&site=ehost-live>
- *MarketLine Industry Profile: Online Retail in United States. (2020). *Online Retail Industry Profile: United States*, 1–72. Retrieved from

<http://search.ebscohost.com.ezproxy.lib.usf.edu/login.aspx?direct=true&db=buh&AN=142127247&site=eds-live>.

*MarketLine Industry Profile: Semiconductors in the United States. (2019). *Semiconductors Industry Profile: United States*, N.PAG. Retrieved from <http://search.ebscohost.com.ezproxy.lib.usf.edu/login.aspx?direct=true&db=buh&AN=134988196&site=ehost-live>

Mendelow, A. (1981). Environmental scanning: The impact of stakeholder concept. *Proceedings of the Second International Conference on Information Systems*, Cambridge, Mass, December 1981.

*Microsoft AI School (2019). *Microsoft.com*. Retrieved from <https://aischool.microsoft.com/en-us/home>

*Montgomery, C. & Hagemann, R. (2019). *IBM policy lab: Bold ideas for a digital society*. IBM. Retrieved from <https://www.ibm.com/blogs/policy/facial-recognition/>

*National Institute of Standards and Technology. (2019). *U.S. Leadership in AI: A Plan for federal engagement in developing technical standards and related tools*. Retrieved from https://nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf

*Nilson, N.J. (2010). *The quest for Artificial Intelligence: A History of ideas and achievements*. Cambridge University Press. Cambridge, UK.

*Northeastern University & Gallup. (2019). *Facing the future: U.S., U.K. and Canadian citizens call for a unified skills strategy for the AI age*. Retrieved from https://www.northeastern.edu/gallup/pdf/Northeastern_Gallup_AI_2019.pdf

- *Nvidia. (2019). Deep learning AI. *Nvidia.com*. Retrieved from <https://www.nvidia.com/en-us/deep-learning-ai/>
- *Olenski, S. (2016). Why marketers need a SMAC. In *Forbes*. Retrieved from <https://www.forbes.com/sites/steveolenski/2016/05/26/why-marketers-need-a-smac/#537758086a3d>
- *PAI. (2020). About us. *Partnership on AI*. Retrieved from <https://www.partnershiponai.org/>
- *Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., and Kiron, D. (2019). Winning with AI. *MIT Sloan Management Review*. Retrieved from <https://sloanreview.mit.edu/projects/winning-with-ai/>
- *Rao, A.S., Verweij, G., Cameron, E. (2017). *Sizing the prize What's the real value of AI for your business and how can you capitalize?* PWC. Retrieved from <https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf>
- *Rebala, G., Ravi, A.,& Churiwala, S. (2019). *An introduction to machine learning*. 1st edition. Springer.com. Online. Retrieved from <https://www.springer.com/gp/book/9783030157289>
- *Reisinger, D. (2020). Apple buys artificial intelligence startup xnor.ai, but not necessarily for a smarter Siri. In *Fortune*. Retrieved from <https://fortune.com/2020/01/15/apple-buys-xnor-ai-artificial-intelligence-siri/>
- *Rosenberg, N. (1979). Technological Interdependence in the American Economy. *Technology and Culture*, 20(1), 25-50. doi:10.2307/3103110

Ruehle, C.R., (2019). Investigating Ethical Considerations of Machine Learning Adoptions Within Organizations: A Systematic Literature Review. *Proceedings of the Ninth International Conference on Engaged Management Scholarship* (2019). Available at SSRN: <https://ssrn.com/abstract=3454120> or <http://dx.doi.org/10.2139/ssrn.3454120>

*Select Committee on Artificial Intelligence. (2019). *The National Artificial Intelligence Research and Development Strategic Plan – 2019 Update*. Retrieved from <https://www.whitehouse.gov/wp-content/uploads/2019/06/National-AI-Research-and-Development-Strategic-Plan-2019-Update-June-2019.pdf>

*Spitzer, D. (2019). Industry Report 45411a: E-Commerce & online auctions in the US. *IBIS World*.

*Stanford University launches the Institute for Human-Centered Artificial Intelligence. (2019). In *Stanford News*. Retrieved from news.stanford.edu/2019/03/18/Stanford_university-launches_human-centered-ai/

*State Council of the People's Republic of China. (2017). Artificial intelligence development plan. In *Forbes*. Retrieved from <https://www.forbes.com/sites/cognitiveworld/2020/01/14/china-artificial-intelligence-superpower/#4258e332f053>

*Sun, L. (2020). Apple is quietly expanding its Artificial Intelligence ecosystem. In *The Motley Fool*. Retrieved from www.fool.com/investing/2020/01/23/apple-is-quietly-expanding-its-artificial-intellig.aspx

*Terdiman, D. (2018). How AI is helping Amazon to become a trillion-dollar company. In *Fast Company*. Retrieved from <https://www.fastcompany.com/90246028/how-ai-is-helping-amazon-become-a-trillion-dollar-company>

- **The Industries in Which Artificial Intelligence Start-Ups Are Being Funded*. (2019). Harvard Business Review, 97(3), 30. Retrieved from <http://search.ebscohost.com.ezproxy.lib.usf.edu/login.aspx?direct=true&db=buh&AN=135981971&site=ehost-live>
- *The White House. (2020). *American Artificial Intelligence initiative: Year one annual report*. Retrieved from <https://www.whitehouse.gov/wp-content/uploads/2020/02/American-AI-Initiative-One-Year-Annual-Report.pdf>
- *Thomas, R. (2019). *The AI ladder: Demystifying AI Challenges*. Retrieved from <https://www.oreilly.com/online-learning/report/The-AI-Ladder.pdf>
- *Tucker, C. (2019). Privacy, algorithms, and artificial intelligence. In *The Economics of Artificial Intelligence: An Agenda*. NBER. Retrieved from <https://www.nber.org/chapters/c14011>
- **What is Artificial Intelligence?*. (n.d.) Amazon AI. Retrieved from <https://aws.amazon.com/machine-learning/what-is-ai/>
- **Worldwide Spending on Artificial Intelligence Systems Will Be Nearly \$98 Billion in 2023, According to the New IDC Spending Guide*. 21 September, 2019. Investment Weekly News. 546. *Business Insights: Essentials*. Web. 9, June, 2020.

CHAPTER THREE: VECTRA DIGITAL – CAPTURING ARTIFICIAL INTELLIGENCE VALUE AFTER ADOPTION

“Our Artificial Intelligence, Ada, manages budgets, writes her own ads, synergizes data, analyzes customer responses and reviews, and develops business intelligence. A human being can do all those tasks, but it will take hours, days, and weeks to get the information. Ada can make that change in a matter of hours. Velocity is the key. She frees the team from spending their time in spreadsheets, staring at numbers, and making simple decisions. Instead they are able to focus on providing really big picture valued-added initiatives to help our clients...Our digital ads team loves it.”¹

-Harrison Ambs, Chief Strategy Officer and Co-Founder of Vectra Digital

In February 2019, Vectra Digital was recognized as a *GrowFL Company to Watch*. Firms that were selected for this prestigious award displayed innovative intellectual property, entrepreneurial acumen, and leadership skills that positioned the firm for future growth. This discussion case explored those characteristics to extend our understanding of artificial intelligence adoptions. According to the GROWFL program website,

“The GROWFL Florida Companies to Watch awards program, now in its ninth year, honors 50 select second-stage companies from throughout Florida for developing valuable products and services, creating quality jobs, enriching communities, and broadening new industries throughout Florida.² Chosen from 500 growing second-stage nominations from throughout, Florida, the 50 companies named as the 2018 GrowFL Florida Companies to Watch honorees generated nearly \$957 in revenue and added over 1000 employees, reflecting a 113-percent increase in revenue and employment between 2014 and 2017. Together, the honorees project a 56 percent increase in revenue and 40 percent increase in job growth in 2018 compared to 2017.”³

¹ Interview with Harrison Ambs, May 2020.

² 2018 Florida Companies to Watch Honorees. (2018). GrowFL. Retrieved from <https://www.growfl.com/flctw18/2019-flctw-honorees-2/>

³ 2019 Florida Companies to Watch Honorees. (2019). GrowFL. Retrieved from <https://www.growfl.com/flctw20/2019-flctw-honorees/>

Vectra Digital’s Founding

Located in the sunny, resort community of Fort Myers, Florida, Vectra Digital was founded in 2017. At that time, Harrison was the Chief Strategy Officer at Stickboy Creative which predominantly focused on software development and website design⁴. The firm was performing well and consistently growing. However, Harrison “liked to build things” and was seeking a new career development challenge. He and his partners had a brainstorming meeting and decided to start a new digital marketing agency. Most business professionals expected artificial intelligence knowledge and expertise to reside within firms that were in technology hubs such as the Silicon Valley region in California, or the metropolitan areas of Boston, Massachusetts or New York City, New York. Vectra Digital and Stickboy Creative possessed that same high level of talent and technology acumen. Yet, this specialized and valuable expertise emerged nearly three thousand miles away from the Silicon Valley in this tourism focused community.

Protagonist background

Initially, Harrison Ambs served as the Chief Strategy Officer at Vectra Digital and has continued in that role since the firm’s founding. To be successful in this unique role, he needed to have natural creativity, inquisitiveness, and a collaborative, transformational leadership style since leading change and innovation were important aspects of the position. As the firm’s Chief Strategy Officer, he described his role as:

“My job is to sit down with our clients, and ourselves as a company, and work with them to understand their business model. We learn where they are taking their company, and then how best we can strategically align their marketing efforts to help them reach their goals.”

⁴ Optimize Your Business. (2020). Stickboy Creative. Retrieved from <https://www.stickboycreative.com/>

To understand Vectra’s business philosophy, we needed to examine its heritage. During Harrison’s tenure at Stickboy Creative, the firm considered outsourcing this function of promoting the firm as a first step towards growth. Like many software firms, the leadership team began approaching traditional marketing agencies. Harrison reported on their experience:

“We tried to get marketing companies to grow Stickboy when it was a software company, and we couldn’t get them to do it. We did not like how they worked, and we felt like we weren’t getting the value of what we were putting in as an investment, so we started our own marketing company.”

Make or buy decision

The decision to either outsource or develop the in-house capabilities to manage this function was certainly a critical one at this stage of the lifecycle for a growing firm like Stickboy. After performing a cost-benefit analysis along with careful deliberation, the firm decided to develop their own marketing agency. Notably, Harrison responded:

“We asked ourselves, ‘Why don’t we just sort of do this ourselves?’ The solution was to get some smart people, put them in a room, and decide this is how we want it to run. If we wanted to run a marketing company, this is how we would want to be their client, and then work from there.”

Consequently, the team took this “client” experience and used it to design an experience that would appeal to entrepreneurial and growing firms like Stickboy. The firm applied a phased approach towards building its client base. Initially, Vectra Digital focused on marketing Stickboy Creative. Since the leadership team already possessed a deep knowledge base of Stickboy’s products and services, this allowed the firm to develop and polish its digital marketing offerings and client management approach. Once the firm had systematized its client management processes, the leadership team approached Stickboy’s clients. Vectra began providing digital marketing services such as social media campaigns and email campaigns for Stickboy’s clients because it was a straightforward process of connecting digital marketing initiatives with the

firm's websites which were already managed by Stickboy. As the firm developed success stories and use cases, along with further systematizing its business model, Vectra proceeded to approach outside firms. (See Table 4, Ada's Development Timeline and Milestones.)

Table 4. Ada's Development Timeline and Milestones

Year	Milestone
2017	Vectra Digital was founded.
2017	Ada was conceptualized.
2017	Ada's budget management function was created.
2018	Ada's reporting features were implemented.
2018	Ada began writing her advertisements.
2019	Digital ads team began creating ads inside Ada which resulted in a quality of life improvement.
2020	Vectra Digital acquired iPartnerMedia, a digital marketing and public relations firm.

Source: Compiled by authors, May 2020.

For context, traditional full-service marketing agencies were the dominant industry players. In recent years however, these firms added digital divisions to capture new revenue opportunities as more clients began seeking digital services. This strategy enabled these firms to provide a wide variety of marketing services which streamlined their client management approach and provided cost effective services for clients. As a result, many firms were able to capture and leverage economies of scale. Contrary to this industry trend, Vectra Digital was not formed as a full-service marketing agency with a digital marketing division. Alternatively, the firm concentrated on providing digital services exclusively from its founding. This approach allowed the firm to cultivate a deep knowledge base and comprehension of both effective and

ineffective marketing strategies within the digital space. This strategy enabled the firm to expand to include more than four hundred clients: a mixture of local, regional, and national firms.

Whereas many marketing firms expanded their service offerings to become “one stop shopping” for clients in recent years, Vectra took a different approach. According to the firm’s website, Vectra Digital provided “services ranging from digital ads management, SEO [search engine optimization], email marketing, website design, reputation management, PR [public relations], directory management, and social media marketing.” (See Figure 4, Vectra Digital’s Values and Services.) Through its laser focus, the firm developed deep technical and business knowledge levels which empowered the firm to provide a high degree of value for its clients.

Vectra Values

You're wasting marketing dollars. Whether you have an agency that doesn't maximize your accounts enough or you have a team lacking expertise, you could be doing better. We use proprietary artificial intelligence to assist our team of experts to bring you the maximum marketing value for your budget.

With services ranging from digital ads management, SEO, email marketing, website design, reputation management, PR, directory management, social media marketing, you have all the tools you need for your business to succeed and exceed your vision.

With our team's fanatical customer service approach and a deep understanding of your business, you'll finally understand how your marketing is getting you there and what can make it skyrocket.

Figure 4. Vectra Digital's Values and Services

Source: Vectra Digital’s website, Retrieved May 4, 2020 from <https://www.vectradigital.com/>

The Business Problem

Fundamentally, businesses were formed around the central concept of identifying and solving a business problem. Following Vectra’s launch, Harrison and his team searched for

growth opportunities. They discovered that large firms were a good fit for their service offerings. Part of the firm's value position was that it developed a deep understanding of the client's business, aligned itself closely with the client's goals and objectives, and developed customized campaigns for its clients. Admittedly, this was a labor-intensive and costly approach despite its success. The firm needed an approach that would allow for this high degree of customization while managing its internal resources cost effectively. As reported by Harrison:

“We had a few large clients and a couple of large multi-location national franchises, and it became a lot of investment for us to be able to manage those accounts at that kind of scale.”

Short-term versus long-term orientation

Like many firms facing a similar situation, Vectra explored both short-term and long-range options. The first option, according to Harrison, was to create scripts, which are “*little pieces of code which do things like automatically adjust budgets*”. Scripts were commonly used as a tool for automating routine tasks. A second option included intermingling the work of scripts and employees whereby the script tool assisted workers with the copywriting process. In this scenario as Harrison described:

“Employees filled in 10 headlines and 10 descriptions, then the script synergized and randomized these together to make a recommendation. Then, our copywriters wrote the ads using the recommendation in such a way that they worked with any headline, any description, and any image. And then our copywriters created a lot of these, and then we just do it again.”

The third option entailed performing the work using their initial process which was entirely performed by humans. The current process functioned for the initial group of clients but did not provide scaling opportunities to manage the workload as the client base expanded. In hindsight, options 1 and 2 provided short term solutions that would solve the problem that the

firm faced at that point in time. Yet, those options did not allow for future growth. As Harrison stated,

“We can create a script that automatically adjusts the budget, but that is all it is going to do. It is never going to think for itself. It is never going to optimize itself. It is going to make things a little bit easier and faster. It is going to streamline things a bit. However, it is not going to improve on what it is given. And that has always stuck with me because I thought if we are going to invest time in this, then I want one plus one to equal three. I do not want one plus one to equal two, because anybody can do that approach.”

The fourth option was to build their own proprietary artificial intelligence (AI) to bolster efficiencies and scalability for the firm. This option contained a great deal of risk and required a long-term commitment as well as a culture of experimentation at the firm. Digital transformation such as this one required creativity, persistence, and tolerance of failure. Not every firm had the capabilities to tackle this initiative. Yet, after reviewing these four options in detail, Harrison and his team decided to move forward with fourth option.

Ada’s Introduction

After reflecting on this business problem prompted by the firm’s growth, Harrison decided to brainstorm options with Bryant Jackson, Head of software development at Stickboy Creative. Bryant replied, “Over here at Stickboy, we are doing a lot of work in AI and machine learning. If you think you can sketch something out, I think we can build it”. Subsequently, Harrison conceptualized the AI using his Apple iPad device while his family drove from Tampa to Fort Myers, Florida following a fun visit to Busch Gardens. Like many entrepreneurs, he wanted to maintain his productivity and capitalize on his creative inspiration. Collaboration was a key to his success. From Harrison’s perspective,

“She didn’t have a name yet until I got home. I decided to name her Ada. Then, the next day I pulled everybody into a room, got out the whiteboard, and told everybody I would like to introduce you to your new co-worker, Ada. Going forward, this will be our new focus for growing the firm.”

Despite the startup status of this project, the team decided to fund Ada internally. They had the talent, technology acumen, and motivation to tackle this initiative in-house. Harrison shared the following insight about Ada's development:

“We are fortunate enough to have a team of really talented developers that use this to end develop technology like this all the time. Bryant, as the Head of software development at Stickboy, was the one who volunteered for it because they were starting to experiment, and it functioned like a skunkworks project. We worked on it on the side, outside of our normal client work, and we just funded it with our time, so it did not cost any additional resources. The team members setup a development schedule and it was a little project inside the company that was squirreled away. Initially, we kept it secret because we did not know what we were building yet, and we did not want to hurt morale. The development cycle lasted for two to three months, then we gradually added to projects. Now she does a myriad of things.”

How does Ada work?

Budget management

Initially, Ada concentrated on two areas: budget management and reporting. From an account management standpoint, in digital marketing it was critical that workers routinely monitored digital advertising performance to manage costs. Proactively managing the budget was a critical element of a successful digital advertising campaign. Consequently, reviewing accounts daily was considered a best practice. The budget was based on activity which was derived from a cost-per-click formula, so it was easy for costs to get out of control if they were not managed properly. Vectra focused on maximizing the value of its clients' advertising dollars, therefore having the ability to frequently monitor digital advertising activity was important. Ada had the capability to monitor the accounts daily and rapidly adjust the budget according to the advertising performance data collected. Prior to Ada's introduction, an employee performed this labor-intensive work. However, speed and consistency were two distinguishing characteristics of Ada. Harrison offered his insights into this service:

“Excellent agencies reviewed the accounts every two to three days during the week. Most firms examined the accounts every week and maybe every other week. Ada, on the other hand, was in the accounts and made changes every day. Shen even worked on weekends when every other marketing company in Southwest Florida was closed.”

Report development

Reporting was the other important function that Ada originally provided. The digital advertising team at Vectra relied heavily on advertising performance data to make decisions about campaign strategies. Given the firm’s clientele, which was predominantly comprised of large multi-location firms, generating advertising performance reports by market required heavy lifting from a personnel and time resource standpoint. Moreover, while a human employee could provide this service, it would often take several weeks to complete this comprehensive analysis. Time was critical in the digital space. There had to be a better approach. Harrison expanded on this need in further detail:

“We imagined a large franchise with 300, 400, or even 500 locations. Each location had a personalized campaign that was running. It was very difficult and time consuming to pull out performance data from each location. Our objective was to evaluate the campaigns. This campaign was performing well while this one was not performing well. And so, Ada was designed to go in and pull that performance information. Since then, she does a lot more now. But that was what she was originally designed to do.”

Over the years, AI has experienced multiple transformations. (See Figure 5, Ada’s Background.) The first generation of AI was known as a recommendation engine. Harrison invoked Netflix as an illustration and provided the example of “*you like this movie, so we recommend trying this movie too.*” The recommendation was developed from the user’s profile which was derived from tracking viewing habits within certain categories of films. The second wave of AI contained recommendations that were based on comparing and analyzing profiles of individual viewers and their connections. As Harrison explained, “*You like this movie, a person that we think is very close to you likes this movie. Therefore, we recommend that you try this other movie.*” For the AI to function correctly in the first and second wave AI models, a human

needed to intervene and provide data. With a third wave AI system, the AI acted independently. According to Harrison, *“Third wave AI just does. It is the next generation, which means that it knows what do, it knows what the success criteria is, and so the AI just does the change.”*

Ada’s Ideal Clients and Business Model

Naturally, the question emerged during our interview, *“what is the ideal client for a third generation AI like Ada?”* Initially, the firm utilized Ada for projects related to franchises and ecommerce clients as they required extensive support resources. Over time, Ada was able to automate many operational and administrative tasks which allowed employees to focus on larger, more strategic issues. Vectra experienced significant benefits by using Ada on those client projects. Hence, they decided to adapt Ada so that she could work with any Vectra clients that matched its business model, beyond the franchises and ecommerce clients.

To fully leverage the value of a third generation AI like Ada, there were some functions and capabilities that client firms needed to have in place. First, they needed to develop the appropriately sized advertising budget. Digital marketing, when done effectively, required sizeable financial resources that were available to support this project. Ada did not know or understand the nature of the client’s business. Rather, she relied on the budgetary and performance numbers that were fed into her to decide how to set and manage the budget.

As Harrison discussed:

“Ada knows what she knows, which is just numbers coming at her. So, the more numbers you feed her, the faster she can react and optimize the budget. The bigger the budget you can put into her, she will be able to make changes and adjustments faster based on the performance data that is being returned to her.”

Introducing Ada:

Ada is a proprietary artificial intelligence platform created to launch your marketing into explosive growth with digital campaigns that are continually optimized. This saves you money, increases quality lead volume, and projects future performance.

This powerful tool continually increases your marketing ROI, giving your business insights from your customers. This is the game-changer when it comes to planning your marketing campaigns.

All our next-generation website design is Ada-ready. So not only is artificial intelligence optimizing your digital campaigns, but now it can optimize your website as well, bringing even more value to your marketing campaigns.

FEATURES | REPUTATION MANAGEMENT

- Big level data is turned into easy-to-understand actionable insights
- Data gives you an understanding of what customers feel are positives and negatives about your business
- Natural language processing algorithms provide deep analysis on topics important to your daily business
- Reviews are indexed from multiple platforms to show trends, or you can upload your own survey data
- Reviews are broken up into different star ratings to show satisfaction levels at a glance
- Every review is analyzed, sorted, and cataloged by keyword using our proprietary AI platform
- Review responses are automated using brand-voice to ensure an appropriate and timely response
- An analysis of your competition is generated to see where to stack up to stay ahead of the game
- Market smarter after reviewing your unique, AI-powered snapshot of customer personality traits

Figure 5. Ada's Background

Source: Vectra Digital's website, Retrieved May 10, 2020 from <https://www.vectradigital.com/service/ada/>

Second, the client firms needed to have a strong digital focus and an analytics culture. A key piece of this digital focus was having access to large databases of customer information for processing and analysis. Interestingly, Harrison observed:

“Clients that are digitally focused, I find, tend to have more organization inside the company. They have a CRM (customer relationship management) system, a sales platform, they have funnels and metrics, and numbers. Because Ada reacts to numbers. But she also produces numbers. She tells you your cost per lead acquisition, estimated cost per click, along with a future projection for our search impression share.”

To fully take advantage of this information, the firm needed to have a background in analytics. Employees needed to understand these performance indicators and have knowledge on how to apply them to their business along with a mindset of continuous improvement. Harrison indicated:

“Clients that valued analytics, business process automation, and business intelligence especially tend to do very well with Ada and what we offered. She was fun, very powerful, open to learning, and she was a very, very dedicated employee.”

Potential Barriers to Adoption

Fear of change

Based on their experience at Vectra Digital and working with a wide variety of clients, the team identified three potential challenges related to adoption of AI technology like Ada. Fear of change was the principal concern that firms faced. Larger, well established businesses that have existed for many years sometimes struggled to adopt this new technology. On the surface, the firm recognized that they needed to adopt this new technology to move the business forward. Conceptually, firm leaders acknowledged they needed to embrace digital transformation in response to environmental factors and customer dynamics. However, they struggled with fully implementing the technology throughout the organization. Harrison commented,

“A business would say they wish to change things and it is going to do things differently. However, it was very difficult for employees to adapt to new technology that they do not fully control because they feared where it may lead them.”

Data quality

The second barrier that firms encountered was a lack of consistent data. Ada relied on customer data that was input as well as customer data that was generated to make predictions. For instance, firms that had a high degree of customer engagement on their social media channels over time had sufficient data to yield insights. However, firms that were at the beginning stages of digital marketing and social media engagement had limited data. Therefore, it was difficult to fully leverage the power of a tool such as Ada. They did see a rise in leads that were generated, but until they had a strong data structure in place, it was difficult to fully leverage Ada's capabilities. Harrison offered this insight:

“Ada relied heavily on structure. If there were no walls, no ceiling, no structure, no numbers, no data, and that data is not consistently coming at it in the right way for the computer to make sense of it, it will not be able to figure out the path forward.”

Lack of control

Finally, the third adoption barrier concerned a lack of control over the actions of an AI. Third generation AIs like Ada were focused on initiating action without human intervention. Harrison provided the example of Salesforce's Customer Relationship Manager. As customers began building a purchasing history with the company, the system learned about customer and salesperson preferences and began developing a customer profile. When a lead came in, the system prompted the salesperson to respond to the customer by telephone or email. Over time, the system learned those preferences, and had the capability to contact the customer directly by telephone or email without the salesperson's intervention. Many firms had difficulty allowing the AI to take ownership of this important business function. Yet, firms such as Vectra, estimated this task could effectively be performed. The key was establishing boundaries, guidelines and systems that functioned as control measures and guardrails.

Client and Employee Perceptions of Ada

Throughout its lifecycle and by its nature of being a marketing firm, Vectra continuously monitored client perceptions of Ada. Initially, clients were excited about Ada and the unique functionality it offered. Conceptually, Ada generated a high degree of enthusiasm amongst its clients and the public. Vectra offered the services of Ada for no additional charge, hence, it served as a true value-differentiator for the business. The home grown and proprietary nature of Ada presented a degree of control over the results which was appealing to customers.

After describing the data collection approach used by Ada, clients acknowledged there was a certain degree of “creepiness” derived from tracking social media posts. However, they began to see the speed and volume of incoming qualified leads increase, and resultingly their perceptions changed. Harrison acknowledged there was a ramp-up period ranging from one month, three months, or even six months which is common in every agency. This rapid infusion of both data and qualified leads enabled Vectra to take a proactive position in managing the client’s digital marketing. Accordingly, Harrison and his team began asking “what if” questions:

“What if we marketed towards women between the ages of 35 and 45 years old, we showed them these images, and we used this language? How would they respond to this approach?”

Notably, Ada was used as an internal tool and she did not interact with clients. Harrison mentioned that clients regularly requested seeing her. However, he explained that Ada was an internal tool that was used predominantly by the Vectra team. Since AI was a cognitive tool and difficult to fully understand, the clients were likely seeking a visual confirmation to eliminate any uncertainties.

Employees interacted with Ada through a dashboard. The dashboard was accessible to all Vectra employees, however, the primary users were the digital advertising team. The dashboard displayed marketing analytics and campaign performance results. Initially, the digital advertising

team designed the campaigns manually, formatted them for Ada, then inserted Ada into the campaign to run it and make changes as needed. Through some investigation, the team decided this was a duplication of efforts and an unwise use of resources. The software team revised this function recently and programmed Ada to allow the digital ads team to setup new campaigns inside the system. Harrison explained this programming adjustment as follows:

“The digital ads team gave Ada all the pieces she needed in order to create the campaign, and then she created it in the way that she needed to in order to read and make sense of what she was seeing in the results.”

Employee experience with Ada

When Ada was first introduced to the team, employees experienced some confusion due to the difficulty with conceptualizing her functions. They did not have any previous experience with this technology from which to draw. Harrison offered the following explanation:

“Two and a half years ago, AI and digital marketing were sort of rumbling in the background. Many software engineers that had been doing a lot with AI were working on the sales side. We started experimenting on the marketing side. Both Google and Facebook started saying they were experimenting with AI, but there was not a lot of evidence out there publicly to understand how it worked. At that point, we could not state, ‘it’s like Uber for pizza’ which would have made it easier for people to understand.”

Over the years, Ada developed the ability to write her own ads using the data that she collected. They approached it similarly to an Art Director assigning work to a copywriter. The process as described by Harrison:

“We start by providing her with ten ads. She ran with those and learned from them. And then, over time she started experimenting with her own ad creative. She changed things around and wrote her own copy, and she tested it. She knew what success looked like and she tried new things. But she never went sideways and will never think outside the box.”

The digital advertising team benefitted because they did not have to invest time and resources in developing new copy or figuring out how to perform A/B testing. Instead, they made strategic decisions about campaigns and advised clients using the information that Ada

provided. Essentially, Ada handled the dull and highly repetitive tasks which freed up the team to focus on using their creativity and generating new marketing opportunities as well as generating increased value for their clients. They referred to that as a quality of life improvement.

Ethical Issues Encountered and Potential Resolutions

Managing customer data

During Ada's development, there were several ethical issues that emerged which required Vectra to develop resolutions. One significant issue concerned anonymizing customer data that was collected. Harrison offered the following perspective on this issue:

“Ada doesn't just write, she also reads. We have partnered with IBM to use their A.I., Watson, to give even more insight to our clients. Ada can read and analyze thousands of online reviews and survey responses, giving insight into what customers are saying about a business. We wanted to find out more about customers that leave 5-star reviews; every business wants more customers, but they really want 5-star customers. For one Fort Myers business, Ada analyzed 2,000 online reviews, integrated with Watson to get IBM's insights, then took that data to generate a new report that showed the 5-star customers for this business aren't influenced to buy from social media, but instead are influenced by online ads. We changed their digital strategy to make social media more about branding and culture and shifted budget to online ads. The goal wasn't to just get more customers, but more of their "5-star" customers.”

As demonstrated in this example, this information has powerful impacts on both customers and the business. In this scenario, there was a high volume of data that was captured between the social media posts, digital advertising analytics, along with the client's CRM system. Vectra maintained data anonymity while establishing boundaries between these data sets to ensure they were using this powerful information in an ethical manner.

Maintaining data boundaries

Another potential ethical landmine concerned the issue of cross pollination of data. Vectra focused on maintaining customer data boundaries. Given the high volume of data that

was collected, this could have been an issue for firms that did not have a strong ethical culture and systems in place. Harrison offered the following insights:

“We do not cross pollinate. Even if a client shares data between two audiences, we do not want to take data from one client and use it to help another client. Further, we maintain the integrity of data sets. So, if a customer purchases a product from a company, and subsequently agrees to sign up for their newsletter. That does not automatically mean that when a customer signs up for one newsletter, they are automatically giving permission to sign up for every newsletter that the company is related to simply because we have their customer data. Keeping it that way keeps things ethical.”

Targeting customers for advertisements

Fundamentally, this issue was related to honoring customer requests. The ethical concern of targeting advertising emerged when Harrison discussed the issue of deciding who to target for online advertising. He provided an example of a young man that shared his use of an ad-block extension to “*keep advertisements from showing up and it allows me to hide from the advertisers*”. After reflecting on the comment for a moment, Harrison responded by stating he was fine with that approach because he would not wish to advertise to prospects that have no interest in purchasing from a business. It was perceived as a waste of valuable resources. Notably, Harrison conveyed that Vectra’s approach was targeting the customers that were genuinely interested in purchasing the product. He relayed this philosophy:

“Ada allows us to get away from people that do not care about our clients’ products and services and find the people that do. And that is who I want to sell to. If I wanted to show an advertisement 500 times and earned 400 sales, then I am fine with that because I know those people are interested in our products. If you approach it that way, ethics falls in line.”

Not all digital marketing agencies took this approach. Some tried to overstate performance figures whereas others concealed the unsubscribe links in emails. Effectively, these firms were wasting valuable resources trying to entice people into purchasing their products that had no interest in the firm’s offerings.

The Future for Ada and Vectra Digital

As discussed in this case study, Vectra Digital has continuously searched for opportunities to fully capture and expand the value that Ada provides to the business. There were two forces operating within the market that presented opportunities and challenges for Ada and her super-computing powers.

Competition from big tech

The first challenge was that Google and Facebook were competing against each other head-to-head for online advertising revenues. Google wanted to keep its customers advertising within the Google ecosystem whereas Facebook wished to maintain advertising revenues within its ecosystem. However, Vectra's clients were advertising on both platforms and the firm wanted to extend the value of its clients' advertising dollars as well as capture additional value for them.

What could Vectra and Ada do to proactively address this competitive situation?

New market opportunities

The second opportunity concerns an expanding home services market in Southwest Florida. Services such as HVAC, pest control, plumbing, electrical, roofing, storm protection, and landscaping were in demand as families continued to invest in their homes. *How could Vectra and Ada efficiently target firms in this market for digital marketing services?*

References

2018 Honorees. (2019, July 30, 2019). Retrieved May 30, 2020, from <https://www.growfl.com/flctw18/2019-flctw-honorees-2/>

2019 Honorees. (2020, February 18). Retrieved July 19, 2020, from <https://www.growfl.com/flctw20/2019-flctw-honorees/>

Optimize Your Business. (2020). Stickboy Creative. Retrieved from <https://www.stickboycreative.com/>

CHAPTER FOUR: INSTRUCTOR MANUAL, VECTRA DIGITAL – CAPTURING AI'S VALUE AFTER ADOPTION

Synopsis

Despite the pervasiveness of Artificial Intelligence, few cases have been written about this technology and its impact on the workplace. This case study explored the decision-making process behind Vectra Digital's development and adoption of its proprietary Artificial Intelligence (AI) software named Ada. A newcomer to the digital marketing agency scene in Fort Myers, Florida, Vectra Digital was founded in 2017. Most firms expected to find this expertise in technology hubs like Silicon Valley or New York/Boston areas. Vectra decided to provide this technology acumen to clients that were seeking value and a local presence.

For context, McKinsey Global Institute studied over four hundred AI use cases and estimated that sales and marketing presented substantial value for firms (Chui et al., 2018). Further, McKinsey projected that AI generated between \$1.4 trillion and \$2.6 trillion in marketing and sales enhancements towards the global economy in 2016 (Chui et al., 2017). Firms that possessed large databases of historical customer purchasing data and utilized social media channels for data mining were well positioned.

Vectra Digital used AI to automate the labor-intensive and tedious processes of managing the online advertising budgets, providing performance reports, and even writing local ads. This freed up time and brainpower for workers to focus on strategic initiatives. Moreover, Ada worked 24/7 and proactively managed client budgets which benefitted customers and employees.

This case study explored the adoption process, particularly the role of ethical considerations, using the Technology Acceptance Model (TAM) and TAM-2 as a theoretical lens.

Target Courses and Usage

The primary objective is to aid students in understanding the AI adoption process. This case study was prepared for and tested in an Integrated Management Capstone course comprised of undergraduate business and management students. This course focuses on applying relevant theories to real world business problems for senior students nearing graduation. Given the course structure, this case study could easily be included in a change management and innovation module.

Learning Objectives (LO)

The intention of this case is to put students in the position of the protagonist, Harrison Ambbs, Chief Strategy Officer of Vectra Digital, and provide experience in preparing recommendations along with supporting the decision to adopt a proprietary AI system at the firm. The “Make or Buy” decision is one that most managers will face in their careers. Vectra Digital had a unique competitive advantage due to having high tech talent in-house, however, not all firms will have access to these resources. They may need to seek outside assistance. Accordingly, the author developed the following learning objectives to focus the learning experience of students:

1. Apply the Technology Acceptance Model (TAM) and TAM-2 to the AI adoption decision.
2. Analyze ethical considerations for the decision to adopt proprietary AI in a firm.
3. Formulate an evidence-based argument and recommendation for the adoption of AI.

Linkage to Concepts and Theories

TAM and TAM-2

The Technology Acceptance Model (TAM) and Technology Acceptance Model-2 (TAM-2) are routinely used in the information technology space to explore adoption decisions. This case study allows management students to examine this adoption decision through the lens of TAM and TAM-2. According to TAM, perceptions of two factors including *perceived usefulness* and *perceived ease of use* influence the *intention to use* which, in turn, may direct *usage behavior* (Davis, 1989). Venkatesh and Davis expanded TAM, thereby formulating TAM-2, by adding the constructs of *social influence processes* and *cognitive instrumental processes* to the model (Venkatesh & Davis, 2000).

The construct of social influence processes included “subjective norms, voluntariness, and image”, whereas cognitive instrumental processes encompassed “job relevance, output quality, result demonstrability, and perceived ease of use” (Venkatesh & Davis, 2000, p. 187). This empirical study by Venkatesh & Davis (2000) revealed that subjective norms play a vital role in this model which is a socialization process. Users rely on guidance from subject matter experts and seek opportunities to attain prestige and respect through adoption of an innovative technology, especially when they have no prior experience with that technology. However, after the initial adoption the research demonstrated that the value of these social influences declined, and users began to rely on their own judgment and experience instead. Moreover, another interesting finding in this study suggested that the direct linkage between job relevance and output quality bolstered perceived usefulness. Figure 8 displayed below contains a diagram adapted from Venkatesh & Davis (2000) and Appendix A contains a mini lecture on the TAM and TAM-2 theories that can be used in the classroom to introduce these theories.

Suggested supplementary reading for the instructor:

- Venkatesh, V. & Davis, F.D., (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46(2):186-204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Manyika, J., Silberg, J., Presten, B. (2019). What do we do about the biases in AI? Harvard Business Review. Retrieved from <https://hbr.org/2019/10/what-do-we-do-about-the-biases-in-ai>
- Davenport, T., Guha, A., Grewal, D. *et al.* How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*. 48, 24–42 (2020). <https://doi-org.ezproxy.lib.usf.edu/10.1007/s11747-019-00696-0>
- Cam, A., Chui, M., & Hall, B. (2019). Global AI survey: AI proves its worth, but few scale impacts. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact>

Utilitarianism

The ethical theory lens that was applied in this case study was Utilitarianism which is part of the Consequentialism family of normative ethical theories. When applying Utilitarianism, the user evaluates several actions based on the outcome and selects the action that maximizes net happiness for the greatest number of people (Nathanson, n.d.). Typically, there is a calculation involved, which entails weighing risks and benefits in addition to applying a formula to make the determination. Many business decisions which involve cost and benefit calculations are based on this ethical theory.

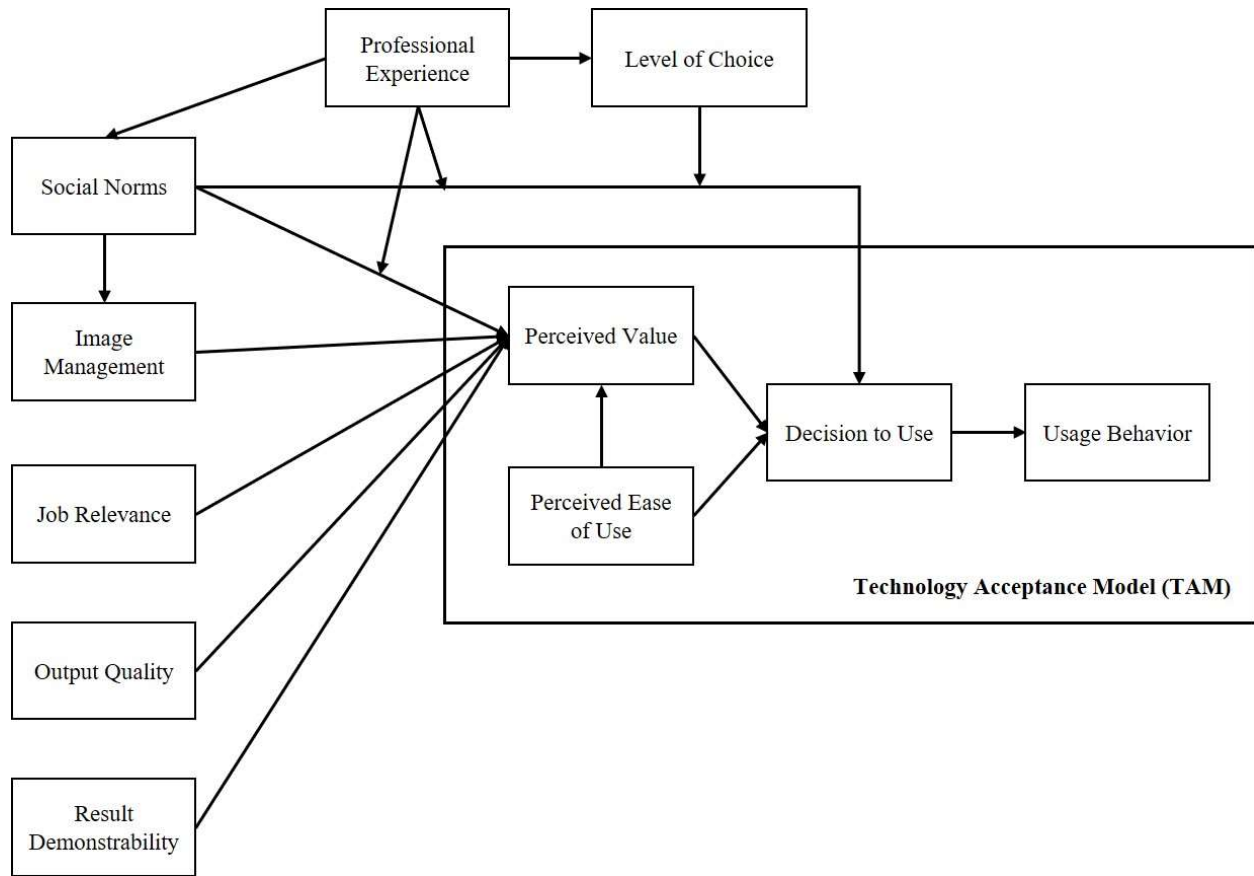


Figure 6. Adapted Technology Acceptance Model (TAM) and TAM-2

Adapted from Venkatesh & Davis, 2000.

On the surface, Utilitarianism appears to be a straightforward theory. Below the surface, however, there are some additional considerations to examine including: 1. How do we define a good outcome? 2. Which individuals or groups are the target of our intended action? 3. Should we rely on actual outcomes or predicted outcomes in our decision-making? (Nathanson, n.d.). Well respected classical utilitarianism advocate, Jeremy Bentham, argued that a “good outcome” is one that yields the highest level of happiness; yet many contemporary utilitarian scholars emphasize “well-being” as the greatest target given that happiness is challenging to measure (Nathanson, n.d.). In decision making, individuals often have an opinion about the action that will generate the greatest benefit to the individual. According to the Utilitarianism approach,

users must weigh the interests of all impacted stakeholders equally and avoid placing a higher priority on self-interest when selecting a course of action (Nathanson, n.d.).

The issue of relying on actual versus predicted outcomes is relevant for AI adoptions, and is controversial. The controversy stems from actual outcomes that vary significantly from predicted ones. This is a serious consideration for the adoption of AI, particularly systems that use sophisticated technologies like Deep Neural Networks, in which developers do not fully understand how the system arrives at the recommendations that are provided in what is referred to as a “black box” problem (Humphreys, 2009). Utilitarians who favor predicted outcomes utilize a rational decision-making process whereby they calculate the costs and benefits of an expected outcome as the first step, and then estimate the probability of an estimated outcome that prompts a decision.

Utilitarianism contains two sub-categories: Act Utilitarianism and Rule Utilitarianism. When a user applies Act Utilitarianism, they decide whether an action is morally right or wrong by calculating the net pleasure or happiness provided to a company or society derived from an action. Users that subscribe to this form of Utilitarianism emphasize the importance of assessing utility on a case-by-case basis and selecting the course of action that will generate the greatest overall utility (Nathanson, n.d.). On the contrary, Rule Utilitarian advocates place a high priority on morals derived from rules. Accordingly, when an action complies with a rule that is established by a higher authority, it is subsequently codified if the action generates greater utility than other potential rules being considered (Nathanson, n.d.).

Suggested supplementary reading for students:

- Nathanson, S. (n.d.). “Act and Rule Utilitarianism,” in *The Internet Encyclopedia of Philosophy*, ISSN 2161-0002, <https://www.iep.utm.edu/util-a-r/>, April 7, 2020.

Research Methodology

This decision-focused case utilized a field research methodology. Congruent with Naumes and Naumes (2015), the authors started by investigating online news articles that contained information about Vectra Digital, Stick Boy Creative, and key company leaders. Subsequently, the author reviewed the firms' websites to understand the firm's mission and product offerings along with the firm's social media posts on LinkedIn, Facebook, and Twitter to understand the firm's positioning and approach towards the marketplace. The next phase included reviewing ABI/Inform and Google Scholar to gather industry information.

After gathering preliminary information for triangulation purposes, the author contacted Harrison Ambs, Chief Strategy Officer at Vectra Digital, to obtain approval for the case study and arrange for interviews. Notably, this data collection occurred during the Global Covid-19 Pandemic which required data to be gathered remotely. The author conducted interviews with Harrison Ambs via Google hangout sessions, received a demonstration of Ada's capabilities, and invited him to serve as co-author on the case. The interviews were transcribed, the case study was written and approved by Vectra, and subsequently tested in a Management Capstone class. Based on student and faculty feedback, the Instructor's Manual was revised to connect closely with the case.

Discussion Questions

Introduction to discussion

Artificial Intelligence has existed since the 1950's. Since that time, this technology has experienced ebbs and flows in public support, usage, and financial backing. The most recent upswing began in 2012 with the ImageNet Challenge which was a competition among developers of computer vision algorithms (Warren, 2018). The latest AI revival can be attributed

to the onset of big data, enhanced computing capabilities, and increased processing capacities of algorithms (Warren, 2018).

Initially, AI was introduced predominantly as a cost-savings measure to automate operations of functions within a business. Recently, marketers have leveraged the predictive capabilities of AI to strengthen the effectiveness of marketing campaigns and deepen their insights of consumer behavior. Davenport, Guha, Grewal & Bressgott (2019, p. 24) estimate “In the future, artificial intelligence (AI) appears likely to influence marketing strategies, including business models, sales processes, and customer service options, as well as customer behaviors”.

The following questions were developed to facilitate in-class discussion:

- *What business is Vectra Digital in, and how is the firm utilizing AI within its business model?*
- *What benefits is Vectra Digital deriving from utilizing its proprietary AI, named Ada?*
- *What potential ethical issues appeared in the case, and who faced those ethical dilemmas?*
- *How would users best apply the Utilitarian ethics framework to the decision to adopt the AI?*

Opportunities for Student Analysis and Discussion

- *What business is Vectra Digital in, and how is the firm utilizing AI within its business model?*

Vectra Digital is a digital marketing agency that is based in Fort Myers, Florida which is unique considering that most high-tech firms are in technology hubs in Silicon Valley, New York, or Boston. The firm specializes in digital communications which sets it apart from its competitors. This specialization has allowed the firm to develop a high degree of expertise in the digital space.

The firm designed its own proprietary artificial intelligence program, called Ada, which manages digital advertising campaigns for clients. The firm uses Ada’s prediction capabilities to manage and scale national and local digital advertising campaigns. Ada performs many of the

highly repetitive, data driven tasks which frees up other employees to focus on managing client relationships and developing client strategies which is a strongpoint for the firm. The introduction of Ada has allowed the firm to take on national clients with multiple locations (300, 400, 500 locations). A human could perform this work, however, it would take a long time to complete these detailed tasks. Ada performs these tasks in a timely manner which raises the level of customer support and serves as a competitive differentiator. Further, she helps with managing customer budgets which aids in the firm's profitability.

- *What benefits is Vectra Digital deriving from utilizing its proprietary AI, named Ada?*

Since Ada had the ability to rapidly process large amounts of data and develop advertising models based on this analysis, this capability allowed Vectra Digital to target and secure large, national restaurant chains as clients. Performing this level of service of customers would be virtually impossible or at least very challenging manually. Ada allowed the firm to scale quickly and adapt to the changing needs of its clients.

From a positioning standpoint, the firm emphasized Ada's ability to monitor accounts 24/7 for 365 days a year which is a stark contrast to most agencies which monitor customer accounts and make changes to campaigns less frequently. Ada's capabilities allowed the firm to rapidly adjust to a dynamic marketplace and make real time changes to advertising campaigns which increases the effectiveness and value of advertising spend for its clients. She serves as a unique "hook" to generate interest in the firm and subsequently new business.

Internally, Ada has helped to boost morale as employees can delegate the detailed, time consuming and labor-intensive work of preparing performance reports and making online budget adjustments to her. This allows employees to focus on creative and strategic tasks which is a

better use of their natural talents and energy. The firm focuses on maximizing value and organizing work this way provides greater value for the firm as well as its clients.

- *What potential ethical issues appeared in the case, and who faced those ethical dilemmas?*

Ethical considerations.

One ethical issue raised in the case was maintaining data boundaries of the information gathered by Ada. The case discussed Ada collected consumer information from online reviews as well as the client's customer relationship management system. As discussed in the case, Vectra had the ability to cross reference customer data from the online reviews with customer profiles in the CRM (customer relationship management) system. The firm made the decision to keep those databases separate and maintain consumer anonymity as an ethical approach that benefitted both consumers and their clients.

Another ethical concern is derived from maintaining separation between customer databases and avoiding cross pollination of data. Vectra works with multiple clients within the restaurant industry and has amassed large amounts of data on customers, their preferences, as well as purchasing behaviors. The firm has made the ethical decision, out of respect for its clients and their customers, to keep data sets separated. Respect and data integrity are important to Vectra and is a key component of its culture.

- *How would users best apply the Utilitarian ethics framework to the decision to adopt the AI?*

As referenced previously in this Instructor's Manual, Utilitarianism is defined as "When applying Utilitarianism, the user evaluates several actions based on the final outcome and selects the action that maximizes net happiness for the greatest number of people" (Nathanson, n.d.). The decision to adopt a proprietary AI system contains several ethical issues that need to be considered. First, leaders like Harrison, need to develop an understanding of the tasks and types

of work that is being performed in the firm. As part of the evaluation process, Harrison and his team needed to perform a value analysis to prioritize tasks and organize them in a manner that would best utilize the resources they had available. As part of the evaluation, they had to decide which tasks are best performed by a human, and which ones are best performed by machine. During this assessment, they had to select the model that would maximize the greatest amount of “happiness” to their various stakeholders including clients, firm managers, and employees. Based on this analysis, it was apparent that some tasks could be performed most effectively by a machine whereas other tasks are best performed by a human. Utilitarianism was deployed throughout this process of structuring the work of humans and machine (Ada).

Teaching Suggestions (Face-to-Face Format)

Consistent with the Harvard Business case teaching approach, instructors should assign pre-class preparation questions to be submitted via the university’s learning management system prior to the class discussion.

Pre-Class Preparation Questions

- Based on the case study, what environmental factors motivated Vectra Digital to develop and adopt its own proprietary Artificial Intelligence system, Ada?
- What factors were included in Vectra Digital’s decision-making process for adopting Ada?
- What challenges did Vectra Digital face during the adoption of Ada?
- Based on your preliminary analysis, what should the protagonist, Harrison Ambs, do?

To engage students and create a learning environment that is conducive to different learning styles, this teaching plan contains four pastures or sections. Each pasture builds onto one another and is designed to transition students through the learning objectives listed previously in this Instructor’s Manual. This teaching plan is designed for a one hour and fifteen minute class,

however, the timing could be modified to fit the instructor's needs (i.e. fifty minute class) or extended if the instructor wishes to cover this case across multiple classes.

Pasture 1: Terminology activity

The instructor could open the class with an interactive activity to engage students and generate enthusiasm for the discussion. Students can work individually or in small teams to complete this AI Definitions Matching Game. See Appendix B for the handout which could be distributed to students along with the correct answers. The goal of this assignment is to familiarize students with common terminology and definitions within the AI field. This assignment takes approximately ten minutes.

Pasture 2: TAM and TAM-2 lecture

The next section would contain a lecture on the Technology Acceptance Model (TAM) and TAM-2. The instructor should explain that TAM and TAM-2 are common theories used in the Information Technology discipline to explain adoption behavior within organizations. Figure 8 listed previously provides an illustration of these theories and can serve as a visual representation to aid students in learning. Appendix A contains a mini lecture that explains these models. The instructor should draw the TAM and TAM-2 models on the board to facilitate discussion (See Figure 8). This pasture should take about twenty minutes and the faculty member should seek opportunities to allow students to ask questions to facilitate learning.

Pasture 3: Cooperative learning

The third section of the class should provide students an opportunity to collaborate on the Discussion Questions provided in this Instructor's Manual in small groups. The instructor can post the four questions on the overhead projector, encourage students to organize themselves into small table teams of three or four students, and discuss each of the questions. The instructor

should allow approximately thirty minutes for this discussion and circulate throughout the classroom to answer questions.

Pasture 4: Student presentations and wrap-up

The final section of this class consists of a course wrap-up. After the student teams have completed their discussions, the instructor can review the discussion questions and request a few groups to share their responses. This is an opportunity for students to synthesize their learning from this case study experience. To close the discussion, the instructor should ask the students whether they have changed their minds on their recommendation to the protagonist, Harrison Ambs, based on the class discussion, and if so, please have them explain their rationale. The instructor should allow approximately ten minutes for this segment.

Teaching Suggestions (Remote or Online Format)

In response to the global pandemic that occurred during the spring semester of 2020, most universities had to rapidly transition their courses to a remote format. Given the uncertainty of course formatting during the fall semester of 2020, the author decided to include a teaching plan for a remote or online format to support instructors with facilitating this case effectively.

From a pedagogical standpoint, we recommend including both asynchronous as well as synchronous elements to foster a rich learning experience for students. The Pre-Class Preparation questions (list previously) could be posted in the learning management system as either a drop box assignment or discussion post that students complete several days prior to the synchronous class discussion.

If this assignment is structured as discussion post, it is recommended that the instructor uses a “post first” format so that students have to prepare independently prior to seeing their classmates’ posts. In addition, the instructor may wish to specify a word count such as 150 words

and require that students include evidence and citations from the case study to illustrate key points.

Grading in the remote or online environment can be challenging and time consuming for instructors. Therefore, it is recommended that grading rubrics are used to streamline the grading process. Instructors should post the grading rubric along with the assignment instructions in order that students are aware of these expectations. See Appendix C for a grading rubric (adapted from Thompson, 2019) that could be setup in the learning management system for the discussion or drop box assignment.

Pasture 1: Terminology activity

This section of the class is intended to be held synchronously, however, this could also be an asynchronous assignment if needed. The rationale behind using this activity synchronously is that the instructor would have an opportunity to discuss these terms and address misconceptions immediately to ensure that students are utilizing the appropriate terminology. Many conference functions that are provided through learning management systems include a polling feature. For instance, Canvas Conferences' BigBlueButton contains a poll feature that would fit well with this activity. Alternatively, if this is used asynchronously, a quiz could be setup in the learning management system that students could complete independently to ensure they acquire this baseline knowledge. The instructor should plan to allow for ten minutes for this activity if included during class time. See Appendix B for the terminology activity.

Pasture 2: TAM and TAM-2 lecture

This section of the class includes a mini lecture on TAM and TAM-2 which is provided by the instructor. See Appendix A for the lecture and Figure 8 for the diagram. This pasture is designed for twenty minutes.

Pasture 3: Cooperative learning – small group breakouts

Like the face-to-face curriculum, this section of the class is structured to provide students experience discussing and grappling with the complexities of this case study in a small group setting. Many learning management system conference functions (i.e. Canvas BigBlueButton) and alternate conference programs (i.e. Microsoft Teams, Zoom) allow for small group breakout sessions. The estimated time for this assignment is thirty minutes. From a content perspective, students will be working through the discussion questions listed earlier within this Instructor's Manual. Since students are working remotely, instructors should consider providing structure and encouraging students to prepare a deliverable (i.e. PowerPoint slides) that they will be presenting to the rest of the class during the wrap-up session.

Pasture 4: Wrap-up and synthesis

This is the wrap-up and synthesis section of the class. The instructor should have each team prepare and present a two-minute summary of their discussion to the class. In addition, one representative from each team should submit their presentation on behalf of the team to a drop box located in the learning management system for review and evaluation by the instructor. This activity could be extended into an additional class period if the instructor wishes for students to prepare a longer presentation. This activity is designed for ten minutes.

If the instructor decides to combine asynchronous and synchronous pedagogies, they need to recognize that students may have some difficulties participating synchronously for a variety of reasons. Therefore, they should consider recording the synchronous sections and posting the video for the class so that all students have access to this important learning opportunity.

Epilogue

There were several areas of future development in the works for Ada. First, there was a well-known software program that used AI to manage digital advertising campaigns. Weekly, this software analyzed campaign results and provided a suggested optimization plan for the account. It encouraged users to enter “what if” scenarios and see what the results would be if changes were made to demographics or timing of the ads along with other variables. Due to its popularity, Google developed a similar product that resided within the Google advertising platform. Given this competitive behavior, Vectra decided to begin preparing for changes that Google may potentially make to its platform.

The second opportunity resulted from the intense competition for advertising revenue between Google and Facebook. Google wanted to keep its customers advertising within the Google ecosystem whereas Facebook wished to maintain advertising revenues within its ecosystem. Vectra’s clients, however, were advertising within both ecosystems. Given this structure, Vectra had to develop separate ads according to the specifications of each system.

However, Harrison raised some interesting points:

“Our clients’ customers are using both Google and Facebook. We asked, ‘Why can’t we have one campaign that follows the customer between the two platforms? And why can’t we have an AI that creates ads between the two? Why can’t Ada optimize the budget between the two and then integrate with the client’s website? Then, looking at the website, why can’t Ada make changes to the website and have separate versions of the website that align with different customer interests? Because it knows the ads that we clicked on to get there. We are working on making an ecosystem of artificial intelligence.”

In addition, Vectra Digital and Ada developed and expanded its strong working partnership with IBM and its AI, Watson. Ada possessed the capability of collecting and analyzing online reviews through engines such as Yelp, TripAdvisor, and other channels. The team fed that data to IBM’s Watson, in turn, which was able to perform some personality

assessments on the aggregated results which was based on the Big Five Personality Traits Model (Fort Myers, 2019). This has been a successful collaboration and the team anticipated expanding this service offering.

The home services industry represented a lucrative market opportunity, given the thriving Southwest Florida economy. iPartnerMedia, an established digital marketing and public relations firm in Bonita Springs, Florida, had a strong foothold in the areas of water filtration, HVAC, pest control, plumbing, electrical, roofing, storm protection, and landscape services (Digital Marketing Made Easy, 2020). Vectra acquired the firm in March 2020 as a strategy for accessing this market (Digital Marketing Firm Primed, 2020). Lead generation was an important function for these types of businesses and was a good fit for Ada's functionality.

References

- Cam, A., Chui, M., & Hall, B. (2019). Global AI survey: AI proves its worth, but few scale impact. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact>
- Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., Malholtra, S. (2018). Notes from the AI frontier, insights from hundreds of use cases. Retrieved from <https://www.mckinsey.com/~media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20AI%20frontier%20Applications%20and%20value%20of%20deep%20learning/Notes-from-the-AI-frontier-Insights-from-hundreds-of-use-cases-Discussion-paper.ashx>
- Chui, M. & Malholtra, S. (2018). Notes from the frontier: AI adoption advances, but foundational barriers remain. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain>

- Davenport, T., Guha, A., Grewal, D. (2020) *et al.* How artificial intelligence will change the future of marketing. *J. of the Acad. Mark. Sci.* 48, 24–42. <https://doi-org.ezproxy.lib.usf.edu/10.1007/s11747-019-00696-0>
- Digital Marketing Firm Primed for Growth. (2020, March 12). *Business Observer*. Retrieved from <https://www.businessobserverfl.com/article/digital-marketing-firm-primed-for-growth-even-in-pandemic>
- Digital Marketing Made Easy. (2020). iPartnerMedia. Retrieved from <https://ipartnermedia.com/home-services-marketing/>
- Fort Myers Business creates English-speaking AI program. (2019, October 3). Naples Daily News. Retrieved from <https://www.naplesnews.com/story/news/local/communities/the-banner/2019/10/03/fort-myers-business-creates-english-speaking-ai-program/2273768001/>
- Humphreys, P. (2009). The philosophical novelty of computer simulation methods. *Synthese*, 169(3), 615–626
- Kraut, R.E., Rice, R.E., Cool, C., & Fish, R.S. (1998). Varieties of Social Influence: The Role of Utility and Norms in the Success of a New Communication Medium. *Organization Science*, 9(4), 437.
- Martin, K., & Murphy, P. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, 45(2), 135–155. <https://doi-org.ezproxy.lib.usf.edu/10.1007/s11747-016-0495-4>
- Naumes, W., & Naumes, M.J. (2015). *The Art and craft of case writing*. (3rd ed.). Routledge.
- Nathanson, S. (n.d.). “Act and Rule Utilitarianism,” in *The Internet Encyclopedia of Philosophy*, ISSN 2161-0002, <https://www.iep.utm.edu/util-a-r/>, April 7, 2020.

- Thompson, K. (2019). "Weekly Online Discussion Rubric". *iRubric*. Retrieved from <https://www.rcampus.com/rubricshowc.cfm?sp=true&code=SX9B5B&>
- Venkatesh, V. & Davis, F.D., (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46(2):186-204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Warren, P. (2018). A Brief history of artificial intelligence: 1956 to now. In *CodeMentor Community*. Retrieved from <https://www.codementor.io/@paulwarren/a-brief-history-of-artificial-intelligence-1956-to-now-mgoracvnx>
- Webster, J., & Treviño, L.K. (1995). Rational and Social Theories as Complementary Explanations of Communication Media Choices: Two Policy-Capturing Studies. *The Academy of Management Journal*, 38(6), 1544.
- Wu, J., & Lederer A. (2009). A Meta-Analysis of the Role of Environment-Based Voluntariness in Information Technology Acceptance. *MIS Quarterly*, 33(2), 419. <https://doi-org.ezproxy.lib.usf.edu/10.2307/20650298>

CHAPTER FIVE: ETHICAL ARTIFICIAL INTELLIGENCE ADOPTIONS – COULD TRUST BE THE PANACEA?

Abstract

Through this research, I developed a framework for understanding the role of ethics throughout the Artificial Intelligence (AI) adoption planning process. Cultivating trust plays a foundational role and permeates the other constructs contained within the proposed framework, dubbed the **Ethics Integrated AI Adoption Framework**. Two important dimensions of AI trust included defining the need for AI for people and overcoming fears of this technology. Concerns about AI replacing jobs was the primary driver of this fear. Approaches such as anthropomorphism, designing new ways of working, preparing an ethical framework, and engaging with AI were useful strategies. I used a constructivist grounded theory approach in interviewing technology executives and leaders along with some high intensity users across multiple industries including technology, entertainment, professional services, healthcare, airline transportation, higher education, financial services, and automotive manufacturing. In addition to AI Trust, the other constructs that emerged from the data included Developing Human and AI roles, Making Ethical Decisions, Developing Technochange Strategies, and Positioning AI Within the Business. This research effectively addressed two questions: *1. What ethical perspectives/principles do managers follow when adopting AI and Machine Learning (ML) systems? and 2. What ethical issues exist within firms that adopt AI and ML systems?*

Introduction

“Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves” (1996, p. 381). Although Artificial Intelligence (AI) has existed since the 1950’s (Buchanan, 2005), there has been a resurgence and vitality around this technology recently. McKinsey Analytics estimates that many organizations have expressed interest in deploying this technology and initiated pilot programs to generate revenues ranging from \$9.5 to \$15.4 trillion (Bisson et al., 2018). Firms saw the promises of AI in capturing new revenues in the areas of marketing and sales along with leveraging AI efficiencies to streamline production operations while reducing costs. It seemed to be the perfect formula for firms. After surveying 1,000 companies worldwide, McKinsey discovered that only about 8% of these organizations had successfully adopted analytics across their respective organizations (Bisson et al., 2018). This prompted the question, *what factors are preventing these firms from adopting this technology?* The McKinsey figures suggest this should be a linear decision for firms, yet the adoption is a complex decision and requires an understanding of these issues.

In recent years, the academic community has been sounding the alarm about ethical concerns juxtaposed against the growing interest in AI. As a researcher, I was drawn to investigate potential ethical issues that may be generating complexity and complications related to the adoption of this emerging technology. I decided to begin this research by interviewing industry experts, specifically technology Executives and leaders as well as high intensity users to gather their perspectives. Since this research focused on ethics, I proceeded to use the constructivist grounded theory approach (Charmaz, 2006). Through this research, I was able to develop an **Ethics Integrated AI Adoption Framework**.

After proceeding with this research to explore ethical issues, the concept of trust, specifically trust in AI, began to emerge as a paramount concept. On the surface, trust was often implied to be related to ethics by many people. However, from a research standpoint, trust and ethics were routinely positioned as distinct research streams. Organizational theorists focused on trust in relation to social factors including “individual expectations, interpersonal relationships, economic exchanges, and social structures” (Hosmer, 1995, p. 381). In his seminal work, LaRue Hosmer (1995) applied the organizational theory context and defined trust as “the reliance by one person, group, or firm upon a voluntarily accepted duty on the part of another person, group, or firm to recognize and protect the rights and interests of all others engaged in a joint endeavor or economic exchange” (p. 393). Alternatively, philosophical ethics researchers have published limited research on the concept of trust. The ethics literature revealed several salient themes underpinning trust including: moral duty, cooperation, prioritizing the needs of others over self, and focusing on goodwill. (Hosmer, 1995). As a result of this analysis, Hosmer offered the following blended definition of trust from the organizational theory and ethics literature, “trust is the expectation by one person, group, or firm of ethically justifiable behavior—that is morally correct decisions and actions based on ethical principles of analysis—on the part of the other person, group, or firm in a joint endeavor or economic exchange” (Hosmer, 1995, p. 399). Since that time, the literature which connected ethics and trust was very limited; therefore, this manuscript seeks to elaborate on this connection.

This disconnect raised an important question of why these research streams of trust and ethics were treated as separate groups. Flores and Solomon (1998) referred to this relationship as “a social *and* ethical phenomenon” (p. 208), and asserted that organizational theorists emphasized trust as being an “object” whereas ethicists viewed trust as being a function of one’s

belief system. One of the distinguishing characteristics of trust was its changing nature (Flores & Solomon, 1998). Identifying the boundaries of trust was an important step towards linking trust and ethics. Rather than conceptualizing trust as an object, Brekert (1998) contextualized it as “an attitude, feeling, or emotion which is connected with one’s character” (p. 199). The author asserted there was consensus among researchers that trust represented an attitude which many people associated with moral responsibility. The underlying assumption was that higher levels of trust correlated with higher degrees of moral responsibility and ethics. However, that was not necessarily the case. Brekert posited there were limits on trust and he raised the ethical issues of “cronyism, favoritism, and personalismo” that can occur when trust is abused (Brekert, 1998, p. 199). When examining the concept of AI trust, it was important to consider both the social and ethical aspects and recognize there were applicable boundaries. While AI technology offered many advantages with its predictive and processing capabilities, leaders needed to develop an awareness of the potential ethical downsides to using this technology. Since the research in this area has been limited, this manuscript elucidates this connection.

AI trust reflected the characteristics from its source, which in this case was the AI or ML technology (Brekert, 1998). Glikson and Woolley (2020) proposed a model which included cognitive as well as emotional trust. These researchers defined *cognitive trust* as encompassing “tangibility, transparency, reliability, task characteristics, and immediacy behaviors” while *emotional trust* included “tangibility, anthropomorphism, and immediacy behaviors” (Glikson & Woolley, 2020, p. 4). Through their research, Glikson and Woolley (2020) learned that awareness of the technology, its functionality, and potential performance errors could bolster *cognitive trust*. Likewise, they discovered tasks that required social skills and emotional intelligence were perceived as being more trustworthy when performed by humans as compared

to AI. *Emotional trust* was influenced by the degree of awareness of AI presence, characteristics of the AI, and communication of errors (Glikson & Woolley, 2020). These researchers called for future studies on the use of AI for decision-making in real-world settings, therefore, this grounded theory research connected well with their proposal (Glikson & Woolley, 2020).

The characteristics related to cognitive and emotional trust listed in Glikson & Woolley's study (2020) on AI trust were an important component of job design. Another important facet of AI trust was the leader's decision to use automation versus augmentation or a combination of both strategies. According to Raisch & Krakowski (2020), automation entailed humans assigning tasks to machines for completion independently whereas augmentation included humans and machines cooperating to complete tasks. Leaders needed to think strategically about using these approaches to cultivate trust in their decisions among workers. When deployed exclusively, automation was used to facilitate the handoff of high volume, routine tasks from humans to machines which helped firms achieve efficiencies in the short term, yet did not produce long term benefits for the firm (Raisch & Krakowski, 2020). Alternatively, the sole use of augmentation facilitated cooperative learning between humans and machines, yet it was challenging to maintain long term due to the experimentation culture that was required and the subsequent prolonging of human bias (Raisch & Krakowski, 2020). This research team recommended using a combination of automation and augmentation which balances the strengths of human judgment and creativity with machine automation (Raisch & Krakowski, 2020). Like previous researchers, Raisch & Krakowski recommended field research as a subsequent step which reiterated the value of this research study.

In addition to illuminating the connection between job design and AI trust, Raisch & Krakowski (2020) connected their study to societal outcomes which has ethical implications. An

overreliance on machines due to a high level of automation may lead to declining worker skillsets and worker-to-worker relationships. To offset this decline, firms needed to provide additional training and development opportunities for employees. Raisch & Krakowski (2020) recommend utilizing a balanced mixture of augmentation and automation as a way to bolster creativity and innovation as well as decrease bias and infuse increased fairness in decision-making. They also cautioned firms to develop patience as the process for establishing this balance is a continuous learning cycle.

Along with deciding which tasks to automate and which ones to augment with machines, leaders needed to consider how the work was perceived by co-workers and customers. Evaluating the degree of genuineness or authenticity was an important step in this process of determining whether a product or service produced by algorithms was ethical. Jago (2019) conducted an interesting study that examined people's perceptions of authenticity in evaluating work that was performed by algorithms. This researcher conducted a series of four experiments which focused on: people's evaluation of work performed by algorithms as compared to the same work performed by humans (experiments one and two), people's perceptions of algorithmic decisions in safety-critical domains like air travel and healthcare (experiment 3), and people's perceptions of a task when humans and algorithms collaborated (experiment 4) (Jago, 2019). The research revealed that people generally perceived work performed by algorithms as being less authentic due to its lower level of moral authenticity. Hence, the researcher advised firms to use humans and algorithms jointly in the production of the item and convey that human involvement to stakeholders to bolster perceptions of moral authenticity (Jago, 2019). My grounded theory study included industry experts from these safety-critical domains which aligns well with this research.

There was a connection between job design, particularly focused on the development of human-AI roles, and ethical leadership. Piccolo, Greenbaum, Den Hartog, and Folger (2010) introduced the concept of ethical leadership and its connection to the job characteristics model (JCM) (Hackman & Oldham, 1976). Piccolo et al. (2010) focused on the factors of task significance and autonomy which were embedded in JCM. Their research revealed that ethical leaders displayed transparency and invited workers to participate in the decision-making process along with making fair decisions and recognizing them for ethical behaviors. Task significance was derived from the worker's perception that their job had relevance to other people inside and outside the firm, while autonomy related to the employee's authority to direct their own work (Piccolo et al., 2010). A Google scholar search revealed limited research in this area, particularly in the context of AI, ethical leadership, and ethical job design, therefore this presents an opportunity for this grounded theory research.

Notably, most of the firms represented in my study had a long tenure of using AI and/or ML. Some of the interviewees worked for technology providers whereas others were employed by firms using AI/ML in-house. Their perspectives were based on their extensive use of the technology. This manuscript was prepared with an eye towards firms that were considering adoption or seeking to expand the distribution of AI throughout their organization. As a result of this work, my study provided three primary theoretical contributions which added to the extant literature. The first contribution was **cultivating AI trust**. Consistently, interviewees indicated that most people had misperceptions about AI; their perceptions were based on how AI was portrayed in television shows like Star Trek or movies such as The Terminator (Cave et al., 2018). Contrary to popular estimates, most AI is rather prosaic according to interviewees, but efficient. Defining the need for AI so that people have a solid understanding of what it can and

cannot do will aid in alleviating fears. Moreover, the interviews revealed that many people are fearful of AI. They are concerned that AI will be taking jobs away from humans. Educating and informing people about AI functions along with positioning the technology as being approachable and affordable will help bolster trust.

The second theoretical contribution consisted of **designing human and AI roles** and responsibilities. Managers will need to carefully consider the strengths and competencies of both humans and AI in addition to seeking opportunities to maximize the strength of all team members. Since processing speed is a strongpoint for AI, managers should search for opportunities to delegate high volume processing tasks to the AI and reserve decision making to humans. Further, leaders should consider combining automation and augmentation, which is an iterant cycle, to foster a culture of efficiency, learning, and continuous improvement. The interviewers routinely commented on the importance of humans maintaining some control and oversight over the AI. Huang & Rust (2018) offers the theory of AI job replacement to function as a roadmap for how managers can gradually replace tasks and intelligences with AI within service businesses. Throughout this process, it will be important for managers to build trust amongst their workers. One key approach for establishing emotional trust is using anthropomorphism which is assigning human qualities to a non-human entity (Glikson & Woolley, 2020).

My conceptualization of **connecting ethics and AI trust** is the third theoretical contribution. Theorists and ethicists emphasized the social relations versus the attitudinal perspectives, respectively. However, my research revealed these perspectives are linked due to the *moral responsibility* which was a function of the nature of AI. The interviews suggested this technology has powerful impacts on society; people's access to careers, homes, financing,

healthcare, and sometimes even lives were at stake. When managers decided to use this technology, they recognized the societal impact which extended beyond the walls of their firm. The industry expert interviews revealed that many firms utilized a utilitarian approach to decision-making in which they were balancing costs and benefits. As the price of AI and ML decreased and the technology became more affordable, the value of judgment and ethical decision-making began to rise accordingly (Kolbjørnsrud et al., 2016). Managers considered how they were spending their time and resources, and then adapted to this change as needed. In addition, managers searched for ways to raise awareness of ethics and empower employees using an ethical framework. Many industry associations have developed ethical guardrails and frameworks as a service to their members; this served as a good starting point.

The term “Artificial Intelligence” has many different definitions and conceptions. The human mind has limitations regarding the amount of information or cognitive load that can be effectively processed within a given amount of time. Herbert A. Simon, one of the founders of AI, describes this decision-making phenomenon as bounded rationality in his seminal publication, *The Sciences of the Artificial* (1996). Computer systems, specifically AI, have the capability to process large volumes of data within a short period of time and provide predictions based on the data that is provided. Machine Learning (ML) is a subset of AI and effectively functions as the “workhorse” of data processing. ML has the capacity to process large data sets within a short period of time with a high degree of accuracy and identify patterns within the dataset. The user provides a training data set such that the machine “learns” how to spot patterns. Subsequently, the program applies this pattern matching formula to a new data set to generate predictions. Of course, the accuracy of Machine Learning depends on the quality of the data that is provided for training purposes.

The first section of this manuscript examines the extant literature to determine what research has already been conducted and position this qualitative research within this domain. The next section provides an overview of the research methodology including the sampling, data collection, and data analysis. Subsequently, the methods section focuses study findings which includes the data structure and propose a framework based on this research. The discussion section addresses both theoretical and practical implications of this investigation as well as limitations and future research. The final section consists of concluding remarks for the study.

Theoretical Foundation

After completing the three stages of coding per the constructivist grounded theory approach (Charmaz, 2006)--initial coding, focused coding, and theoretical coding--six themes emerged from the data. The purpose of this section is to summarize the theoretical underpinnings to aid in positioning this emerging **Ethics Integrated AI Adoption Framework** which is comprised of these themes.

Technology adoptions

It is important to begin this review by conveying the nature of a technology adoption. Simply stated, the individual begins with not having the technology and transitions to a position of being in possession of it (Wolfe et al., 1990). This may refer to the individual's acquisition of the technology. Alternatively, it can designate the firm's decision and commitment to implement this new technology (Wolfe, et al., 1990). There are multiple characteristics of the adoption process that may create complexity around the adoption. For instance, there are many interactions and individual decision processes occurring between stakeholders and the technology which are contained within the adoption process. Further, sometimes firms will make

a technology adoption decision as a cost savings measure without considering longer term and far reaching consequences of the decision (Wolfe et al., 1990).

There are a variety of frameworks that are used to investigate adoption motivations within the Information Services discipline. For this analysis, I decided to use the Diffusion of Innovations (DOI) Theory as a theoretical lens since it encompasses both firm and individual level factors in the communications process. A common thread that runs through the adoption process is communications which connects with this theoretical underpinning. In his seminal work, the *Diffusion of Innovation*, Everett Rogers originally developed the DOI theory in 1962 and defines diffusion as “the process in which an innovation is communicated through certain channels over time among the members of a social system. It is a special type of communication, in that the messages as concerned with new ideas” (Rogers, 1995, p. 5).

Technological innovations typically include a tangible component like the hardware that is bundled with less tangible items such as software and data. This bundling approach enables the user to transfer confidence in the tangible item to the intangible one, and decreases uncertainty or hesitation surrounding the use of a technological innovation. One of the challenges concerning the use of AI is that users struggle to fully understand this technology due to its intangibility, which of course is the nature of this technology. To bolster tangibility and receptiveness to this technology, developers will often assign human-like characteristics to the AI which is referred to as anthropomorphism (Glikson & Woolley, 2020). Developers may assign human names and add human features to the design to increase human receptivity to the AI.

Rogers defines technology as “a design for instrumental action that reduces the uncertainty in the cause-effect relationship involved in achieving a desired outcome” (1995, p. 13). Users will traditionally adopt a technology to reduce uncertainty related to a problem they

are attempting to solve. The AI technology often provides a solution in the form of a prediction or recommendation (Davenport & Ronanki, 2018). An example is Netflix's recommendation engine. What movie should I watch? What movie is my family watching? These recommendations are derived from the user's viewing history. Netflix tracks the users viewing history and the recommendation engine identifies patterns, assumes the user is likely to watch similar types of movies, and provides a recommendation (Davenport & Harris, 2017).

Adoption included two phases; "an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about advantages and disadvantages of the innovation" (Rogers, 1995, p. 14). Netflix has developed a recommendation algorithm, called Cinematch, that provides users with movie recommendations (Davenport & Harris, 2017). Developed by mathematicians, Cinematch examines customer profiles, identifies similar viewing habits and customer rankings, creates customer groups and matches them with similar movie clusters (Davenport & Harris, 2017). The company intends to make the customer information-seeking and information-processing steps more streamlined, which in turn, leads to an improved customer experience. Sitting through a bad movie for two hours could be frustrating and may even lead to a lost customer. Therefore, Netflix is seeking to minimize uncertainties in the movie selection process and mismatches between customers and movies. The introduction of this innovation resulted in Netflix developing a culture of experimentation and continuous learning, which Davenport and Harris have designated an "analytical competitor" (2017, p. 29).

According to the DOI Theory, there are multiple attributes that play a critical role in the adoption process. The first characteristic is relative advantage. Prior to adoption, the user calculates and compares costs and benefits of using an AI innovation. As the price of the innovation decreases, the pace of adoption accelerates (Rogers, 1995). Along with financial

measures, users consider factors such as social standing and likelihood of performance (Rogers, 1995). Users will often review use cases to aid in the adoption decision, especially if they have no experience on which to rely. One adoption theory, the Technology Acceptance Model (TAM-2), emphasizes the social aspects of adoption . If users believe that adopting a technology will raise their social profile within the organization and position them for future promotion opportunities, they will be more likely to adopt the technology. Further, alignment with beliefs and values systems of the organization is another consideration for adoption (Rogers, 1995). If the innovation provides value, yet is not compatible with the firm’s belief systems, the adoption of that innovation is likely to be slow and arduous. To adopt the technology, the firm will need to shift its belief structure which is often challenging.

Rogers proposed there are multiple factors that influence an organization’s receptiveness to adopting new technology. Those variables include: “individual leader characteristics-attitude towards change, internal characteristics of organizational structure-centralization, complexity, formalization, interconnectedness, organizational slack, and size, and external characteristics of the organization-system openness” (Rogers, 1995, p. 411). New technology implementations often require a champion with a growth mindset to facilitate adoption and foster a learning-centric culture. Further, the organizational structure plays an important role in transmitting new knowledge throughout the organization.

Building Trust in Technology

Understanding the complexities of trust begins with examining the underlying fears. Why are people fearful of AI? According to McClure (2018), people are concerned about losing their jobs to AI and the financial implications. McClure studied data from the Chapman Survey of American Fears—Wave 2, and identified the following fears related to AI “trusting AI to do the

work, technology you don't understand, decision-making robots, and robots replacing people in the workforce" (2018, p. 149). The results revealed that "women, non-whites, and the less educated...report being most fearful of technology" (McClure, 2018, p. 151). The study revealed that increasing the level of education and providing exposure to this technology aided in reducing this technophobia. In addition, the study suggested that technophobia may contribute to "higher than average anxiety mental health problems" which leads to other social impacts (McClure, 2018, p. 152). Ironically, Big Tech tends to emphasize the societal leveling aspect of this technology in reducing the digital divide, yet 37% of survey participants reported experiencing technophobia which is problematic (McClure, 2018).

Glikson and Woolley (2020) propose two categories of trust: *cognitive trust* and *emotional trust*. Characteristics of *cognitive trust* include "tangibility, transparency, reliability, task characteristics, and immediacy behaviors" while emotional trust contains "tangibility, anthropomorphism, and immediacy behaviors" (Glikson & Woolley, 2020, p. 4). Mayer, Davis & Schoorman define trust as "willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (1995, p. 712). Critical components of this definition include risk and vulnerability. This seminal work suggests that ability, benevolence, and integrity are critical factors that enable trustworthiness (Mayer et al., 1995). When AI is first introduced to the workplace, it is common for humans to be suspicious of the technology. However, as the humans begin increasing their interactions with the AI, trust gradually begins to increase. This is a similar development with trust being built over time between humans (Glikson & Woolley, 2020).

Defining Human and AI/ML Roles

To determine how to best use AI in the workplace, it is important to clearly understand the value of this technology in relation to employees. Agrawal, Gans and Goldfarb (2018) contend its core value is transforming the task of prediction and making this function accessible and affordable for many firms. ML prediction entails taking raw data, like customer purchasing history or social media posts, and forecasting future behavior-based spotting patterns in the data. The machine learns by studying large data sets. The cost of this technology has decreased recently due to the explosion of data, increased computing power, and wide variety of software applications available in the market (Davenport & Harris, 2017). As well, the cost of prediction has declined (Agrawal et. al, 2017). As the volume of data continues to increase, the value of prediction will continue rising as firms will have a greater need to make sense of this data. Tasks with a clear outcome and a simple decision requirement will be easy to automate via ML (Agrawal et al., 2017). Whereas complex tasks with a wide variety of variables and outcomes will be challenging and may still require human intervention (Agrawal et al., 2017).

Based on history, it is likely that AI's predictive qualities will continue improving in the future. This raises the question of how AI and employees will co-exist in the workplace. First, leaders need to remember that prediction is one component of the process. Agrawal, Gans and Goldfarb (2017) stressed that “tasks are made up of data, prediction, judgment, and action. Machine learning involves just one component: prediction” (2017, p. 6). There is still an important role for humans in this work process. Second, the value of human judgment will rise as the need for prediction increases (Kolbjørnsrud et al., 2016). According to these researchers, “employers will want workers to augment the value of prediction; the future’s most valuable skills will be those that are, complementary to prediction—in other words, those related to judgment” (Agrawal et al., 2017). Demand for complex judgement skills like ethical decision

making will increase as the volume of data rises and the cost of prediction technology decreases. Third, the role of the manager will shift from prediction to judgment. For instance, today's manager evaluates hardware and software purchases and estimates the likely impact on productivity and performance. In the future, they will have the capability to delegate this prediction function to machine learning that can generate models. Instead, they will be able to focus on judgment skills such as examining ethical principles in their firm (Agrawal et al., 2017). Some researchers stress the vital role of ethical reflection in judgment (Kolbjørnsrud et al., 2016).

Perception of authenticity is an important consideration when it comes to deciding how to arrange work between humans and machines. Jago (2019) studied how people perceived work that was performed by machines and humans. His findings suggested that people viewed AI-generated deliverables as being less authentic than human-generated ones. Carroll and Wheaton (2009) identified two different categories of authenticity--type authenticity and moral authenticity. Type authenticity refers to individuals' expectations of how a product or service should perform within a given context. Moral authenticity is derived from the sincere communication of values. Jago's (2019) work reinforced the concept of clearly communicating the human's role in designing the product or service to increase perceptions of authenticity. As firms consider structuring the work of humans and AI, they need to recognize that people use different sets of standards for evaluating the work of humans and AI. Firms should emphasize moral authenticity and the human connectedness components of products or services to improve experience.

Another consideration for leaders is deciding which jobs are best handled by AI and which ones should be managed by humans. Waytz & Norton (2014) researched the concept of

botsourcing; defined as “the use of robots or robotic technology to replace human workers” (2014, p. 434). The authors confirmed there are two components of humanness; cognitive and emotional (Waytz & Norton, 2014). They conducted a series of six experiments and identified several surprising findings. Employees placed a higher priority on the emotional aspects of work versus the cognitive functions, and resultingly expressed a higher degree of comfort replacing cognitive jobs with AI than emotional jobs. They believed that emotional jobs and tasks should be reserved for humans. Also, the study revealed that positioning of the jobs played a key role. When jobs were described in cognitive terms rather than emotional ones, workers were more receptive to *botsourcing* those jobs. For jobs that contained a heavy emotional element, the research revealed that workers were more comfortable interacting with the robot when it displayed characteristics suggesting it was capable of emotions. Alternatively, if the job had a heavy cognitive focus, then people expected the robot to display an intelligent appearance and perceived of the robot as being “creepy” when there was a mismatch between job expectations and the robot’s appearance.

Firms used anthropomorphism to minimize the perception of “creepiness”, reduce uncertainty, and increase trust with workers and customers. Epley, Waytz & Cacioppo define anthropomorphism as “imbuing the imagined or real behavior of nonhuman agents with humanlike characteristics, motivations, intentions, is the essence” (2007, p. 864). The authors use the acronym “SEEK” to identify the three factors that influence this action (Epley et al., 2007, p. 865). The first factor, deemed “social” which represented the “S” in SEEK, suggested that lonely people were searching for social connections, including non-human entities. “Effectance” is the second factor and suggested that humans were motivated to *engage* (the first “E” in SEEK) on a local basis (Epley et al., 2007, p. 865). If other humans were not located in proximity, people

were more likely to engage with non-human actors. The third factor, “EK” stands for “elicited knowledge”, and is dependent on a person understanding their own belief systems, values, actions, and motivations which is used as a reference for interactions with non-human actors (Epley et al., 2007, p.866). These three factor groups functioned cooperatively to either energize or demotivate the tendency to assign human behaviors to non-human entities. For firms, the benefit of humanizing their AI is that this action enables people to view the AI as a moral being, and subsequently assign values of respect and dignity to that item, just as they would assign to a human.

Making AI Ethical Decisions

ML algorithms have pervaded our daily lives; they are being used to assist in decisions for mortgages, recommending exercise plans based on our health data, and even recommending clothing derived from our social media preferences. While some applications may appear innocuous and insignificant, leaders need to understand ethical decision-making, given the onset of these prediction technologies in the workplace. Mittelstadt, Allo, Taddeo, Wachter, & Floridi elaborated on ethical decision-making: “Our map will include ethical issues arising from algorithms as mathematical constructs, implementations (technologies, programs), and configurations (applications)” (2016, p. 2). These algorithms are often employed in complex situations which may create some difficulties in fully comprehending the underlying ethical issues. These researchers identified the following six ethical issues, “inconclusive evidence, inscrutable evidence, misguided evidence, unfair outcomes, transformative effects and traceability” (Mittelstadt et al., 2016, p. 4). These algorithms are designed to aid in identifying correlations, however, establishing direct cause-and-effect relationships is challenging for most

systems. Moreover, it is sometimes challenging for users to fully evaluate the data structure, calculations performed, and the quality of the data input.

These ethical issues reveal the need to establish accountability in the design and use of these ML algorithms. Buhmann, Paßmann, & Fieseler (2020) provide accountability guardrails and contend that firms are concerned with the relationships they develop with external stakeholders—their public reputation. Therefore, they argue for implementing algorithmic accountability to manage the organization’s reputation. ML algorithms are often problematic because the system uses probability estimates to make predictions, and not the actual figures. These formulaic systems can become complex leading to transparency issues, along with creating difficulties with identifying cause-and-effect relationships. Moreover, these algorithms may produce discriminatory outcomes which create unfair situations for certain groups of stakeholders, and subsequently shape public policy. An example is the algorithms that were used in banking that unfairly discriminated against loan applicants based on race or gender (Sandvig et al., 2014).

Bias is a concerning and publicly recognized issue with ML algorithms. Elsbach and Stigliani (2019) discussed implicit bias regarding gender stereotypes in visual recognition AI programs that has developed and been amplified by the program. One example is the research performed by Zhao, Wang, Yatskar, Ordonez, & Chang (2017), which examined image recognition’s labelling of two sets of photographs to be used for training purposes. Upon review of the labels, it became apparent there was a gender bias in sports and cooking activities. The activities that emphasized shopping and cooking contained female labels whereas the activities that focused on recreational shooting and coaching included male labels (Zhao et al., 2017).

Another example of gender bias is an experimental study performed by Bolukbasi, Chang, Zou,

Saligrama, & Kalai (2016). These researchers examined word embeddings within natural language processing systems and ML, specifically occupational stereotypes, and confirmed the existence of gender bias in occupations. In addition, they designed a program to debias the algorithm and confirmed its successful function (Bolukbasi et al., 2016).

Developing technochange management strategies

Traditional change management approaches from the organizational behavior discipline and project management techniques from the information technology field fail to address the important role and influence of organizational culture in the adoption process. Instead, Markus proposes *Technochange Management* as follows “each phase involves both IT functionality and organizational changes, such as redesigning business processes, new performance metrics, and training” (2004, p. 4). The reasons for adopting this approach include: 1. technology functions as a “gate” for the change initiative, 2. technochange initiatives typically span multiple departments and functions requiring organizational silos to be overcome, and 3. technology alone cannot solve the business problem; the workers need to embrace the technology (Markus, 2004). Markus offers several design considerations: 1. technochange needs the technology linked to organizational structure, job design/redesign, workflow and processes, along with training and education, 2. leaders need to develop a realistic and practical technochange initiative that is likely to be adopted. For instance, people are likely to resist a change initiative if it will require their jobs to be eliminated.

For technochange initiatives to be successful, organizational leaders need certain competencies. Based on their research, Harison and Boostra identified the following eight sets of competencies that are prerequisites: “information technology and information systems know-how, organizational change, technochange processes, risks and success factors of technochanges,

communications, process management, leadership, and consequences of change” (2009, p. 289). Based on a systematic literature review and a series of technology firm interviews, the authors proposed a four-phase model for matching project managers and technochange projects, “Step 1: Assess competencies of technochange candidates, Step 2: Build a project profile by assessing project attributes, Step 3: Compare the project profile with profiles of candidates for technochange management, and Step 4: Select best fit between technochange project and project manager” (Harison & Boonstra, 2009, p. 290). By using this matchmaking system, firms can alleviate some of the uncertainty and raise the likelihood of this project achieving its goals.

Structuring AI to Fit Business Needs

There has been a surge in interest from the public and media in recent years regarding the perception of AI. Due to this keen interest, the Royal Society and the Leverhulme Center for the Future of Intelligence partnered on a study to explore the narratives on AI in the United Kingdom. During May 2017 and May 2018, these organizations organized four workshops in London and Cambridge, respectively. The goal was to gather public perceptions, misperceptions, and fears related to the technologies of AI and ML. The researchers discovered the public often assigned human qualities to AI, known as anthropomorphism. The rationale being that humans perceive other humans as having the highest level of intelligence. Therefore, humans will assign human qualities to other intelligent beings like AI. Moreover, AI is portrayed as performing human tasks and possessed a human-like shape and form. A prime example is the AI, Ava, that stars in the movie, Ex Machina in 2015 (Cave et al., 2018). The researchers discovered that anthropomorphism often places an emphasis on gender along with traits that are often associated with that gender. Degree of control over AI was a common theme that emerged. Higher degrees of oversight led to an optimistic view of AI whereas lower levels of control over AI contributed

to a pessimistic view of AI. Commons fears consisted of “AI leading to humans losing their humanity, making humans obsolete, alienating people from each other, and enslaving or destroying humans” (Cave et al., 2018, p. 9). Alternatively, participants were optimistic about AI applications solving healthcare problems, creating workplace efficiencies, providing entertainment solutions, facilitating digital companionships, and addressing national security issues (Cave et al., 2018).

Despite having high expectations for AI’s performance in the workplace, executives and firms continue to lack clarity on certain aspects of its adoption. According to research conducted by Ransbotham, Kiron, Gerbert & Reeves, only 16% of survey participants expressed confidence in their firm’s understanding of adoption costs while only 19% of respondents reported the firm understood data requirements (2017). Further, these researchers were able to identify four categories of firms based on their knowledge of AI adoptions: Pioneers (19%) already adopted AI and have progressed through the learning curve, Investigators (32%) have a solid understanding of AI, but have only piloted the program in a few areas, Experimenters (13%) have piloted AI, but have not developed a comprehension of the technology, and Passives (36%) do not have an understanding of AI nor have they adopted the technology (Ransbotham et al., 2017). The team learned that the primary barriers were “competing investment priorities” and “unclear business cases” (Ransbotham et al., 2017, p. 6). Other obstacles included AI talent hiring challenges, safety and security worries, limited leadership champions, cultural resistance, and limited technology capabilities (Ransbotham et al., 2017). The adoption of AI had a learning curve and the “Pioneer” firms have worked through that learning curve.

These leading edge firms recognized the true business value of data and its vital connection to this technology (Ransbotham et al., 2017). The firm needed to provide historical

data to train the algorithm. In many firms, the data resided in departmental silos and there were challenges with bringing the data together in a common, accessible platform for the AI; particularly if the software systems did not communicate well. In addition, it was important for the data set to contain both positive examples as well as negative or failure data so the AI algorithm could read patterns and learn from these experiences during the training process. This could highlight a cultural issue. If the organization is one in which people only record successes and discard failures or negative data points, the depth of the data provided for learning purposes was shallow and the AI was unable to provide the full value expected by the firm.

The aim of this qualitative study is to explore the AI adoption process in organizations and further develop an understanding of the ethical considerations and principles that are embedded within the adoption process. There have been a limited number of studies (Alsheibani et al., 2018; Ivanov & Webster, 2017; Pumplun et al., 2019) conducted in this area. Given the public interest in this topic, this is very timely and practical for academics and practitioners. This research considers two research questions: *What ethical perspectives/principles do managers follow when adopting AI and Machine Learning (ML) systems?* and *What ethical issues exist within firms that adopt AI and ML systems?*

Methods

Sample and Context

Given the topic of exploring ethical considerations during AI adoptions, I decided to use Charmaz' (2006) Constructivist Grounded Theory approach. By interviewing industry experts and capturing their stories and explanations, the interviewer and interviewee would co-create new knowledge through a deliberate and planned interview approach (Charmaz, 2006). My philosophy was the researcher would need to elicit the knowledge and subsequent theory through

a rigorous data collection process, rather than passively waiting for the theory to emerge (Mills et al., 2006).

After selecting a method, I worked through the Internal Review Board (IRB) process at my institution and received approval for the study as exempt status (See Appendix D for the IRB Approval letter). One of the requirements was submitting an interview protocol and interview questions. I decided to use a semi-structured interview process for conducting the interviews. In preparing the protocol, I modeled the interviews after a study that was conducted in 2019 in which the author interviewed human resource experts to learn about their attitudes and perceptions of AI programs that were used in the hiring and selection process (Robinson, 2018). After reviewing the questions and identifying similarities to my research, I adapted some of the interview questions for this research since these questions had already been validated. Appendix E includes the interview questions.

These interview questions explored previous work history, current use of AI, attitudes and perceptions of the technology, barriers to adoption, and future predictions for AI. To verify the interview structure and length plus ensure the questions were appropriate, I conducted a pilot study with a local law practice. The pilot study revealed that several of the questions needed further clarification and the formatting needed revision, so I adjusted the sequence of the questions and modified several items to provide precise responses.

The interviews consisted of three groups and each group served a specific function in developing a proposed framework. My approach included *purposive and snowball sampling* for the first two groups. The third group used a *theoretical sampling approach*. The first group consisted of five interviews with small to medium-sized technology firm founders and leaders from five unique firms and provided a broad overview of the AI adoption process in addition to

role of ethics in the adoption process. These interviews revealed that many people have misunderstandings of AI and often display a lack of trust in the technology. These firms had an entrepreneurial culture and the interviewees came from technical backgrounds, so they were receptive to technology-driven changes. This insight led me to pivot and inquire about AI used in larger firms by power users of AI that was mandated in organizations. This interview group consisted of one interview with an Information Technology Executive for a large healthcare system and four airline captains/first officers for commercial aircraft representing four separate firms. While I used the same set of questions for all interviews as required by IRB, I probed heavily on the areas of ethical decision-making, human-AI role development, and technochange management strategies during this group of interviews. These interviews led me to recognize that I needed to develop a better understanding of how AI was positioned within the organization to fit business needs.

For the third group, my focus was understanding how AI is operationalized within the firm. This group of five interviews was comprised of a Computer Information Systems Professor, a Chief Information Officer for a technology staffing firm, an Executive Vice President of Model Development for a Financial Services firm, a Founder of a medium sized technology firm, and a Chief Resource Officer for a Digital Marketing Agency. These interviewees provided insights on AI's positioning within the organization which included career competency requirements and educational programs, job design and recruiting initiatives, the impact of bias in AI algorithms, and the decision to build a proprietary AI. Effectively, this final group helped delineate boundaries and fill out the theoretical framework.

In addition to these fifteen interviews conducted with IT leaders at U.S.-based firms, I also facilitated a pilot study with an IT Executive that leads AI initiatives at an automotive

manufacturer in Germany. Since the German economy has a different approach towards innovation and technology compared to the United States, I decided to keep these interview results separate. This pilot study could be expanded and potentially serve as a springboard for future research. The research demonstrated that Germany believes in a wide distribution of technology improvements throughout its economic system, particularly the automotive industry as compared to the United States which tends to concentrate its technology expertise within the high tech sector (Breznitz, 2014). As well, organizational culture played a vital role in innovation. Germany has a stronger long-term orientation which suggests they have the patience needed to adopt new technologies as compared to the U.S. which concentrates on short term initiatives (Hofstede, 2020). Moreover, Germany has a higher degree of uncertainty avoidance than the U.S. which suggests they may value the structure and predictive qualities connected to AI (Hofstede, 2020).

Group 1. I conducted five interviews that spanned 45-65 minutes with small to medium-sized technology firm founders and leaders. Since these interviews were conducted during the Covid-19 lockdown, four were conducted over the telephone and one was conducted via Zoom per the interviewees request. Four participants were LinkedIn connections and one participant was referred by a previous interviewee. The characteristics of this group are listed in Table 5. The industries that were represented in this group consist of technology, entertainment, and professional services. These participants had extensive technology experience ranging from 3 ½ years to 35 years with a median of about 20 years.

Prior to the interview, I examined the participant's LinkedIn profile to develop a sense of their work experience, educational background, and expertise in working with AI. These semi-structured interviews addressed the participant's work experience, current applications of AI and

ML, attitude and intention towards the technology, ethical considerations and principles included in the adoption, and estimates on future use of this technology (See Appendix E).

Table 5. Characteristics of Participants (n=15)

Interview	Gender	Job Title	Industry/Sector	Length of industry experience
Group 1				
1	Male	Founder and Owner	Technology	14 years
2	Male	Executive Producer and Technical Director	Entertainment	35 years
3	Female	Owner	Technology	25 years
4	Male	Web Developer and Marketing Manager	Professional Services	3 ½ years
5	Male	Founder and Vice President	Technology	22 years
Group 2				
6	Female	Director of IT Applications	Healthcare	23 years
7	Male	First Officer, Boeing 777	Airline Transportation	23 years
8	Male	Captain, 737, Pilots Union Safety Representative, Director of Air Traffic and Instrument Procedures	Airline Transportation	21 years
9	Male	Aircraft Sales Manager, Corporate General Aviation	Airline Transportation	38 years
10	Male	Captain, A321	Airline Transportation	24 years

Table 5 (Continued). Characteristics of Participants (n=15)				
Group 3				
11	Male	Founder and Owner	Technology	30 years
12	Male	Chief Information Officer	Technology	40 years
13	Male	Associate Professor	Higher Education	25 years
14	Male	Executive Vice President for Model Development	Financial Services	25 years
15	Male	Chief Resource Officer	Professional Services	26 years
International Pilot Study				
16	Male	Head of Artificial Intelligence and Virtual Reality	Automotive Manufacturer	14 years

In addition, I reviewed the company websites for these participants as well as follow-up articles that some interviewees shared to validate discussion points from the interview. Following the interviews, I used Rev.com to prepare the transcripts. Upon their receipt, I listened to the audio, reviewed the transcript for accuracy, studied my field notes from the interview, and prepared analytic memos to capture my impressions and begin processing the information (Thornberg & Charmaz, 2014).

I used the NVivo program to manage all the transcripts, prepare analytic memos and code the interviews as having a strong organizational system in place is vital. In following this methodology (Thornberg & Charmaz, 2014), I used initial coding, line by line, as a first cycle coding method open up the data and identify its separate components (Saldaña, 2016). During this cycle, I searched for processes and relationships within the data, and assigned action phrases

using gerunds to make those relationships visible (Saldaña, 2016; Thornberg & Charmaz, 2014). This first round of coding led to preparing a list of first cycle concepts which were assigned codes in NVivo. I observed many of these interviewees perceived that people do not have a solid understanding of AI. Several participants commented that people often perceive of AI as it is portrayed Terminator movies. The reality is that most AI performs more lower level, arguably mundane, tasks like email management or monitoring. Hence, I assigned a code in NVivo denoted as “*defining the need for AI*” to represent these perceptions.

Another issue that appeared was a lack of trust in AI, despite many of these leaders working in the technology sector and having extensive experience with the technology. Several interviewees commented that the technology depends on the data that is input, and the competencies of the people using the system. For instance, one participant discussed the use of machine learning for providing closed captioning on videos. The interviewee stated that “sometimes the captions are just wrong and as a result, staff has to manually fix the mistakes” which raises the question of the technology’s reliability (1-2)⁵. Due to these performance issues, this was coded as “failing performance issues” which is a key component of lacking trust in the technology.

Group 2: This group of five interviews had interview durations of 50-60 minutes and consisted of high intensity technology users in highly regulated industries including the airline transportation and healthcare sectors. The common denominator is these AI/ML-enabled decisions made by these leaders affect the lives of people and contain a high degree of risk. For instance, airline captains make decisions related to flying a commercial aircraft through a thunderstorm based on data provided by their machine learning programs which could result in

⁵ When interviewee quotes are provided, the group along with their unique identification figure is listed in parentheses (i.e., Group-Identification).

an airplane crash. Whereas AI is used in healthcare to provide healthcare treatment plans based on predictions of a patient's "likelihood of having a congestive heart failure, risks of falling, or having pressure injuries" (2-6). These interviews were also conducted during the Covid-19 lockdown and were recorded using my Apple I-Phone. Two of the interviewees were my LinkedIn connections and the other three were referrals from these contacts. Refer to Table 5 for the demographic information listed for these interviewees. These leaders also had extensive industry experience as their level of experience ranged from 21 to 38 years with a median figure of 25 years. Hence, they were able to provide historical context as well as deep insights into the use of this technology within their respective work setting.

From a methods standpoint, I began the process by reviewing the contact's LinkedIn profile to gather information on their work experience before the interview. I used a semi-structured interview technique which included the questions listed in Appendix E along with asking respondents to elaborate on defining human-AI roles, making decisions that included ethical considerations, and managing change that was prompted by the AI. Similar to Group 1, I reviewed their company website after the interviews, used the same transcript development process with Rev.com, prepared analytic memos and performed initial, line-by-line coding in NVivo (Charmaz, 2006; Saldaña, 2016; Thornberg & Charmaz, 2014).

Both healthcare and the aviation sectors are considered safety critical industries, and healthcare executives often search within the aviation industry to identify best safety practices (Reason, 2004). Within the healthcare setting, the interviewer shared that AI was being leveraged for its predictive capabilities. One interviewee stated that "One of the most valued aspects of AI is its ability to determine the patient's projected return rate from an inpatient stay" (2-1). Managers could use that information to determine follow-up care for the patient and

develop appropriate staffing and supply plans to ensure they had the resources to support the aftercare plans. In addition to delineating the roles of AI and humans, this use had the purpose of providing a care plan that was in the best interest of the patient which is an ethical decision.

Within the airline industry, several pilots discussed the Boeing 737 Max jet crashes which highlighted the predictive and warning functions of the system as well as the role of the human pilots as making the final decision. The question arises regarding how much autonomy does the machine learning have in making decisions for the flight. One pilot commented, “the pilot is always primordial with Boeing. And it is [Boeing] always thinking ahead and it [Boeing] knows what we want. Whereas with Airbus, the pilot is not primordial in the decision-making process” (2-7).

These interviews also revealed there is a high degree of loyalty and preference amongst the pilots for one airplane manufacturer versus the other one. The level of automation relates to the airplane manufacturers’ design philosophies. One pilot commented, “I have friends that will retire early and quit flying in the next one to three months because they don’t want to retrain on the other manufacturer’s airplane after 40 or 45 years of flying” (2-7). Change management in these environments which is driven predominantly by technology is very challenging as emphasized during the pilot interviews. It became apparent that firms need to carefully consider their strategies for positioning AI and ML within the business, for these initiatives to be effective.

Group 3. These five interviews ranged from 35 – 50 minutes in length and covered a variety of industries including two interviews from technology, one from higher education, one from financial services, and one from professional services. A common thread amongst this group was the successful implementation of AI and/or ML within these organizations. They were

selected strategically from my LinkedIn connections to help elaborate on the concept of positioning AI to fit within the business. Like the others, these interviews were conducted remotely during the Covid-19 lockdown using either telephone or Zoom meetings (as requested by the participant). Table 1 contains the demographic information for this group. These participants held senior positions within their organizations and the level of experience ranged from 25 to 40 years with a median tenure of 29 years.

The interview questions listed in Appendix E were used for these interviews, plus respondents were asked to elaborate on how their firms effectively positioned AI within the business. When asked what factors contributed to the successful adoption and use of AI within an organization, one respondent stated, “There are two factors that come to mind for me. *One, is it financially practical? Two, is it welcomed within the corporate culture? Is it welcomed within the organization’s belief systems as appropriate?* If there is a bad return on investment, then the organization should not invest in it, or if it conflicts with the firm’s belief system.” (3-11). This concept of aligning financial interests alongside the organization’s belief system is an important one and deserves further exploration in subsequent sections of this manuscript.

Data Analysis

The interpretation of the data collected was performed using a constructivist grounded theory approach (Charmaz, 2006). My approach included the three stages of coding outlined as initial coding-line-by-line, focused coding, and theoretical coding (Charmaz, 2006). A Florida sunset offers a valuable analogy to this coding strategy. One walks outside and observes a pale orange sky in the evening. Then, a few minutes later the sky transitions to light pink, and subsequently transforms to a series of deep red and gold alternating clouds. If one does not have the patience and observation skills, or one leaves the beach early, it is easy to miss the

spectacular colors and variances of a sunset. Coding is an iterative process which allows the researcher to view different aspects of the studied topic over time, assign phrases and names based on the researcher's comprehension, and assemble this new knowledge to eventually create a deeper theoretical understanding of a phenomenon.

Stage 1: Initial Coding, Line-By-Line. Working methodically, I reviewed the transcripts line-by-line and assigned a short phrase that represented the main concept that was addressed in the line (Saldaña, 2016). Upon assigning the codes, I focused on processes along with actions, and utilized gerunds to reinforce this emphasis (Thornberg & Charmaz, 2014). This initial coding process separated a concept into its individual components and enabled a thorough examination of those items prior to reassembling them into new knowledge. After completing the initial coding round, I prepared an analytic memo as a means for processing this new knowledge and began working towards developing a tentative coding system by searching for patterns in common topics/phrases within and across interviews. Two tenants of this coding approach included maintaining an open mindset while reviewing the data and revising the coding as more information became available (Saldaña, 2016).

Stage 2: Focused Coding. The primary purpose of focused coding is to reassemble the codes from the initial coding stage and organize them around themes or categories (Saldaña, 2016). Preparing analytic memos was an important step in this process. My approach was to print out the listing of initial codes from NVivo for manual review and identify opportunities to create clusters of similar topics. As a follow-up, I prepared an analytic memo which aided in structuring the analysis. This approach facilitated a comparison of codes across multiple groups and interviews which extended my understanding of the data.

Stage 3: Theoretical Coding. During this stage, I focused on synthesizing the categories into common themes which moved this analysis towards theory development. This approach focused on addressing “why” and “how” questions to elaborate on the theory. This approach yielded deeper insights into a phenomena (Saldaña, 2016). To facilitate this process, I created color-coded notecards containing the themes and categories identified during stage 2. After laying the cards on a table, I was able to identify connections between categories. In addition, I reviewed the analytic memos prepared previously, and used that analysis to identify the central theme of developing trust in technology. Further, I developed a concept map to explore the relationships between the core theme and the major categories that had been developed. This step was beneficial in solidifying the analysis. Appendix F displays the data structure for Initial Coding, Line-by-Line (First Cycle), Focused Coding (Second Cycle), and Theoretical Coding (Third Cycle).

Findings

In following the constructivist grounded theory approach, I maintained an open and receptive mindset to the data insights. Of course, the researcher plays a role in guiding the data through their interviewing approach, the decision to use NVivo for coding and analytic memo development, as well as the interpretation of the data. During the first and second cycle coding stages, I intentionally refrained from using concepts from the literature review as I wanted the narrative to emerge naturally. During the theoretical coding stage, however, I infused the concepts from the literature review to help shape the framework that was emerging. As a result of this inductive and abductive process, a theoretical framework was revealed. This discussion begins with a focus on cultivating trust in AI which functions as an antecedent to AI adoptions. The subsequent section addresses important aspects of developing and distinguishing human and

AI roles within the organization. Next, I provide some context for making ethical decisions and preparing technochange strategies to empower leaders. The final section addresses strategies for operationalizing AI within the firm. Figure 9 shows the *Ethics Integrated AI Adoption Framework*.

Cultivating trust in AI

My research revealed that many people have concerns and fears about AI. Some of those fears are derived from the way that AI has been portrayed in the movies and television (Cave et al., 2018). Multiple interviewees commented that people often shared their perceptions of and concerns about AI as being like “the terminator”. They acknowledged this is a misperception that many people share and stated the technology is not that sophisticated at this point. They also shared that much of this fear likely originates from this notion that AI is taking away jobs from humans. One interviewee offered this insight:

Where you would see the frontline worker rebel to some degree, you will see it in two ways, and I think one is psychologically in the background. If you are going to eliminate their job, they are not happy about that. So, it is, oh, we are going to introduce this new technology and you must learn to use it, but now it is going to eliminate your job. Another way to look at it--we do not need as many of you to do the job. This happens in aviation and air traffic control all the time. That will get pushed back all on its own. You just have to find a way to sell it the right way. Usually by attrition and less hiring. Although you can get push back in those areas too. But in general, if you tell somebody, learn to use this and we are going to eliminate your friends, that is not going to go over well (2-8).

According to AI researchers (Siau & Wang, 2018), trust in this technology is cultivated during two distinct phases: *initial trust* (Li et al., 2008), and *continuous trust* (Siau & Shen, 2003). As discussed, “trust in technology is determined by human characteristics (personality and ability), environment characteristics (culture, task, institutional factors), and technology characteristics (performance, process and purpose)” (Siau & Shen, 2003, p. 50). Those three factors function cooperatively to enable the user to develop trust in AI.

Connecting AI Trust and Ethics

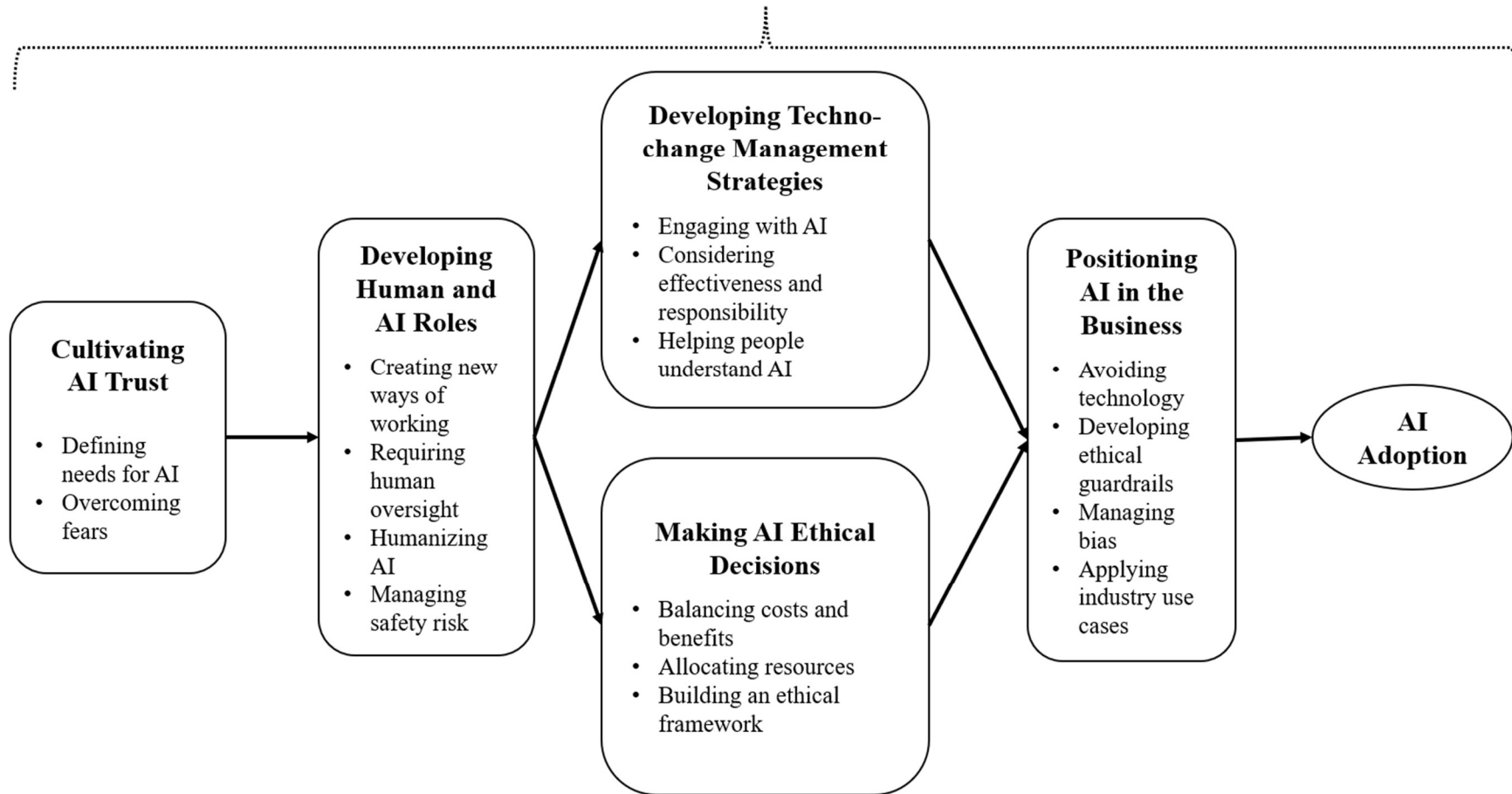


Figure 7. Toward an Ethics Integrated AI Adoption Framework

My interviews revealed that the attitude and competency level of the individual plays an important role. Adaptability and receptiveness to learning are critical. Individuals with a fixed mindset will find it challenging to adopt this technology whereas individuals that possess a growth mindset will be more prepared (Dweck, 2016). One of the interviewees offered the following explanation:

I think you must be really open to new ideas, new thoughts, and a new way of functioning, first. You have to break away from your traditional approach because you're really having to allow and trust a new entity to come in, that doesn't necessarily have a first name and last name, that doesn't necessarily have a heartbeat, but that it knows a tremendous amount about a very deep subject. It has very deep understanding and an ability to function in a very deep area of your business (3-15).

Another aspect of trusting the AI included the delegation of a task or project from the human to the machine. Prior to the delegation, the human needed to determine their role in the process as compared to the machine, and subsequently develop performance expectations for these tasks. It is important that the expectations for the machine's performance are appropriately aligned with the human's role. To form realistic expectations, the human needs a solid understanding of the AI's technical capabilities. If the human has unrealistic expectations, there is a potential for trust to be lost. One participant offered the following insight:

When we are talking about implementing a solution with some sort of artificial intelligence, all we are [discussing] are specific areas where we're letting the machine decide for us what things should take place, rather than a human getting involved. [It could include] creating suggestions or providing suggestive language that can help a human to make a decision, or [prepare] a better, more informed decision through the assistance of that machine, and [provide] us feedback. It is kind of cool. It has been neat to see the development (3-15).

Despite the preconceived notions about the general nature of AI, notably, specific tasks with boundaries are identified for an AI implementation to instill a sense of trust and confidence in the technology.

Developing human and AI roles

Cultivating trust in AI serves as an antecedent for the next phase of the framework which includes designing human and AI roles. When a leader begins the process of evaluating an AI adoption, they need to think critically about the best approach for embedding this technology within their business. To effectively use this tool, they will need to develop a deep understanding of the strengths and weaknesses of both their human and AI team members. Spotting patterns in large datasets and making recommendations based on those patterns is a strongpoint for AI technology. Humans possess the capabilities to perform these calculations, however, their processing speed and accuracy was considerably slower. This can pose challenges for the business if the firm is attempting to expand quickly into new markets, particularly if they are operating in a competitive marketplace in which speed-to-market is a competitive differentiator. Subsequently, the leader needs to think carefully about aligning the technology with the task(s).

As one interviewee shared:

I personally do not want an AI doctor now. I don't even mind that the doctor takes an AI recommendation at their level, but the decision for my care, I would still, even if an AI application influences the doctor's decision, I still want the doctor's decision. I still want the human analytics and not artificial intelligence. (3-11).

Introducing AI into the medical field has required leaders to develop new processes, procedures, and ways of working. As we can see in this interview quotation, there are some tasks that may require human oversight.

Humanizing AI is another component of determining human and AI roles. In many respects, AI may become an integral part of the team. Hence, leaders will need to consider how to best position the AI within the team. Anthropomorphism is an approach that is often used with technology as a means of facilitating an emotional connection between the human and the technology (Glikson & Woolley, 2020). I interviewed a technology leader at a firm that has

developed its own proprietary AI, named Ada. This interviewer offered the following illustration of Ada's role at the firm and the value *she* provided to the firm following *her* introduction:

We use Ada, which is an artificial intelligent engine that we developed, to help manage not only the budget, the location of this money into the different advertising networks, but we actually use it as well to individuals, and Ada came to develop and create these ads on its own by almost providing a set of, let's say, 10 ads. We could have 10 ads that are related to this target audience. And then through the utilization of those ads, as people are clicking on the ad, Ada starts learning, it starts assimilating those clicks, as to when they're coming from--what makes an ad more clickable than the other. And then Ada started [the] process of A/B testing and out of it, creating new ads on its own and over time through this filtration or improvement process of A/B testing, eventually Ada with its intelligence is able to come up with ads that are a lot more clickable and higher performance than the ones that we originally provided.

You know, and this is the neatest thing. I think this is the part where, where artificial intelligence is so powerful. Not only did you come up with a production with a service that is a lot more valuable to the customer because the ads that are being created are very clickable. The body that is being managed is also now very much on point and on target. And you can get later down the road into predicting what kind of outcome you may have in case you increase the budget. How many more clicks can you get? So, there is a predictive model (3-15).

By connecting human characteristics to the AI, this helped workers to overcome their fears and begin to perceive the AI as being a productive member of the team and rather than a threat.

Evaluating risk and determining how to best manage that risk is a critical aspect of this decision. In *safety-critical industries* such as healthcare and the airline industry, AI is often used to manage and prevent harm to stakeholders. The underlying assumption is that humans will make mistakes by virtue of being human. The AI is used strategically in these industries to prevent and manage risk. One participant suggested that decisions on safety need to be evaluated concurrently with financial decisions rather than applying a siloed approach in which the financial and safety decisions are made separately:

So, when you make these decisions, does your company have a safety risk management system? How is it applied? And how does it apply to decisions alongside of finance department initiatives? What is our return on investment? So, at our firm, we have a whole safety department that does that. We have a whole finance department that manages that area. Somewhere along the line, the CEO must take input from all those departments and decide (2-8).

Organizations that promote a finance over safety approach instead of finance *and* safety thinking are likely to foster more of a competitive environment rather than a collaborative one. A collaborative environment is more conducive to facilitating an ethical climate.

Making AI ethical decisions

Once the Human-AI organizational structure has been established, it is important to develop a context that facilitates ethical decision-making. By their nature, businesses are seeking to maximize their profits. Ethical climate researchers have labelled this approach as egoistic-local which means leaders within firms make decisions primarily in the interest of generating increased profits for the firm and subsequently give highest priority to that approach (Victor & Cullen, 1988). Balancing costs and benefits is a key part of this calculation.

Another milestone concerns whether the decision will be centralized or decentralized. With AI, firms are achieving success by using a centralized decision-making approach, particularly regarding the adoption decision. While the AI knowledge can be developed and cultivated over time, some firms are struggling to hire employees with the specialized expertise in AI development and management. Small to medium-sized firms that are located outside of the Silicon Valley or one of the U.S. technology hubs in Boston or New York are experiencing challenges in attracting and retaining AI talent. During the early stages of the AI adoption, firms should consider centralizing AI resources to facilitate organizational learning and knowledge sharing, particularly if the AI is being used for security purposes. Hackers are continuously searching for ways to enter a firm's systems and Information Technology experts need to remain

vigilant for these attacks. A centralized approach and organizational structure facilitated coordination, planning and knowledge sharing. Many firms were using AI extensively to monitor systems as part of their cybersecurity measures. One interviewee offered this insight:

No pilot wants somebody take their control of the airplane on the ground, but it would have prevented airplanes flying into the World Trade Center. I would have taken it [this safeguard measure]. There must be a partnership between labor management, government regulation and we must decide what we want to do. Because, just think about it, if someone can control that airplane from a computer on the ground, how easy would it be to be hacked? (2-10).

AI systems have the capability to monitor networks around the clock for potential hacking attacks and function as an extension of the cybersecurity team, so this is an excellent application for this technology.

Leaders need to cultivate knowledge and experience applying ethical frameworks, so they are prepared when an ethical issue arises in the workplace. Digital marketing is a context in which AI use is rising. The issues of privacy, tracking, data usage, and data leakage are current ethical hotspots. In a marketing context, leaders need to respect consumer privacy and display sensitivity in their online advertising strategies when using AI. Further, they need to be transparent about the data they are collecting and the intended use of that data. One interviewee provided this perspective:

Regarding receiving online ads. Customers see three products being offered to them that they were not anticipating. [Some people see that approach] as being a nice way for companies to [share information about their products], while other people see that as creepy. And [they are thinking], ‘oh my gosh, how did these strange people know that I was looking at water softeners on the internet? And suddenly I’ve got nine ads popping in front of me for plumbers.’ I think advertising is a great example of these AI decisions or a decision to market to an individual based on behaviors that was made by a central process and not by a person (3-11).

Many searches for products and services originate on mobile devices. Data privacy researchers discovered that consumers perceive of their mobile device as being an extension of their personal space. Consumers perceived of these uninvited advertisements as a violation and assigned the

label “creepy” to those communications. Further, they identified unanticipated online advertisements as being an invasion of their privacy (Shklovski et al., 2014).

Developing technochange management strategies

An important strategy for ensuring that AI is adopted throughout the organization is to communicate the value of this technology and provide opportunities for people to actively engage with it so they can experience the value. People are fearful or hesitant about interacting with a technology when it is unfamiliar. One respondent stated they focused on helping to make peoples’ work more productive and demonstrated the value of using the technology for the workers. Their employees responded by adopting the AI because they could see tangible benefits such as time savings and elimination of mundane tasks which freed them to focus on the creative and interesting aspects of their roles. This interviewer offered this insight:

So, my job is very interesting and good in that I get to sit back and try to help make some of these decisions about where machine learning can be applied to make those people's lives better. Right? So, the impact that has on me is that it allows me to make all of those things more efficient and allows me to make our people more efficient, to make those other processes and systems in the business more efficient. But it also allows me to give them tools and, again, help them focus more on the relationship and people side of things, which is where they excel (3-12).

In this scenario, the AI adoption evolved into a considerable morale booster. For this leader, the key was to educate, inform, and demonstrate the value of this new technology to the workers as it helped build a level of trust in this technology.

Another facet of this strategy is assessing the effectiveness of the initiative and assigning appropriate responsibilities along with resources for the program. Leaders will need to examine the competencies and capacities of their current team and decide whether to develop the AI in-house, or purchase the technology from an outside vendor. One interviewee shared, “If I see an opportunity where AI should be utilized, I’m going to go out and find the appropriate resources

either for myself or for the people that I'm working with to find the subject matter experts that are going to be able to help to utilize that" (1-1).

Besides acquiring resources, the leader inevitably will need to address skeptics and workers that challenge the AI adoption. There are a variety of reasons that workers are resistant to change. According to Rosabeth Moss Kanter, motives may include "loss of control, excess uncertainty, surprise, everything seems different, loss of face, concerns about incompetence, more work, ripple effects, past resentments, and sometimes the threat is real" (2012, pp. 1-3).

One interviewee shared the following wisdom on technochange management,

So, that has been our approach so far is again, finding a group of people that are willing to work with us that are skeptical and then demonstrating the value to them. If you can win over skeptics, they are good about helping you then win over others in the organization (3-12).

Ensuring that the skeptical workers play an active role in the adoption is a valuable approach for uncovering practical issues that need to be addressed as well as securing their buy-in for the initiative.

Positioning AI in the business

By this point, the leader has addressed trust issues, established roles for both humans and AI, created a foundation for ethical decision making, and prepared technochange strategies. The next step is to identify approaches for embedding AI within the business to ensure successful adoption. Some key tenants of this approach will include addressing technology avoidance behaviors, preparing ethical guardrails, developing strategies to mitigate bias—both implicit and explicit--and apply industry use cases to motivate and inform employees.

Surprisingly in today's economy, there are professionals within certain sectors that are actively avoiding technology. One interviewee's firm sells technology solutions, including AI, to law firms, and this individual noted there were some attorneys that handled all their paperwork

manually; they did not use computers at all, or used just very basic computer functions. The interviewee shared that these attorneys had been practicing successfully for many years and the firms made the decision not to implement AI solutions for these practice areas until after the attorney retired. The interviewee mentioned that other firms handled these situations by offering incentives such as performance bonuses to encourage conversions to the technology. This approach had a moderate degree of success.

With the introduction of this technology, it is important to establish ethical guardrails to ensure people are clear on the ethical boundaries for using this technology. The firm can begin by reviewing trade association materials to determine whether their respective industries have established ethical guidelines. This is a valuable starting for preparing and communicating these ethical standards as there is automatic credibility built-in which makes adoption somewhat easier.

One key area that needs to be addressed in the ethical guardrails concerns the issues of both implicit and explicit bias in AI and ML. Bias can occur because it is embedded in the data set that is used for training the Machine Learning algorithm. When the algorithm receives the data, it begins to look for patterns, learns from them, and makes predictions based on that data. If the training data is biased, the system will “learn” bias from the training data. The system can also be biased based in the way in which it is programmed. If the programmers have bias, it will appear in the programming unless the programmers intentionally work to prevent this from occurring.

One participant worked in the financial services industry and offered this insight into bias:

But if you use algorithm and if you have a bias, but the bias proves to be incorrect the models will self-correct. So, over a period, the bias will be reduced while a human being, even with user training and all it is, it may not be feasible for the bias to reduce. So, that is the advantage of using machine learning model in some cases. On the other hand, if the people who are designing the algorithm have a hidden bias, it becomes very difficult. I will give you an example and not our bank, but I know some banks where they started using machine learning models for voice recognition. They could not recognize, let us say my accent or a Latino accent, because those guys really struggled with accents. So, they would send them more towards default. They would take, they would put them in the lower income strata and all. So obviously, there was a bias that must be reflective (3-14).

Finally, bias can occur with the output and the way that it is used for making decisions about hiring, business loan, or mortgage applications, just to name a few examples. In summary, the interviewee shared this perception of the different types of bias:

Bias is to me the biggest ethical issue, whether it is race, it is gender, it is ethnicity. So because you make decisions, which impact your customer, are you, and then in the banks and all there are all protected classes, are you not looking at a protected class with the same level of scrutiny. I think that is what is our biggest consideration (3-14).

Unfortunately, this bias can have lasting impacts on society overall due to its impacts on people's livelihoods, employment prospects, standards of living, and home ownership, in addition to other areas. An interview participant noted:

It is just going to prolong the bias in society, because now you have a computer program doing it. They cannot explain why the computer program made that decision, so it will just stay there, and it is harder to prove that it is biased. Whatever problems and biases we have in society, it is just going to prolong it because you are going to have this computer that rote matched it and just carried on. Even if we do not know what the bias is, it is going to stay and not change (1-3).

The issue of bias in ML and AI is a serious one that deserves further investigation. There are quite a few research institutions and organizations that are focused on this important issue that has a significant societal impact.

Finally, the interviews revealed the importance of applying industry use cases as rationale for adopting AI. Many of the consulting firms have experience in developing these use cases and have published their findings for the business community. Organizations such as McKinsey, Deloitte, KPMG, BCG, and many others have published white papers and articles that document their experiences and learnings including successes and challenges experienced in AI adoptions within a wide variety of industries. The use cases are an effective tool that can be used to secure budget and personnel resources for AI adoptions. Appendix G displays the Dimensions, Themes and Exemplary Quotations from the research.

Discussion

My intention for this exploratory study was to investigate the adoption of AI technology and develop a deeper understanding of the accompanying ethical issues surrounding this important event. Many firms are struggling to adopt this new technology and I wanted to illuminate some of the ethical challenges that firms may face during the adoption process. The research revealed that cultivating trust in AI plays a vital and foundational role in the adoption process as there are many misunderstandings about AI which often lead to fear of this technology. The subsequent components of the proposed framework include developing AI and human role expectations, making ethical decisions, designing technochange management strategies, and positioning AI within the business. This research contributed to the literature from both a theoretical and an empirical position as follows.

Theoretical Contributions

Building AI trust was the first theoretical contribution. This research revealed there were some misperceptions about AI in the public space. Many people perceive it as operating similarly to AI's depiction in the Terminator movies. Multiple interviewers shared this

misperception and noted that, in fact, AI is often used in very mundane tasks daily. It was also noted that AI may not be as “intelligent” as anticipated by the public. Some interviewers described the technology as being “rather dumb”. Most AI operates more as a decision support system and provides recommendations and/or predictions. We have not reached the point yet where AI has achieved true intelligence equivalent to the human mind. In most applications, a human must provide the programming and guidance for the AI. Further, I had an opportunity to explore this “fear” of AI that surfaced during the interviews. Most of that fear stems from the idea that AI may potentially replace jobs and have a significant negative impact on people’s livelihoods. Some researchers have investigated this idea and estimate that there will be some jobs that are replaced. However, during these interviews, most technology leaders conveyed that realistically, AI is being used to augment and enhance jobs in their firms, not necessarily to replace human beings. This new knowledge underscored that for adoptions to take hold within a firm, leaders need to focus on cultivating trust in AI.

The second theoretical contribution concerned the **design of human and AI** roles and responsibilities within the firm. Despite the discussion in the media about AI functioning autonomously, according to the technology leaders that were interviewed, most AI still requires some degree of human oversight and control. This will require leaders to embrace their creativity and develop new ways of working. Some of the research revealed this shift in the application of AI’s predictive capabilities. Leaders will be able to offload many of their analytic tasks to AI and potentially ML, which frees them up to focus on applying their judgment skills. Interestingly, my research confirmed that we are not entirely comfortable turning over all the daily decision-making to machines. AI requires some human oversight and management. Managers will need to assess both the strengths and weaknesses of human and AI teammates, and assign roles to align

with the team member's strengths. For these human and AI teams to function effectively, there must be a high degree of trust. The research demonstrated that assigning human-like qualities to the AI, anthropomorphism, does alleviate some of the fear and may cultivate a trusting relationship between the team members.

The empirical data that I collected suggested there is a relationship between cultivating trust and developing human and AI roles. Effectively, trust serves as the antecedent for this role development. This extends the work on trust in AI (Glikson & Woolley, 2020) as well as the work on algorithmic authenticity (Jago, 2019). In addition, *AI trust* emerged as the common thread that connected the other constructs such as Making Ethical Decisions, Developing Technochange Strategies, and Positioning AI in the Business as revealed in the coding cycles.

Connecting AI trust and ethics in the context of making **AI-based ethical decisions** was a third theoretical contribution. My interviews suggested that most firms were using a utilitarian approach and focused on balancing costs and benefits. Yet, they recognized that AI has broader societal implications extending beyond the walls of their firms. It was evident from the interviews that more education and awareness about these ethical issues was needed within the business community as many interviewees were unaware of ethical issues underpinning AI adoptions. Further, many participants were eager to hear about ethical frameworks and ideas for including ethics in the adoption process.

Practical Applications

AI is on the radar for adoption by many firms currently. Leaders and managers that are looking to adopt this technology for the first time will likely have questions about the best approach. This research was developed to inform both technology and non-technology leaders about the adoption process as well as raise awareness of the ethical considerations that need to be

factored into the adoption process. First, leaders need to recognize their workers may potentially have fears and concerns about losing their jobs to AI. They need to be transparent and clearly define the roles and responsibilities of AI and humans on teams. Further, they need to articulate the importance of humans serving in an oversight capacity. Humans will not be working for an AI boss. This approach may help alleviate concerns and worries. Second, leaders need to carefully consider how they will introduce the AI to the team. As discussed previously in this paper, one interviewee shared they named their AI and assigned her some personality attributes to facilitate a smooth transition to the team. Third, leaders should consider including ethics in the AI adoption process. Some of the approaches discussed in this research include developing an ethical framework along with ethical guardrails and educating workers on potential ethical issues that may arise. Then, provide employees opportunities to practice and apply ethical decision-making skills using case studies.

Limitations and Future Research

In using the purposive and snowball sampling approaches initially, I developed a solid cross section and resulting understanding of the AI adoption process within those firms. However, most of these firms focused on the service sector and the AI initiatives were oriented towards growth (i.e. marketing, hiring, etc.). In future studies, I would like to expand the interviews to include representation from manufacturing and the government sectors as those applications are different and may contain some varying perspectives.

Another limitation that may impact generalizability concerns the type of people that were interviewed. The participants in my interviews were primarily Executives and Leaders within their respective industries with extensive work experience. Given the large volume of millennials

that are entering the workplace, it would be interesting and valuable to conduct interviews and collect data from non-management employees as their perspectives may be different.

A third limitation concerns the timing of this study. This research was conducted during the Covid-19 lockdown in the United States which occurred between March and June 2020. All the interviews were conducted remotely from my home office by either telephone or Zoom. Because of this situation, I was unable to visit the workplace and conduct interviews in-person which may have yielded different insights. Also, interviewing multiple leaders and non-management employees from the same organization may have provided unique insights and perspectives for comparison purposes.

During this study, I conducted an interview with the Head of AI for an automotive manufacturer located in the European Union. The interview findings were fascinating and yielded valuable insights, yet there were some variances to the U.S. based interviews which may be attributed to differing culture and political-economic systems. Nevertheless, one area of future research would be to continue interviewing manufacturers in other countries (perhaps the European Union) to perform some comparisons between European and American companies and their AI adoptions.

Conclusion

Despite the hype and media attention on AI adoptions, the fact is that many firms are still in the early stages of adopting this technology. Further, this technology has existed since the 1950's and has experienced peaks and valleys in interest since that time. The intention of this exploratory study was to unpack the AI adoption process and determine what ethical considerations were included within the decision-making process. I used a constructivist grounded theory approach as a means of building onto theory. As a result, a new framework

emerged, an **Ethics Integrated AI Adoption Framework**. Cultivating trust serves as an antecedent within this framework. The other components include developing human and AI roles, making ethical decisions, developing technochange management strategies, and positioning AI within the business. This framework contributes to the extant literature on trust in AI technology and the data displays a relationship between the trust and developing human and AI role constructs. From a practitioner standpoint, this research highlights some of the ethical issues that need to be factored into the decision-making process, particularly implicit and explicit bias. By reviewing this research, the practitioner will be better informed about ethical considerations and gained some ideas on how to adopt AI effectively within their organization.

References

- Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines : the simple economics of artificial intelligence. *MIT Sloan Management Review*.
<https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1798834>
- Agrawal, A. K., Gans, J. S., & Goldfarb, A. (2017). What to Expect From Artificial Intelligence. *MIT Sloan Management Review*, 58(3), 23-27.
<https://search.proquest.com/docview/1885859665?accountid=1474>
- Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *PACIS 2018 Proceedings*, 37. <https://aisel.aisnet.org/pacis2018/37>
- Bisson, P. I., Hall, B., McCarthy, B., & Rifai, K. (2018). Breaking Away: The Secrets to Scaling Analytics. *McKinsey Analytics*. Retrieved June 26, 2020, from <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/breaking-away-the-secrets-to-scaling-analytics>

- Bolukbasi, T., Chang, K.-W., Zou, J., Saligrama, V., & Kalai, A. (2016). Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings [Working Paper].
- Brenkert, G. G. (1998). Trust, Business and Business Ethics: An Introduction. *Business Ethics Quarterly*, 8(2), 195-203. www.jstor.org/stable/3857325
- Breznitz, D. (2014, May 27, 2014). Why Germany Dominates the U.S. in Innovation. *Harvard Business Review*. <https://hbr.org/2014/05/why-germany-dominates-the-u-s-in-innovation>
- Buchanan, B. G. (2005). A (Very) Brief History of Artificial Intelligence. *AI Magazine*, 26(4), 53. <https://doi.org/https://doi.org/10.1609/aimag.v26i4.1848>
- Buhmann, A., Paßmann, J., & Fieseler, C. (2020). Managing Algorithmic Accountability: Balancing Reputational Concerns, Engagement Strategies, and the Potential of Rational Discourse. *Journal of Business Ethics*, 163(2), 265-280. <https://doi.org/http://dx.doi.org/10.1007/s10551-019-04226-4>
- Carroll, G. R., & Wheaton, D. R. (2009). The organizational construction of authenticity: An examination of contemporary food and dining in the U.S [Review Article]. *Research in Organizational Behavior*, 29, 255-282. <https://doi.org/10.1016/j.riob.2009.06.003>
- Cave, S., Craig, C., Dihal, K., Dillon, S., Montgomery, J., Singler, B., & Taylor, L. (2018). Portrayals and Perceptions of AI and Why They Matter. Retrieved 06-30-2020, from <http://www.lcfi.ac.uk/resources/portrayals-and-perceptions-ai-and-why-they-matter/>
- Charmaz, K. (2006). *Constructing Grounded Theory : A Practical Guide through Qualitative Analysis*. SAGE Publications. <http://ebookcentral.proquest.com/lib/usf/detail.action?docID=585415>

- Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
- Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World: Don't Start With Moonshots. *Harvard Business Review*(January-February 2018).
<https://www.semanticscholar.org/paper/Artificial-Intelligence-for-the-Real-World-Don-%E2%80%99-t-Davenport-Ronanki/ef19d8f60311221ca9a16715e3938765a9bb68d2>
- Dweck, C. (2016). What Having a "Growth Mindset" Actually Means. *Harvard Business Review*. <https://leadlocal.global/wp-content/uploads/2016/12/Dweck-What-Having-a-%E2%80%9CGrowth-Mindset%E2%80%9D-Actually-Means-HBR.pdf>
- Elsbach, K. D., & Stigliani, I. (2019). New Information Technology and Implicit Bias [Article]. *Academy of Management Perspectives*, 33(2), 185-206.
<https://doi.org/10.5465/amp.2017.0079>
- Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864-886.
<https://doi.org/10.1037/0033-295X.114.4.864>
- Flores, F., & Solomon, R. C. (1998). Creating Trust. *Business Ethics Quarterly*, 8(2), 205-232.
<https://doi.org/10.2307/3857326>
- Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, 0(ja), null.
<https://doi.org/10.5465/annals.2018.0057>
- Hackman, J. R., & Oldham, G. R. (1976, 1976/08/01/). Motivation through the design of work: test of a theory. *Organizational Behavior and Human Performance*, 16(2), 250-279.
[https://doi.org/https://doi.org/10.1016/0030-5073\(76\)90016-7](https://doi.org/https://doi.org/10.1016/0030-5073(76)90016-7)

- Harison, E., & Boonstra, A. (2009, 2009/08/01/). Essential competencies for technochange management: Towards an assessment model. *International Journal of Information Management*, 29(4), 283-294.
<https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2008.11.003>
- Hofstede, G. J. (2020). Hofstede Insights, Country Comparison Tool. Retrieved July 16, 2020, from <https://www.hofstede-insights.com/country-comparison/>
- Hosmer, L. T. (1995). Trust: The Connecting Link Between Organizational Theory and Philosophical Ethics. *Academy of Management Review*, 20(2), 379-403.
<https://doi.org/10.5465/amr.1995.9507312923>
- Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, 21(2), 155-172. <https://doi.org/10.1177/1094670517752459>
- Ivanov, S. H., & Webster, C. (2017). Adoption of Robots, Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies – A Cost-Benefit Analysis [Conference Proceedings]. *International Scientific Conference "Contemporary Tourism – Traditions and Innovations"*, Sofia University 19-21 October 2017. Available at SSRN: <https://ssrn.com/abstract=3007577>
- Jago, A. S. (2019). Algorithms and Authenticity. *Academy of Management Discoveries*, 5(1), 38-56. <https://doi.org/10.5465/amd.2017.0002>
- Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2016). How Artificial Intelligence Will Redefine Management [Article]. *Harvard Business Review Digital Articles*, 2-6.
<http://ezproxy.lib.usf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=buh&AN=120582134&site=eds-live>

- Li, X., Hess, T. J., & Valacich, J. S. (2008, 2008/03/01/). Why do we trust new technology? A study of initial trust formation with organizational information systems. *The Journal of Strategic Information Systems*, 17(1), 39-71.
<https://doi.org/https://doi.org/10.1016/j.jsis.2008.01.001>
- Markus, M. L. (2004). Technochange Management: Using IT to Drive Organizational Change. *Journal of Information Technology*, 19(1), 4-20.
<https://doi.org/10.1057/palgrave.jit.2000002>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust [Article]. *Academy of Management Review*, 20(3), 709-734.
<https://doi.org/10.5465/AMR.1995.9508080335>
- McClure, P. K. (2018). 'You're fired,' says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, 36(2), 139-156. <https://doi.org/10.1177/0894439317698637>
- Mills, J., Bonner, A., & Francis, K. (2006, 2006/03/01). The Development of Constructivist Grounded Theory. *International Journal of Qualitative Methods*, 5(1), 25-35.
<https://doi.org/10.1177/160940690600500103>
- Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, 3(2), 2053951716679679.
<https://doi.org/10.1177/2053951716679679>
- Moss Kanter, R. (2012). Ten Reasons People Resist Change. *Harvard Business Review*.
<https://hbr.org/2012/09/ten-reasons-people-resist-chang>

- Piccolo, R. F., Greenbaum, R., Den Hartog, D. N., & Folger, R. (2010). The relationship between ethical leadership and core job characteristics [research-article]. *Journal of Organizational Behavior*, 31(2/3), 259.
<http://ezproxy.lib.usf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.41683905&site=eds-live>
- Pumplun, L., Tauchert, C., & Heidt, M. (2019, 01//). A New Organizational Chassis for Artificial Intelligence-Exploring Organizational Readiness Factors. *Proceedings of the European Conference on Information Systems (ECIS)*, 1.
<http://ezproxy.lib.usf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=144241363&site=eds-live>
- Raisch, S., & Krakowski, S. (2020). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review*, 0(ja), null.
<https://doi.org/10.5465/2018.0072>
- Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping Business With Artificial Intelligence: Closing the Gap Between Ambition and Action. *MIT Sloan Management Review*, 59(1).
<https://login.ezproxy.fgcu.edu/login?url=https://search.proquest.com/docview/1950374030?accountid=10919>
- Reason, J. (2004). Beyond the organisational accident: the need for 'error wisdom' on the frontline. *BMJ Quality Safety Healthcare*, (SUPP/2), ii28.
<http://ezproxy.lib.usf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsbl&AN=RN160442826&site=eds-live>

- Robinson, M. F. (2018). *Artificial Intelligence in Hiring: Understanding Attitudes and Perspectives of HR Practitioners* [Wilmington University]. Proquest Dissertations.
- Rogers, E. M. (1995). *Diffusion of Innovations* (5 ed.). Simon & Schuster, Inc.
- Saldaña, J. (2016). *The Coding Manual for Qualitative Researchers* (3rd edition ed.). Sage Publications.
- Sandvig, C., Hamilton, K., Karahalios, K., & Langbort, C. (2014, May 22, 2014). *Auditing Algorithms: Research Methods for Detecting Discrimination on Internet Platforms* 64th Annual Meeting of the International Communication Association, Seattle, WA.
<https://pdfs.semanticscholar.org/b722/7cbd34766655dea10d0437ab10df3a127396.pdf>
- Shklovski, I., Mainwaring, S. D., Skuladottir, H. H., & Borgthorsson, H. (2014). Leakiness and Creepiness in App Space: Perceptions of Privacy and Mobile App Use. 2347.
<http://ezproxy.lib.usf.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsbl&AN=RN366919131&site=eds-live>
- Siau, K., & Shen, Z. (2003). Building Customer Trust in Mobile Commerce [Article]. *Communications of the ACM*, 46(4), 50. <https://doi.org/10.1145/641205.641211>
- Siau, K., & Wang, W. (2018). Building Trust in Artificial Intelligence, Machine Learning & Robotics. *Cutter Business Technology Journal*, 31(2).
<https://www.cutter.com/article/building-trust-artificial-intelligence-machine-learning-and-robotics-498981>
- Simon, H. A. (1996). *The Sciences of the Artificial* (3rd ed.). The MIT Press.
- Thornberg, R., & Charmaz, K. (2014). Grounded theory and theoretical coding. . In U. Flick (Ed.), *The SAGE Handbook of Qualitative Data Analysis* (pp. 153-169). SAGE Publications Ltd. <https://doi.org/10.4135/9781446282243>

Victor, B., & Cullen, J. B. (1988). The Organizational Bases of Ethical Work Climates [Article].

Administrative Science Quarterly, 33(1), 101-125. <https://doi.org/10.2307/2392857>

Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and

German workers are for thinking-not feeling-jobs. *Emotion (15283542)*, 14(2), 434-444.

<https://doi.org/10.1037/a0036054>

Wolfe, S. M., Fleischer, M., Morell, J. A., & Eveland, J. D. (1990). Decision Processes in

Technological Innovation. In L. G. Tornatzky, Fleischer, M. (Ed.), *The Processes of*

Technological Innovation (pp. 300). Lexington Books.

CHAPTER SIX: CONCLUSION

“Analytic competitors will continue to find ways to outperform their competitors. They’ll understand both their internal and their external business environments, and they’ll be able to predict, identify and diagnose problems before they become too problematic. They will make a lot of money, win a lot of games, or help solve the world’s most pressing problems. They will continue to lead us to the future” (Davenport & Harris, 2017, p. 264).

Artificial Intelligence and machine learning were part of our daily lives. These technologies were pervasive. Some firms have achieved success with adopting these technologies while others have struggled. This dissertation was prepared to develop an understanding of the role that ethics plays in the adoption of Artificial Intelligence in firms. There has been considerable interest in the academic and business community around this topic. In August 2019, I attended the Academy of Management conference in Boston, Massachusetts and learned there was considerable interest in this topic amongst management scholars. There were fourteen sessions that focused on various aspect of AI, so I anticipated there will be some publications in the Management discipline academic journals pending.

This closing portion of the dissertation will address the research questions along with key findings based on the research, theoretical and practical contributions, limitations to the studies, as well as future research pathways.

Research Questions

This research included three research questions. The first question focused on environmental forces: *How do market and regulatory forces reportedly shape Artificial Intelligence adoptions?* To address this question, I performed an industry analysis which consisted of reviewing practitioner and academic publications via a systematic literature review.

After examining industry profiles, I prepared an AI Stakeholder Power/Interest Matrix which aided in categorizing the industry stakeholders and identifying strategies for working with those constituents. My analysis revealed that cloud computing providers, semiconductor manufacturers, and the consulting firms have a great deal of power and influence within the industry currently. In addition, U.S. federal regulators have been observing, supporting, and funding AI research. The approach has been to encourage trade associations and industry alliances to develop and manage their own ethics guardrails. However, leaders from Big Tech have proactively reached out and asked the federal government to intervene.

The second research question was: *What ethical principles/perspectives do managers follow when adopting Artificial Intelligence and Machine Learning systems?* There has been considerable discussion in the literature on a variety of ethical issues and it was important to learn how managers are experiencing these issues within the workplace. Most of the work has been theoretical at this point; empirical evidence was limited. The discussion case study and the grounded theory study elaborated on this issue. As expected, most leaders and managers were using a utilitarian approach which entailed performing a cost/benefit analysis and focusing on maximizing profit. Although only one manager mentioned virtue ethics by name, many of the interview participants described an approach to managing AI that resembled virtue ethics.

Despite having worked in their respective roles for many years, most of the interview participants were able to look at AI with a skeptical perspective. They saw the advantages of this technology, yet they were aware of its limitations. Having the ability to observe and realistically assess the challenges with AI led to the participants having a mindset of being receptive to discussing ethics.

The third research question followed: *What ethical issues exist within the firms that adopt Artificial Intelligence and Machine Learning systems?* The Vectra Digital case study revealed several ethical issues that were specific to the digital marketing discipline including managing customer data in a transparent fashion, maintaining data boundaries, and customer targeting practices. The firm focused on targeting and corresponding with customers that were most interested in the products and services.; i.e. loyal customers. The grounded theory study revealed managers' awareness of ethical considerations such as trust in AI, ethical decision-making frameworks, and designing human-AI roles.

Theoretical Contribution

While preparing the Industry Analysis, it became apparent during the research there were a variety of stakeholders operating within this market space with unique relationships and motivations. I was searching for an approach to classify, structure, and frame the context of this industry and subsequently capture these dynamics. After reviewing the stakeholder analysis stream of literature, the Stakeholder Power/Interest Grid emerged as a viable framework for this assessment (Johnson & Scholes, 1999; Mendelow, 1981). I proceeded to assign scores to each of the competitors using the industry profiles that I collected through my research. This framework enabled readers to identify how power is distributed throughout the industry. My literature review revealed that the volume of recent articles in the management discipline applying this Power/Interest Grid framework and researching industry structure appears to be limited. Hence, publishing this article contributes knowledge on this emerging industry and could potentially reinvigorate interest amongst other management scholars that are seeking to investigate industry dynamics.

The discussion case study was designed with the primary purpose of educating and informing undergraduate college students about adopting AI in the workplace, specifically ethical considerations related to the adoption. I collaborated with a Southwest Florida firm, Vectra Digital, to research and prepare this discussion case study along with an instructor's manual to accompany the case. The technology theoretical underpinning for this project was the TAM (Davis, 1989) and TAM-2 (Venkatesh & Davis, 2000). Utilitarianism served as the ethical framework for this investigation. This discussion case provided students the opportunity to practice applying these theoretical lenses to a real business which was a valuable learning experience based on the trial run that was performed in a class in June 2020. Further, this case reinforced the value and relevancy in using these theoretical frames, even with an emerging technology like AI.

The grounded theory study consisted of interviews with fifteen industry experts. Based on the insights gathered, a new framework emerged which I have named the *Ethics Integrated AI Adoption Framework* (See Figure 9). Trust in AI functions as the antecedent. The interviews revealed there are many misperceptions about AI in the marketplace, and people routinely experience fear of this technology as a result. Managers needed to develop human and AI roles which entailed clarifying responsibilities and accountabilities for tasks. Critical parts of the manager's role include assessing the strengths of their human as well as AI team members, and structuring assignments to maximize those strengths. For instance, humans are effective problem solvers. While they have the capabilities to analyze data and apply the data to solve problems, AI is often more efficient with analyzing large data sets and making predictions. In turn, the human can take that prediction and use that information to solve the problem. For this example, to work, the human must trust that the AI is reliable, timely and accurate. If the AI fails to

produce the deliverable in a timely fashion, or the information provided is not correct, this is problematic for the human and they lose trust in the system in response. One important component in this framework revealed by my research was the perception that a human must oversee the work of the AI for trust to be present. From a theoretical standpoint, this study adds to the knowledge and literature related to trust in technology.

Interestingly, an article by Glikson and Woolley (2020), *Human Trust in Artificial Intelligence: Review of Empirical Research*, focused on characteristics of AI that either result in trust or distrust of AI by humans. Specifically, the authors evaluated the “form of AI representation (robot, virtual, embedded) and the level of AI’s machine intelligence (i.e. its capabilities) as important antecedents to the development of trust” (Glikson & Woolley, 2020, p.1). My research confirmed that anthropomorphism, indeed, is an effective approach for building trust in the technology. My research examined leader behaviors such as developing and assigning roles for human and AI team members with trust as a basis. Therefore, my research was positioned to build on to the important work of these authors.

Another theoretical contribution was an expanded viewpoint on trust and ethics along with a connection to AI. For many years, scholars have viewed ethics and trust as being in two separate theoretical camps. However, in his seminal work – *The Connecting Link Between Organizational Theory and Philosophical Ethics*, Larue Hosmer suggests the connection between them is moral duty (Hosmer, 1995). The grounded theory study reinvigorated this conversation about bridging ethics and trust, specifically AI trust.

Practical Contribution

For firms that were considering adopting AI or perhaps they have been slow to adopt this technology, understanding how the industry was structured and identifying the key players was

valuable information. Moreover, the AI Stakeholder Power/Interest Matrix provided helpful knowledge and strategies for working with these different stakeholders. Knowing the various degrees of engagement and the associated management strategies as posted in AI Stakeholder Power/Interest Matrix will help with prioritizing valuable firm resources.

One of the learning objectives for the case study and instructor's manual included providing the students with experience applying an ethical lens to bolster critical thinking skills. This pedagogical approach was designed to be used in a face-to-face setting as well as in an online or remote format. As part of the development, the case study and instructor's manual were tested in an online class in June 2020 with very positive results and feedback from students. If a faculty member is searching for a teaching case study that will challenge students and orient them to this emerging technology, they can apply this discussion case study and instructor's manual in the classroom.

Finally, the grounded theory study yielded some interesting new insights about the AI adoption process and the role of ethics. During planning, we learned that managers needed to think critically about how they will introduce the AI to their organization. They should consider positioning the AI as a team member and orient employees about AI to thwart fears of the AI taking their jobs. Further, they needed to establish performance expectations for the work and tasks that were performed by the AI so that workers develop appropriate expectations for what the AI will and will not do. Further, they need to communicate that humans will retain some degree of control over the AI system to instill trust within the workplace.

References

- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology [Article]. *MIS Quarterly*, 13(3), 319-340.
<https://doi.org/10.2307/249008>
- Glikson, D. E., & Woolley, P. A. W. Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, 0(ja), null.
<https://doi.org/10.5465/annals.2018.0057>
- Hosmer, L. T. (1995). Trust: The Connecting Link Between Organizational Theory and Philosophical Ethics. *Academy of Management Review*, 20(2), 379-403.
<https://doi.org/10.5465/amr.1995.9507312923>
- Johnson, G. and Scholes, K. (1999). *Exploring corporate strategy*. Prentice Hall, London.
- Mendelow, A. (1981). Environmental scanning: The impact of stakeholder concept. *Proceedings of the Second International Conference on Information Systems*, Cambridge, Mass, December 1981.
- Venkatesh, V. & Davis, F.D., (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46(2):186-204.
<https://doi.org/10.1287/mnsc.46.2.186.11926>

APPENDIX A: LECTURE NOTES ON TAM AND TAM-2

TAM and TAM-2 Lecture

Despite the surge in firms that are adopting AI and resulting productivity boosts achieved at those firms (Cam, Chui & Hall, 2019), the scale of adoption throughout those firms has been low. A McKinsey study suggests that only 21% of survey respondents have adopted AI in multiple areas of the business (Chui & Malholtra, 2018). The Technology Adoption Model (TAM) and Technology Adoption Model-2 (TAM-2) seek to understand which forces influence the individual employee in their decision as to whether to adopt the technology. These models enumerate the reasons why some individuals choose to adopt the technology whereas others refrain.

Through the years, many studies have been performed which confirm the original TAM framework. According to this model, the individual bases their decision to adopt a new technology on two primary variables: “perceived usefulness” and “perceived ease of use” which, in turn, impacts “intention to use” and consequently “usage behavior” (Venkatesh & Davis, 2000, p. 188). Further, the “perceived ease of use” plays a role in influencing “perceived usefulness” of a technology (Venkatesh & Davis, 2000, p. 188). While evidence showed that “perceived usefulness” has considerable influence within the adoption process, these researchers estimated that a better understanding of the factors that influence this variable would yield valuable insights for both researchers and practitioners.

TAM-2 primarily concentrates on the relationship between external factors and the “perceived usefulness” construct within TAM. TAM2 is comprised of two categories of forces: Social Influence Processes and Cognitive Instrumental Processes. The construct of Social Influence Processes examines the power of workplace relationships and their resulting influences on the adoption process. Social Influence Processes include “subjective norms, voluntariness, and image” (Venkatesh & Davis, 2000, p.192) . Similarly, the Cognitive Instrumental Processes examines the mental dialogue in which individuals engage during adoption decision making. Components of this construct include “job relevance, output quality, result demonstrability, and perceived ease of use” (Venkatesh & Davis, 2000, p. 192)

Subjective norms are vital elements of social influence processes as they directly influence the employee’s behavior. The employee observes technology adoption activities of other employees, pays close attention to leaders in their direct chain of command, and decides whether to proceed with using the technology. The worker estimates the value of the leader’s advice, infers how important it is to gain their approval, and subsequently follows (or ignores) their advice based on their calculation.

Image is another essential component of TAM-2. Venkatesh & Davis (2000) assert that an employee develops his/her own reference group within organizations and subsequently makes important decisions about their work. Within the context of AI, if a reference group is using this technology and the team has established a positive reputation throughout the organization, the employee will decide to adopt the technology in order to bolster his/her social status, establish referent power, and raise productivity levels.

Voluntariness is the next socialization aspect to be examined in TAM2. According to Wu and Lederer, “voluntariness is defined as the degree of free will involved in the adoption of an

information system” (2009, p. 429). There are several directive forces that mandate an employee using an AI system such as industry requirements, company policy, supervisor expectations, and job description responsibilities (Wu & Lederer, 2009). The research of Venkatesh & Davis (2000) compared worker motivations within workplace contexts of compliance versus voluntariness. These researchers defined voluntariness as “the extent to which potential adopters perceive the adoption decision to be non-mandatory” (Venkatesh & Davis, 2000, p. 188). They facilitated four longitudinal studies across four organizations and discovered, interestingly, that subjective norms play a significant role with influencing adoption decisions in mandatory, compliance-driven workplace settings, particularly when users have limited to no experience with the technology. However, as users develop experience in with AI, these social influence forces play a lesser role and users place a higher priority on their own experiences (Venkatesh & Davis, 2000). Organizations need to realize that when they decide to mandate adoption of AI, they should recognize that subjective norms and image will play an important role initially. However, as time progresses, employees will begin making adoption decisions based on their own experiences rather than relying on compliance and mandates. Hence, firms need to find a communications channel that allows users to share experiences.

The Cognitive Instrumental Processes cluster consists of four variables, “job relevance, output quality, result demonstrability, and perceived ease of use” which directly influence “perceived usefulness” which leads to “intention to use” and ultimately “usage behavior” (Venkatesh & Davis, 2000, p. 192). The authors invoke image theory as a lens to view the specific adoption decision making process. According to this theory, there are two stages within the adoption. The first stage, referred to as the “compatibility test” consists of the user comparing alternatives to a standard that he or she has mentally established (Venkatesh & Davis, 2000, p.

191). Subsequently, the next stage is denoted as the “profitability test” which entails performing a cost/benefit analysis for each alternative and selecting the action that will move the individual closest to the mental image that he or she has envisioned. Accordingly, TAM-2 estimates that individuals will use this aspirational image to evaluate the consequences and select the course of action that best aligns with their work goals (Venkatesh & Davis, 2000).

When adopting AI, one of the first items users will review is job relevancy. The user examines their set of tasks, prioritizes their assignments, identifies ones that are enhanced by the AI, and assigns a relevancy score to the AI. Fundamentally, users perform a “compatibility test” to assess the impact of the AI on their work (Venkatesh & Davis, 2000, p.191). In addition to evaluating how well AI fits with job relevancy, users assess the quality of the work output (Venkatesh & Davis, 2000). Users may examine several different AI and non-AI products, evaluate the estimated results, and select the solution that aligns closest to their mental image. They will rely on a “profitability test” to make this determination (Venkatesh & Davis, 2000, p.191).

Users need to be able to see tangible and quantifiable performance results along with a direct connection to their work. As stated by Venkatesh & Davis, “if a system produces effective job-relevant results desired by a user, but does so in an obscure fashion, users of the system are unlikely to understand how useful such a system really is” (2000, p. 192). Therefore, it is very common in the Information Technology field to apply use cases as an approach for demonstrating results to facilitate information gathering throughout the AI adoption decision-making process.

TAM-2 utilizes the variable dubbed “perceived ease of use” (Venkatesh & Davis, 2000, p. 192) similarly to TAM. When an emerging technology such as AI requires limited effort to

implement, it creates the perception that higher job performance will occur. There is considerable supporting evidence from researchers that a technology product that is perceived as being easier to use will possess a higher degree of usage intention among users, which leads to increased usage behavior (Venkatesh & Davis, 2000).

References

- Cam, A., Chui, M., & Hall, B. (2019). Global AI survey: AI proves its worth, but few scale impact. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact>
- Chui, M. & Malholtra, S. (2018). Notes from the frontier: AI adoption advances, but foundational barriers remain. Retrieved from <https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain>
- Venkatesh, V. & Davis, F.D., (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46(2):186-204.
<https://doi.org/10.1287/mnsc.46.2.186.11926>

APPENDIX B: TERMS AND DEFINITIONS ACTIVITY

Terms and definitions

Instructions: Please fill in the blank listed in the definition with the correct AI Term from the list provided.

Artificial Intelligence Terms

Artificial Intelligence
Computer Vision
Facial Recognition Technology
Machine Learning
Natural Language Understanding
Reinforcement Learning
Robotic Process Automation
Supervised Learning
Unsupervised Learning
Virtual Agents

Artificial Intelligence Definitions

1. _____ is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment” (Nilsson, 2010, p.13) **Answer: Artificial Intelligence**
2. _____ consists of computer systems that generate statistical models and algorithms independently, solve complex problems, and predict results using either training data sets or historical performance records (Bringsjord & Govindarajulu, 2019) **Answer: Machine Learning**
3. In a/an _____ application, the user provides a set of data that has been labelled or identified to the system; subsequently, the system studies and learns the characteristics of that data set. When a new data set is introduced, the system applies those characteristics to the data to predict the results of a proposed calculation or formula (Rebala, Ravi, & Churiwala, 2019) **Answer: Supervised Learning**
4. In a/an _____ application, the user provides a large dataset, but does not provide an answer key or labels per se. Instead, the system studies the data set, identifies patterns in the data, and begins to assign groups of items that have similar characteristics based on its analysis which is subsequently used for predictions (Rebala, Ravi, & Churiwala, 2019). **Answer: Unsupervised Learning**

5. _____ entails the computer system studying its external environment for signals and responding with an appropriate action. The system “learns” based on responses to modify its actions in response to those external signals (Rebala, Ravi & Churiwala, 2019).

Answer: Reinforcement Learning

6. _____ is a field of AI that trains computers to interpret and understand the visual world. Using digital measures from cameras and videos and deep learning models, machines can accurately identify and classify objects, and then react to what they see” (Halper, 2017, p.6).

Answer: Computer Vision

7. _____ is a field of AI that trains computers to interpret and understand the visual world. Using digital measures from cameras and videos and deep learning models, machines can accurately identify and classify objects, and then react to what they see” (Halper, 2017, p.6).

Answer: Natural Language Understanding

8. _____ is used to identify defective parts or products on an assembly line, study diseased crops in a field, or even identify passengers via digital passports for airport security. Despite the benefits of this technology, there are some documented issues and problems with the technology.

Answer: Facial Recognition Technology

9. _____ can assist with routing customer service calls to the appropriate department, or even fielding frequently asked questions from customers such as providing store operating hours, directions, and customer account balances or inquiries. The value in utilizing these programs is that the firm can provide customer service twenty-four hours a day, seven days a week, three hundred sixty-five days a year and it allows for flexibility in handling shifting call volumes in a cost-effective manner.

Answer: Virtual Agents

APPENDIX C: GRADING RUBRIC FOR PRE-CLASS DISCUSSION QUESTIONS

Criteria	Rating Level 1	Rating Level 2	Rating Level 3	Points
Assignment Responsiveness- Effectiveness in addressing the discussion prompts.	All components of discussion prompt addressed in initial post and reply posts.	Some of the prompt components addressed in one or more postings.	Post did not address most or all of prompt components in multiple postings.	3
Case Study application- Application of assigned case study and supplementary readings.	Clearly, readings were completed and understood by inclusion in postings as supporting evidence.	No clear indication that case and supplemental readings were reviewed and understood by inclusion in postings as supporting evidence.	Postings reflect no evidence of assigned readings.	3
Discussion engagement- Active and regular participation in group discussion.	At least one point from multiple participants clearly built upon/refuted in postings.	One or more points from one or more participants only vaguely built upon/refuted in postings.	No evidence that any other postings have been read/Unintentional repetition of questions or points made by others.	3
Posting timeliness- Timeliness of discussion contributions.	Postings somewhat distributed throughout the week.	Postings somewhat concentrated during the week (i.e., all posted within a somewhat brief period).	Postings very concentrated during the week (i.e., all posted within a very brief period).	3
Posting quantity- Quantity of contributions	Exceeded or met the minimum number of postings (original post and replies) as listed in the instructions.	Original posting and one reply only.	Original post only and no replies to classmates.	3

APPENDIX C (CONTINUED)				
Discussion instruction adherence- Adherence to discussion assignment instructions.	At least 90% of the online instructions were followed.	Most of the online instructions were followed.	25% or less of the online instructions were followed.	3

(Adapted from Thompson, 2019).

APPENDIX D: INTERNAL REVIEW BOARD APPROVAL



EXEMPT DETERMINATION

April 22, 2020

Chrissann Ruehle
125 Bermuda Road
Marco Island, FL 34145

Dear Ms. Ruehle:

On 4/22/2020, the IRB reviewed and approved the following protocol:

Application Type:	Initial Study
IRB ID:	STUDY000796
Review Type:	Exempt (2)
Title:	Understanding the Complex Ethical Landscape of Artificial Intelligence Adoptions in Technology Firms
Funding:	None
Protocol:	• <u>HRP-503a Ethical Considerations of AI Adoptions Protocol</u>

The IRB determined that this protocol meets the criteria for exemption from IRB review.

In conducting this protocol, you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Please note, as per USF policy, once the exempt determination is made, the application is closed in BullsIRB. This does not limit your ability to conduct the research. Any proposed or anticipated change to the study design that was previously declared exempt from IRB oversight must be submitted to the IRB as a new study prior to initiation of the change. However, administrative changes, including changes in research personnel, do not warrant a modification or new application.

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about

Institutional Review Boards / Research Integrity & Compliance

FWA No. 00001669

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APPENDIX D (CONTINUED)



whether these activities impact the exempt determination, please submit a new request to the IRB for a determination.

Sincerely,

Various Menzel
IRB Research Compliance Administrator

APPENDIX E: INTERVIEW QUESTIONS

Thanks for joining me today for our interview. I want to begin with some questions that help me understand how long you have been in your field, a bit about your artificial intelligence (AI) professional history, and some about your current responsibilities, including your job title.

1. How long have you worked in the industry?
2. What is your current job title, and please tell me a bit about your job responsibilities?
3. What IT and AI roles were you previously in before your current role?
4. How is your firm currently using AI? For how long?
5. What was your experience in adopting AI? What challenges did you and your team face in adopting this program?
6. Research shows there is often a connection between attitude and intention towards use of an object or thing. How does your attitude towards the adoption and use of AI impact your intention to use?
7. How would you describe your decision to adopt AI in your organization?
8. What factors contributed to the successful adoption and use of AI in in your organization?
9. Research has shown that some firms fail to adopt AI throughout their organization. What factors would contribute to the failure of adoption and use of AI in your organization? What are some potential barriers that firms face with AI adoptions?

APPENDIX E (CONTINUED)

10. Were there any ethical considerations and principles that were factored into your decision to adopt AI? If so, what were they?

11. Without sharing any proprietary information, what are the considerations for how AI is used or would be used in your organization?

12. Again, without sharing any proprietary information, what technology specific factors would be important to you in the adoption and use of AI in your firm?

13. What social and environmental considerations, meaning any factors that you believe are relevant to the AI adoption decision, but are outside of your specific organization, influence your attitude or perspective towards the adoption and use of AI?

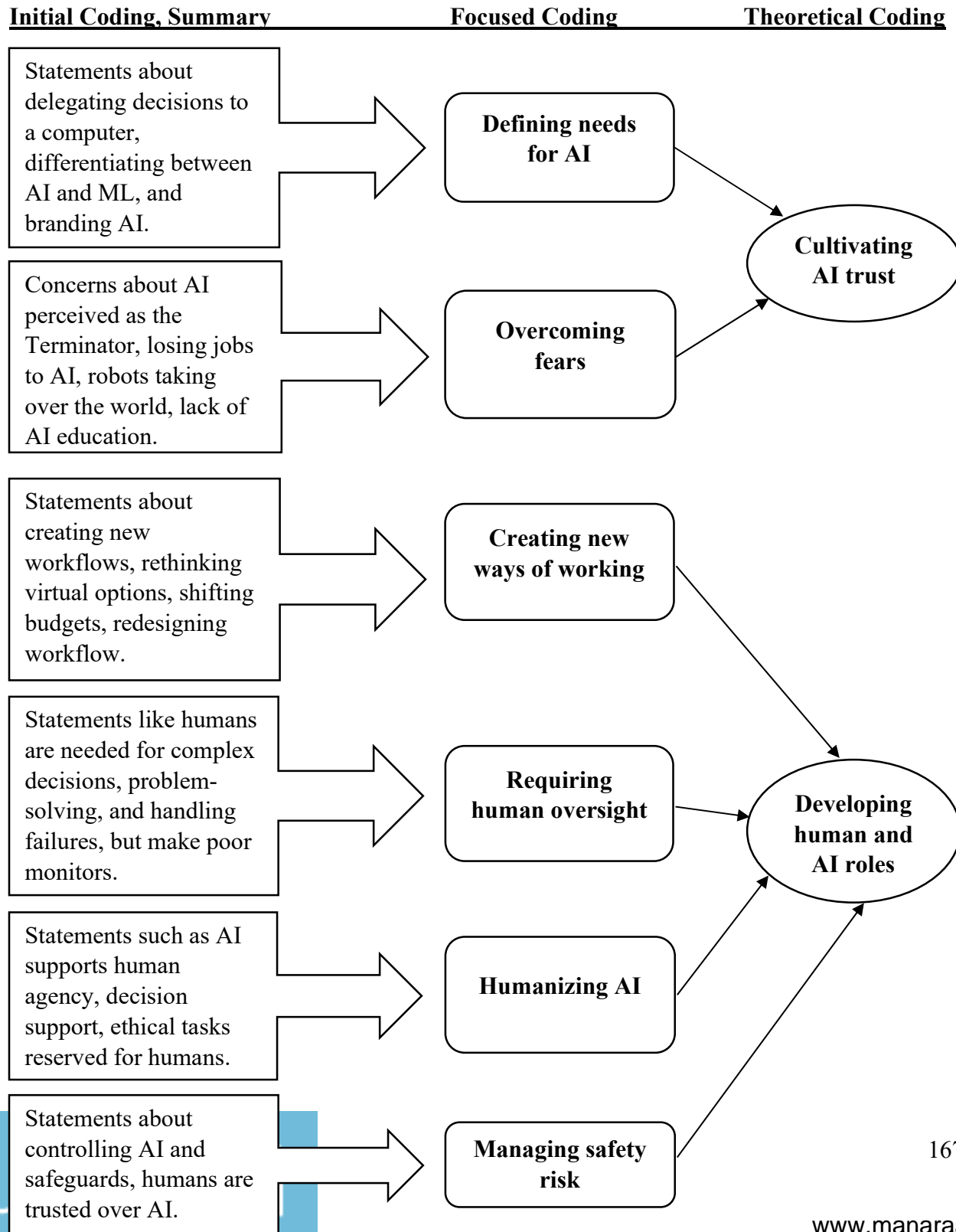
14. How does your experience with prior organizational technology changes inform your attitude towards the adoption and use of AI?

15. How do you think the use of AI in your firm will change your specific job role in the short term, meaning the next 1-3 years?

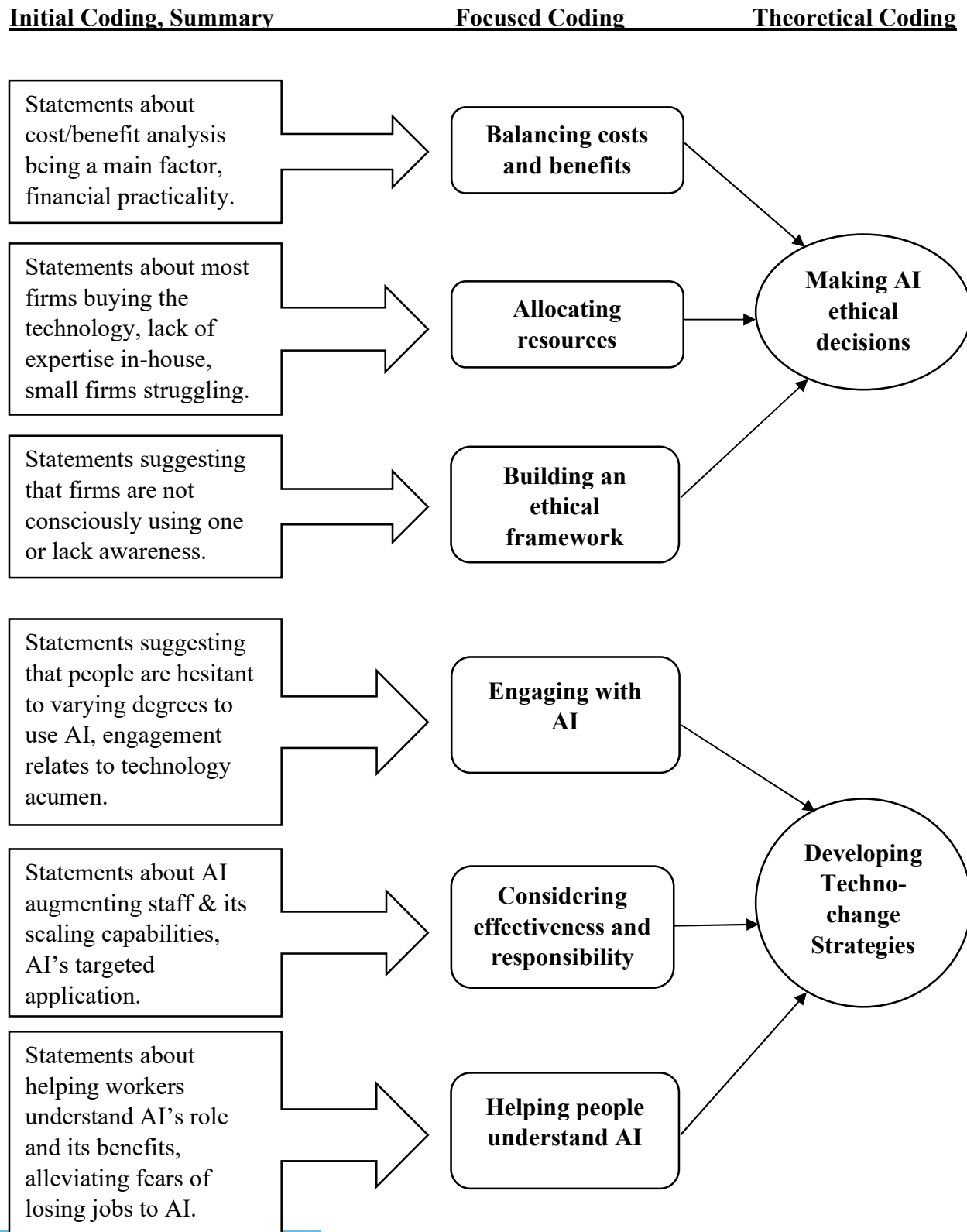
16. Is there anything else you would like to share about your experiences with the AI technology?

(Adapted from Robinson, 2018. Artificial Intelligence in hiring: Understanding attitudes and perspectives of HR practitioners.)

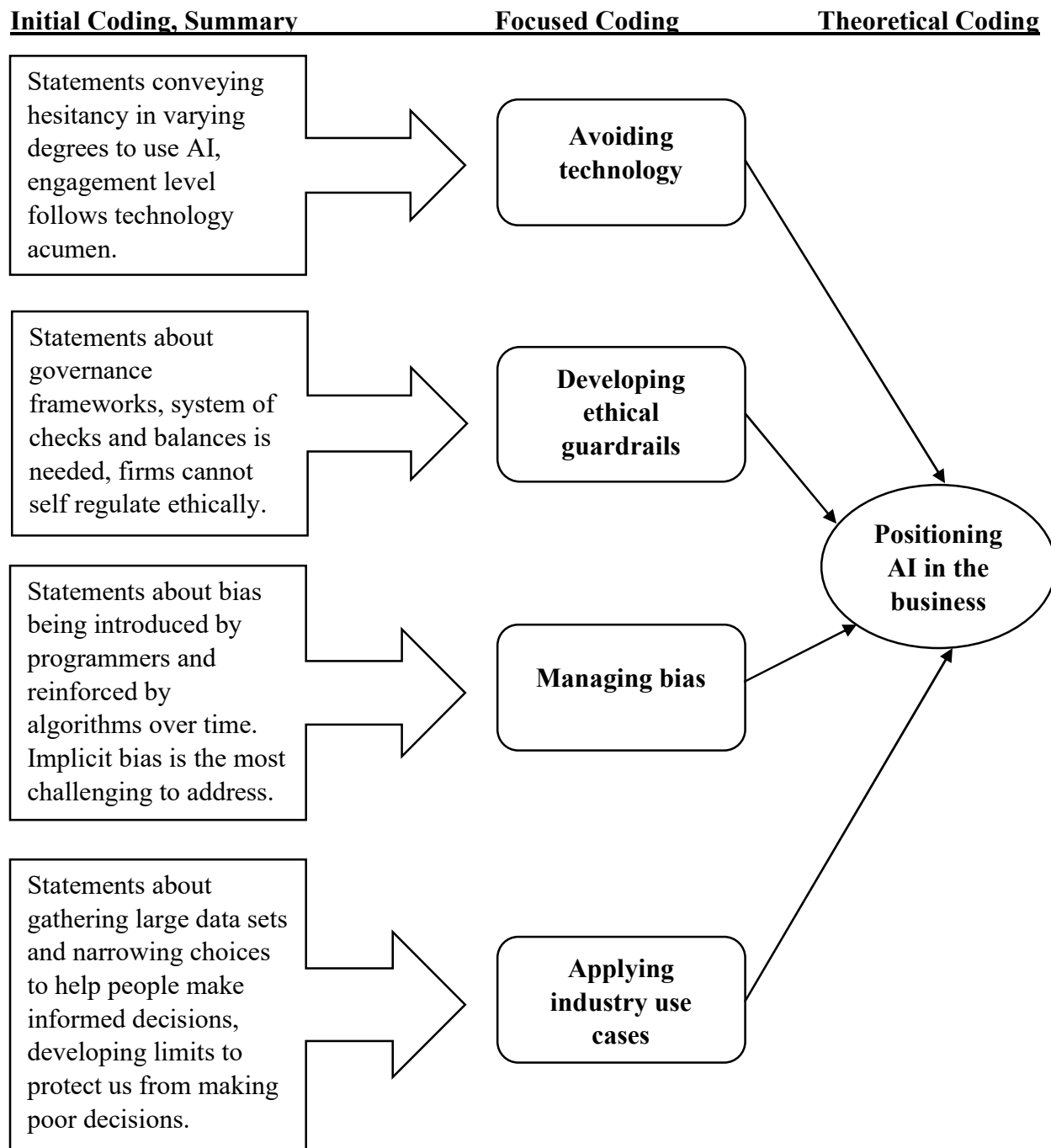
APPENDIX F: DATA STRUCTURE



APPENDIX F (CONTINUED)



APPENDIX F (CONTINUED)



APPENDIX G: DIMENSIONS, THEMES, AND EXEMPLARY QUOTATIONS

Theoretical Dimensions	Second Cycle Categories	Exemplary Quotations
Cultivating AI Trust	Defining needs for AI	<p>“There is a predictive model there, but the real disruption, I think, is for a company like ours to be able to provide an excellent service without having to augment the staff. Without having to grow the number of people involved to manage these campaigns. So, we have a client that has so many ads, they manage so many locations, and there are so many campaigns that we need to manage. And simply put, it is not humanly possible. So, when you look at them, now we are talking about technology, addressing challenges, and redefining the value. It is what companies used to offer. It might even have been able to provide not only a much better value on customer experience, but also a whole new business proposition have been created because the cost effect on the production is so much more effective, that we can actually give more for a lot less to some degree (3-15).</p>
	Overcoming fears	<p>“There’s probably the fear of the failure in part. There is a fear of the network becoming alive. There is also the fear of decision making that cannot be turned off. I think that our fear should be more about somebody who is incompetent and uses AI to write something intended to be good but turns out to be bad. In other words, it is dumb algorithms instead of intelligent algorithms that should be more of our fear. There are misconceptions about automation. There are misconceptions about robots taking over the world, things like that (3-13).”</p>

APPENDIX G (CONTINUED)

Developing Human and AI Roles	Creating new ways of working	“So, the future, looking forward, is figuring out new workflows and using machines to our advantage, and doing television production in a completely, utterly different way. I think it is going to affect budgets. I think that we are going to put more money into the technology and less money into the travel and the people. And it's really affecting tens of thousands of sports broadcast workers right now (1-2).”
	Requiring human oversight	“Because while I still think it is a very valuable asset and oftentimes the most ethically safe thing to do, I will give you a great example, AI, for medical care. You really want to take the decision from the doctor and you just want to better support the doctor and still have the doctor decide. It is like flying a plane. You've got the sophisticated technology to be able to fly a plane by itself, but I still want a human there (3-11).”
	Humanizing AI	“But when it comes to making decisions about the fit of someone from a cultural perspective, would this person be a good fit for that company? Those are decisions that are made at the human level. And this is something that we would continue to enforce. And this is, again, the approach (3-12).”
	Managing safety risk	“In aviation, we use a system called safety management system. It is a unique thing that hospitals and doctors should use, the one with checklists, but that is a whole other discussion. I think a lot of businesses are using this now too. It is called safety risk management and it must be done right and it can really, really be politically misdirected. But you go in and you look at the risks and you sit down with the experts and you go, <i>‘what's going to happen if this and this happens?, and what is the risk to our company when that happens?’</i> And then, in the end, they look at what is the frequency and what is the ultimate risk and I will tell you in aviation, even the frequency is extremely improbable if you have a risk factor of catastrophic, i.e., we fill a triple seven full of 300 people. It's very hard to go, that's usually a show-stopper (2-8).”

APPENDIX G (CONTINUED)

Making AI Ethical Decisions	Balancing costs and benefits	“And then, once you get over that, there becomes a little bit of a factor of cost, a big factor, actually. It is not so much the implementation and the startup cost of an AI. It is the maintenance of it. So, in a QA position as I was working, you could maybe automate the testing of a mobile app through AI. And replace someone who makes \$40,000 a year. Or you could automate it and pay a developer \$120,000 a year to make sure that your tests are running smoothly, and they are not going to fail. And they update every time a new cellular device comes out or a new operating system update, like iOS, the cloud or Android (1-4).”]
	Allocating AI resources	“So, you have to lean on the experts potentially even within the industry or even within the actual business problem you're trying to solve with AI. You need to make sure that you're bringing in the appropriate people to help you make sure that it's a good (1-5).”
	Building an AI ethical framework	“What kind of frameworks do they use? I do not think any of them use anyone, especially in Apple's case. They would probably take someone to historically analyze through various ethical frameworks, such as utilitarianism, the ontological thought, and then virtue ethics that's direct from Aristotle (1-4).”
Developing Techno-change Management Strategies	Engaging with AI	“Even in that messaging, it's still difficult. People still do not quite trust it. They still think they can do a better job than the technology. And they are still a little cautious that, again, is this somebody that is going to take my job? So again, a lot of change management around this, a lot of messaging, a lot of getting them involved is how we're approaching it (3-12).”
	Considering effectiveness and responsibility	“I feel like where AI is really successful right now is in solving very targeted problems, right? Like this email situation or this cybersecurity situation. It's very specific on what it's trying to solve (1-5).”
	Helping people understand AI	“There's a big change management aspect of this, the people side of it (3-12).”

APPENDIX G (CONTINUED)

<p>Positioning AI in the Business</p>	<p>Avoiding technology behaviors</p>	<p>“Excellent question for especially a pilot, and an old pilot. I have flown primarily Boeing airplanes, a lot of them. So, I have only missed the 727 and the 747 in the whole fleet of current Boeing airplanes. Well, the 787, but my firm has never purchased any of those. But for the last 12 years, my firm has owned a huge fleet of Airbus A320s. Three models of the A320. And I have avoided that. Why? Because I know the airplane thinks differently, and you cannot change how it thinks. And that airplane, when it thinks differently, and you're trying to do something maybe without the right knowledge, or you revert to your age-old technique or habit pattern or crisis response pattern, that airplane will fly itself into the ground just to prove to you that you don't know what you're doing (2-7).”</p>
		<p>“Lots and lots of pilots, especially at my firm, that have only until recently had any Airbus airplanes, there's a great hesitancy to transfer and fly that airplane. So, it ends up being a junior airplane, where I cannot say there is a huge variation in the seniority or experience level. It is not as if an inexperienced captain in and inexperienced copilot who have almost no aviation experience are flying that, but it is a difference of years. And after five or 10 or 20 years on-call, it's a pretty good body of brainpower built up in a professional pilot (2-7).”</p>
	<p>Developing AI ethical guardrails</p>	<p>“Oh yeah, the internet should be free, and everything should be open. I get that but you there's been plenty of studies on AI and the uses of AI where you get really terrible results that are purely based on decisions that have been made by people that in the data and that have impacted the data that the machine is getting. So, that is a huge concern (1-1).”</p>
		<p>“And are we building that level of intelligence into the AI that says, <i>'Wait a minute, this data doesn't look like what my expectation of the data set should be.'</i> If the computer doesn't have any data set, it's just expectations of the data and it's just churning through it, it may not think... it may be fine to say, okay, well, all males have a higher credit score, and it may come out with the outcome of all males have a 200 point higher credit score than females. (1-1).”</p>

APPENDIX G (CONTINUED)

Positioning AI in the Business	Managing bias	“Bias is to me the biggest ethical issue in banking, whether it is race, it is gender, it is ethnicity. So, because you make decisions, which impact your customer, are you not looking at a protected class with the same level of scrutiny? I think that is what is our biggest consideration (3-14).”
		“It's just going to prolong the bias in society, because now you have a computer program doing it. They cannot explain why the computer program made that decision, so it will just stay there, and it is harder to prove that is biased. Whatever problems and biases we have in society, it is just going to prolong it because you are going to have this computer that wrote matched it and just carried on. Even if we do not know what the bias is, it's going to stay and not change (1-3).”
Positioning AI in the Business	Applying industry use cases	“If I just look at day to day, we use it for when our clients are sending requests our way for IT help. We use AI to evaluate the email that is coming in asking us for help to determine where the triage path, where does that email need to flow to? What person? What department? What group or team? And that all happens automatically with AI. So that is one example. Another is, so we have a robust cybersecurity practice and as a result, AI has really become huge in cybersecurity. So, with that, as you can imagine, the old days of security, it was a very manual process. Well, today what that looks like is AI just enables us to take care of our clients and really watch out for them just way more efficiently (1-5).”
		“Look, I mean, with AI, like even with this email filing for law firms, you need to have some lawyers present. You cannot just buy a piece of technology and then just say, ‘Go’. So, having the right expertise sometimes it does not just mean technology expertise. It means those job functions that also are going to be affected by AI (1-5).”