The Nature of Leadership in Artificial Intelligence Environments: Reconceptualizing Human and Machine Collaboration

Shawn G. SEJERA[1]
Mihai BOCARNEA[2]

Abstract

An exploration regarding the nature of leadership in organizations that have implemented artificial intelligence technologies in an effort to improve organizational performance is presented with specific discussions about the role, process of development, identification of favorable organizational attributes, and resulting leadership changes necessary in the application of artificial intelligence technology. This qualitative phenomenological study used leadership and artificial intelligence as the conceptual frameworks for guiding research. The critical incident technique (CIT) served as the method for collecting observations of behavior and discovering practical solutions to complex organizational problems. Research findings may offer leaders information they can use to more effectively lead their organization's efforts in artificial intelligence environments. Implications for further research regarding the dynamic of leadership, artificial intelligence technology, and the future of organizational leadership development are noted.

Keywords: *leadership, Artificial Intelligence, innovation, organizational development, technological change*

JEL classifications: O1, O2, O3
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1. Introduction

The purpose of this phenomenological qualitative study focuses on determining the nature of leadership in organizations that have endeavored to integrate artificial intelligence (AI) technology in their organizations. Recent advances in AI promise to transform society and their embedded organizations through disruption and innovation of the fundamental systems that govern rules, processes, and leadership practices by which organizations are managed (Daugherty & Wilson, 2018; Executive Office of the President, National Science and Technology Council Committee on Technology [NSTC], 2016; Russell, Dewey, & Tegmark, 2015). However, emerging AI advancements reveal low levels of leadership in contrast to organizational needs and low capacity for

[1] Shawn G. Sejera, Regent University, Virginia Beach, VA, USA, shawsej@mail.regent.edu
[2] Mihai Bocarnea, Regent University, Virginia Beach, VA, USA, mihaboc@regent.edu

reconceptualization of organizational, business, cultural, and political systems to maintain a competitive and sustainable future in AI environments (Schwab, 2016).

According to the Oxford Dictionaries (2018), AI is the "theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" ("Artificial intelligence," n.d.). Poole, Mackworth, and Goebbel (1998) described it as the "study and design of intelligent agents" (p. 1). Luger (2009) defined AI as the "branch of computer science that is concerned with the automation of intelligent behavior" (p. 1), and then further refines it as the "study of mechanisms underlying intelligent behavior through the construction and evaluation of artifacts designed to enact those mechanisms" (p. 675). Russell and Norvig (2015) explained that intelligent, or rational, agents as systems that "operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, create, and pursue goals" (p. 4) while using data from their experience to reason and act in a way that maximizes their success. At its core, each iterative definition of AI has involved programming computers and machines to work and act in ways typically attributed to human beings with emphasis on traits simulating knowledge, learning, perceiving, reasoning, problem solving, communication, planning, and the ability to move physical objects (Russell & Norvig, 2003).

Modern descriptions of AI segment it as a field within computer science that concentrates on the idea of understanding and building machines that broadly imitate, in whole or in part, human cognition and act intelligently or rationally with the distinctive ability to adapt to changing conditions (Luger, 2009; Marr, 2018; Russell & Norvig, 2015). Though a subfield of computer science, AI has grown into an interdisciplinary subject that includes a wide range of other sciences and remains intellectually relevant to virtually every endeavor (Russell & Norvig, 2015). AI research encompasses the fields of mathematics, philosophy, psychology, economics, biology, linguistics, leadership, and engineering (Daugherty & Wilson, 2018; Durodié, 2019; Luger, 2009; Russell & Norvig, 2003, 2015; Schwab, 2016). Previous efforts at integrating the sciences into a common direction for AI suffered division and miscommunication due to conflicting goals and ambitions. However, recent progress in the study of intelligence has aligned scientific direction with the capabilities of AI systems, which has begun to bridge subfield impasses and provided a portion of common ground for mutual advancement (Russell & Norvig, 2015).

The steadily evolving field of AI has shifted over time from researching and building mechanical tools and systems that automate and optimize basic processes to ideas expressed through machine capabilities that reflect problem solving, reasoning, and communication (Luger, 2009; Minsky, 1967; Russell & Norvig, 2015). This understanding categorizes AI into two types (strong and weak or general and narrow) based on intended applications and purposes (Hammond, 2015; Luger, 2009; Russell & Norvig, 2015). The strong, or artificial general intelligence (AGI), type refers to the development of systems that simulate or actually have all of the cognitive ability and consciousness that a human mind has, while weak, or *narrow AI*, refers to the development of systems that act intelligently, simulating the human mind to varying degrees but operating only within a narrow framework of rules imposed on it for specific tasks without revealing how the human mind works or consideration of consciousness (EOP NSTC, 2016; Luger, 2009; Hammond, 2015; Russell & Norvig, 2015).

Both AGI and narrow AI have enjoyed significant attention in mass media, business, and academic fields. Narrow AI has been broadly embraced for its potential to transform organizational processes and create competitive advantages, while AGI has been more cautiously examined as a momentous change in the relationship of mankind with technology and humanity's existential beliefs (Barrat, 2013; Bostrom, 2014; Daugherty & Wilson, 2018; Luger, 2009; Russell & Norvig, 2015). Theoretical physicist Stephen Hawking posited that "the development of full artificial intelligence could spell the end of the human race" (Cellen-Jones, 2014), and Shane Legg, one of the founders of DeepMind, a leading AI development company, hypothesized that "human extinction will occur, and technology will likely play a role in this" (Dowd, 2017). Microsoft founder, Bill Gates, theorized that AI has more destructive potential than nuclear war (Rose, 2017). Political scientist, diplomat, and political consultant, Henry Kissinger warned that AI "could cause a rupture in history and unravel the way civilization works" (Kissinger, 2017). Barrat (2013) criticized leadership in AI environments and declared humanity's understanding of AI as broadly inconsequential, which unnecessarily contributes to an inevitable collision with present leadership systems that may eventually result in machine hegemony. Ultimately, negative concerns and perspectives revolve around the computing power of AI, vast amounts of data, its potential to evolve and become self-aware (achieving singularity), and the possibility of AI taking important decisions out of the hands of human decision-makers, which all may pose varying threats to human progress and existence without ample consideration and frameworks that allow for the freedom and sustainability of humanity (Barrat, 2013; Bostrom, 2014; Cellen-Jones, 2014). Discussion of AI's impact on the world in such dystopian terms of societal destruction, human extinction, and the unraveling of societal systems underscores the importance of researching and developing leadership theory that considers the technology's potential with the needs of humanity.

In contrast, positive commentary paints AI technology as a major revolution that promises to transform mankind in ways that will profoundly improve the way people live, work, and relate to each other and their environments. Schwab (2016) theorized that the world has just entered the beginning of a Fourth Industrial Revolution characterized by connected intelligent machines and their integration into "physical, digital, and biological domains" (p. 14) that will make possible new innovations in science, business, and culture to make life easier and more productive. Instead of mere mechanical automation of organizational processes, AI systems may enable people to work collaboratively with machines in an organic, flexible, and adaptable way that could result in an order-of-magnitude improvement in organizational performance (Daugherty & Wilson, 2018). Ng (2017) described AI as *the new electricity* that will transform every industry, field, and endeavor through significant improvements in data analysis and cognitive tasks that once required exclusive or substantial human effort at great expense. With the potential for improving life for large segments of society, Tegmark (2018) posited that AI represents a huge technological leap that could lift mankind from the Stone Age to an “Age of Amazement.” As such, AI has the potential to transform organizational processes, optimize work, stimulate innovation, deliver growth, and sustain competitive advantage for organizations that understand how to use the technology and implement it effectively (Daugherty & Wilson, 2018; Durodié, 2019; Ng, 2017; Schwab, 2017; Tegmark, 2018).

Regardless of negative or positive opinion about AI, belief that the technology will significantly transform systems, processes, people, groups, organizations, and society with increasing velocity, breadth, and depth seems unquestioned (Bishop, 2017; Schwab, 2017). Bostrom (2014) posited that recent breakthroughs in AI would precede an explosion of super intelligence that leaders will need to manage to affect a survivable and favorable outcome. Should a super intelligence explosion follow AI’s legacy of over-predictions about the extent of its capability occur, the current level of AI technology to adapt and optimize work processes will still necessitate reconceptualizing human and machine collaboration (Daugherty & Wilson, 2018; Durodié, 2019).

For this study, leadership theory and the concept of artificial intelligence provided the conceptual frameworks for researching leadership in AI environments. By building on the foundations of leadership theory and AI, research findings may offer leaders valuable information to more effectively lead their organization’s AI efforts and more expertly navigate increasingly competitive environments. Through the identification of critical elements that contribute to specific outcomes, the critical incident technique (CIT) may explain the nature of leadership efforts in organizations wanting to manage AI technology. Maintaining legacy leadership theory and practice in the context of rapidly changing and increasingly challenging environments will not sustain organizational performance and offers unique challenges to organizational leaders that result in greater threats and opportunities that did not exist previously (Huber, 2004).

The extreme and dichotomous predictions, positive and negative, utopian and dystopian, over outcomes involving AI illustrate the lack of understanding by organizational leaders to effectively lead AI-enabled organizations and manage the technology’s development. Reconceptualizing how leaders may collaborate with the ever-advancing AI field in challenging and changing organizational environments represents a neglected area of research with profound implications.

The purpose of the study centers around how organizational leaders theorize the role of AI, how they develop and implement the technology, what organizational attributes have importance, requisite organizational changes, and theories about the future of human and AI collaboration in organizational settings. Using qualitative inquiry, phenomenological method, and the CIT as a technique for collecting data, this study attempts to provide in-depth data from knowledge-rich sources to reveal how AI affects organizations and leadership theory and practice.

2. Literature Review

The theories of organizational leadership and AI comprise the theoretical foundations for guiding this research study. A basic comprehension of their relationship has only recently emerged due to the rapid development of technology and digitization (Schwab, 2016). Organizational leadership theory, which focuses on the nature of leadership in formal organizations that require managerial leadership (Yukl, 2013), provides one of the conceptual frames. AI, the second concept underlying the study, refers to a branch of computer science dedicated to the theory and practice of automating intelligent behavior (Luger, 2009).

2.1 Leadership

Bass and Bass (2008) posited leadership as a universal phenomenon occurring "among all people" (p. 3) within every society that has existed. The phenomenon inspires images of powerful, intelligent, and dynamic individuals associated with great events and noble or ignoble feats (Yukl, 2013). Yet, it remains difficult to define and its precise definition remains largely concealed due to misapplied terms, ambiguous attributions, and a plethora of characterizations from those with disparate interests (Janda, 1960). While some theorists have questioned leadership's usefulness as a scientific construct (Alvesson & Sveningsson, 2003), most behavioral science researchers and practitioners believe leadership exists as an important factor in the success of individuals, groups, and organizations (Yukl, 2013).

Yukl (2013) described the concept of leadership as having five major approaches that help explain the phenomenon in greater perspective: trait, behavior, power-influence, situational, and integrative. Each approach represents a general category formed by leadership literature, theories, and empirical study.

2.1.1 Trait

Representing one of the first theories of leadership research, the trait approach regards successful leaders as uniquely possessing certain extraordinary, heritable, and naturally occurring traits, such as skill, personality, motivations, and values (Galton, 1869). Galton (1869) posited that these personal qualities, defining effective leadership, likely stem from inherited characteristics or genotype, pass from one generation to the next, and appear as immutable from birth. On the basis of research in the 1940s and 1950s (Mann, 1959; Stogdill, 1948), many researchers rejected the trait approach due to its insufficient explanation of effective leadership. However, research that conceptualized new theoretical models of charismatic and transformational leadership in the 1970s and 1980s reexamined the role of qualities of individuals and pointed once again to the trait approach as a determinant of effectual leadership (House, 1977, 1988).

2.1.2 Behavior

Yukl (2013) posited that the behavioral approach began from researcher discouragement with the trait approach's lack of findings assuring leadership success. As a result, Stogdill (1963) declared that the research and discovery of shared traits of effective leaders had essentially failed. Researchers then began examining management actions, patterns of activity, and leader behaviors or interactions with followers (Yukl, 2013).

Stogdill's (1963) research in the behavior approach resulted in the concepts of initiation of structure and consideration. Initiation of structure includes specific tasks that define, organize, and structure work environments (Stogdill, 1963). Initiation of consideration relates leadership effectiveness to developing rapport with followers, supporting their self-esteem, and consulting with followers about organizational decisions (Stogdill, 1963). Kahn and Katz (1960) found relationship-oriented behavior generally more successful though leaders exercising both task and relationship orientation, and the wisdom of when to emphasize one over the other, developed productive and satisfied followers.

2.1.3 Power-Influence

Yukl (2013) stated that the power-influence approach "seeks to explain leadership effectiveness in terms of the amount and type of power possessed by a leader and how power is exercised" (p. 13), with additional focus on the dynamic of influencing peers, superiors, and others outside of the organization. French and Raven (1959) identified two groups of power that contained five sources of it. Organizational power derives from legitimate, reward, and coercive power, while personal power originates from expert or referent power (French & Raven, 1959). Effective leaders have the ability to influence outcomes and change others' behavior through the implementation of organizational or personal power (French & Raven, 1959). Furthermore, depending on the situation, effective leadership may use the different sources of power in a blend of varying combinations (Lunenburg, 2012).

2.1.4 Contingency

Hersey and Blanchard (1977) described contingency, or situational leadership as an adaptive framework for leaders to match behaviors to the context of the situation with the objective of improving organizational outcomes. This adaptive framework requires leaders to vary leadership styles to meet the changing needs of their organization and its environment with the understanding of when to change and what leadership style to adopt (Hersey & Blanchard, 1977). Yukl (2013) described the contingency approach as generally having two categories with researchers sometimes referencing it as situational theories of leadership. One category "attempts to discover the extent to which leadership processes are the same or unique across different types of organizations, levels of management, and cultures" (Yukl, p. 13). The other category endeavors to identify the factors that moderate the relationship between leader attributes and leadership success (Yukl, 2013). Contingency leadership contends that leader attributes will have different effects in differing circumstances and that a given attribute cannot guarantee success in all situations (Yukl, 2013).

2.1.5 Integrative

According to Yukl (2013), the integrative approach deals with the use of more than one type of leadership theory in relation to leadership effectiveness. Avolio (2007) contended that leaders can better identify and integrate components that compromise effective leadership research through an integrative approach. Avolio (2007) suggested that the integrative approach may adequately address research issues relating to questions of leadership effectiveness from universal or culturally specific factors, forms of leadership emerging out of varying contextual bases, or leadership styles having more or less effectiveness based on contingencies and organizational demands. In practice, Martin and Austen (1999) described integrative leadership as a method of using multiple styles of leadership as a way of managing the complexity, uncertainty, and tension inherent in modern organizations. Yukl (2013) provided the self-concept theory of charismatic leadership as an example of the integrative approach due to its use of multiple leadership variables that resulted in an increase of followers' collective self-conceptualization.

2.2 Artificial Intelligence

AI represents one of the newest fields in science and engineering and concentrates on the theory and practice of automating intelligent behavior (Luger, 2009; Russell & Norvig, 2015). Though segmented as a branch of computer science, AI involves many different scientific disciplines and exists as relevant to almost every facet of human life (Russell & Norvig, 2015). Not content with simply understanding the concept of intelligence, AI research intends to create and build intelligence into machines (Bostrom, 2014, Russell & Norvig, 2015).

Six disciplines encompass a comprehensive view of AI and describe the necessary categories for AI capability. Each category represents a general technology field within AI shaped by academic literature and theories, practitioner application, and empirical research.

2.2.1 Automated Reasoning

Russell and Norvig (2015) described automated reasoning as the "use of stored information to answer questions and to draw new conclusions" (p. 3). Automated reasoning represents a theoretical field of research that attempts to provide a general framework and algorithms for a machine to process, define, approach, and solve problems (Luger, 2009). Though not a specific technique, automated reasoning forms the theoretical foundation for machine learning procedures with the ultimate objective of creating learning systems that model human deduction without human inference ("Automated Reasoning," n.d.).

2.2.2 Computer Vision

According to Russell and Norvig (2015), computer vision represents the theory underlying AI's ability to see and understand its surrounding environment. Computer vision involves a machine's ability to perceive objects and provides the connection from the computer to the "raw, unwashed world" (Russell & Norvig, 2015, p. 944). Computer vision includes all tasks relating to sensing a visual stimulus, "understanding what is being seen, and extracting complex information into a form that can be used in other processes" ("Computer vision," n.d.). Computer vision automates aspects of human vision through sensors, computing systems, and algorithms with the objective of obtaining information needed for recognition, manipulation, and navigation (Russell & Norvig, 2015).

2.2.3 Knowledge Representation

Russell and Norvig (2015) defined knowledge representation as a machine's storage of what it has seen, heard, sensed, and knows. Brachman and Levesque (2004) described knowledge representation as the field within AI concerned with "how knowledge can be represented symbolically and manipulated in an automated way by reasoning programs" and how this knowledge contributes to intelligent behavior (xvii). Knowledge representation essentially refers to how a machine applies what it knows in deciding what to do (Brachman & Levesque (2004).

2.2.4 Machine Learning

Machine learning refers to the field within AI of machines adapting to new situations and learning to act without specific programming for those situations (Russell & Norvig, 2015). Machine learning represents a data analysis approach to creating and building adaptive models through the development of algorithms that can detect and reason data patterns ("Machine learning," n.d.). As a form of designing algorithms, machine learning enables the creation of AI agents ("Machine learning," n.d.). Should a machine solve a problem or improve a situation through the process of learning, then the machine has fulfilled the concept of machine learning (“Machine learning,” n.d.).

2.2.5 Natural Language Processing

Natural language processing (NLP) refers to the relationship between computer systems and human language through the ability to communicate audibly and textually (“Natural language processing,” n.d.). Though programs can process structured data exponentially quicker than humans, natural languages like English, Spanish, or Japanese exist as unstructured data that are abstract and challenging to define (Russell & Norvig, 2015). NLP research seeks to use computers in the processing and analysis of natural language data and so serve as an effective medium of communication (Russell & Norvig, 2015).

2.2.6 Robotics

Russell and Norvig (2015) described robots as physical agents that complete tasks through the manipulation of physical objects through an array of sensors and effectors. Robots perform these functions through sensing their environment and then acting through effectors: legs, wheels, joints, and gripping mechanisms (Russell & Norvig, 2015).

Robots segment into three categories: manipulators, mobile robots, and mobile manipulators (Russell & Norvig, 2015). With over one million units worldwide in industrial applications, manipulators represent the most common robots, as they physically anchor to their workstations and work through a chain of controllable joints (Russell & Norvig, 2015). Mobile robots use sensors, legs, wheels, joints, and gripping mechanisms to move around their environments and perform their tasks (Russell & Norvig, 2015). Mobile manipulators combine mobility and manipulation and use their effectors in broader ranges than anchored manipulators though their tasks exist as more difficult due to a lack of rigidity (Russell & Norvig, 2015).

2.3 Research Questions

To understand how leaders conceptualize and manage AI technology initiatives to disrupt industries, create innovation, and competitive advantages for their organizations, the following six open and probative research questions formed the foundation for this study:

RQ_1: Why have organizational leaders implemented AI in their organizations?

RQ_2: How have leaders developed AI technology within their organizations?

RQ_3: What attributes of leadership have been identified and desired in the management of AI technology?

RQ$_4$: What impact has AI had in the effective leadership of organizations?

RQ$_5$: How has organizational leadership practice changed due to the application of AI technology?

RQ$_6$: How will organizational leadership collaborate with AI technology in the future?

3 Method

This study used a qualitative phenomenological format to collect data relating to the lived experiences of organizational leaders that have implemented AI technology in their organizations. The qualitative format seemed most appropriate as it "inquires into, documents, and interprets the meaning-making process" (Patton, 2015, p. 3) while allowing for the type of in-depth questions necessary to more fully understand the nature of leadership in AI environments. While previous research has focused on ethics and moral management of AI technology, this study's topic of exploring the lived experiences of organizational leaders that have implemented AI technology remains largely unstudied.

3.1 Critical Incident Technique

This research used the CIT as the method of collecting qualitative data for phenomenological analysis. The well-established CIT effectively collects "direct observations of human behavior in such a way as to facilitate their potential usefulness in solving practical problems and developing broad psychological principles" and "should be thought of as a flexible set of principles which must be modified and adapted to meet the specific situation at hand" (Flanagan, 1954, p. 1). The CIT has helped to determine the critical requirements needed for improved performance in fields as varied as aviation, automotive, medicine, and orthopedic surgery, and in the development of complex machines and systems (Fivars & Fitzpatrick, 2018). By identifying critical requirements that contribute to effective and ineffective outcomes, the CIT can help to illuminate the nature of leadership and human and machine collaboration efforts in AI environments.

3.2 Sample

Considering Green and Thorogood's (2009) research that posited saturation resulting from "interviewing 20 or so people" (p. 120), Creswell's (1998) suggestion for phenomenological studies of between five and 25 participants, and Lee, Woo, and Mckenzie's (2002) recommendation of reducing sample size when conducting in-depth interviews with the same participants, this study conducted 25 initial interviews and then reduced the amount to selected participants. From the 25 initial interviews, participants that demonstrated a high level of rapport, candidness, and competence on AI subject matter and alignment with the study's objectives were asked to participate in the second phase of structured interviews until saturation was reached. These participants then proceeded to multiple interviews within the in-depth structured interview phase, which Seidman (2006) considered beneficial to build momentum and Morrow and Smith (1995) asserted as providing evidentiary sufficiency.

The participants selected for this study were leaders of AI-enabled organizations in the communications, financial, technology, transportation, manufacturing, aerospace, energy, non-profit, and business consulting industries. Leaders of AI-enabled organizations were defined as those managing and leading AI related initiatives in their organizations.

3.3 Data Collection Method

Padgett (2008) stated that interviews allow researchers to more fully investigate study participants' experiences and often exist as the cornerstone of qualitative studies. Interview design and sequence were aimed at progressively deepening the understanding of leader experiences using AI technology. The initial semi-structured interview phase provided for basic questions relating to, and confirming, AI experience and the leadership role of each participant while also providing pilot-testing research design (Creswell, 1998). Subsequent in-depth interviews used an interview guide that provided a semi-structured framework of inquiry, which allowed for the sanction of new questions based on responses and context that more fully answers the study's research questions (Patton, 2002). The use of in-depth structured interviews also allowed for the potential of multiple interviews that fill-in data gaps to more comprehensively understand the participants' lived experiences (Padgett, 2008).

3.4 Data Coding and Analysis

As one technique of qualitative analysis, this study employed coding to acquire a pattern of "repetitive, or consistent occurrences of action/data that appear more than twice" (Saldaña, 2008, pg. 5) and to determine the critical link between data points and clarification of meaning (Charmaz, 2002). More than a simple process of labeling, coding represents significant phrases that links and "leads you to from the data to the idea and from the idea to all the data pertaining to that idea" (Richards & Morse, 2013, p. 154).

3.4.1 First and Second Cycle Coding

This study's first cycle coding consisted of Elemental coding using Descriptive (for field notes, documents, and other artifacts), In Vivo (deriving from participants' language), and Concept (extracting and labeling broad ideas inferred by the data) methodologies to better understand meaning and the dynamics of the situation before theming the data (Saldaña, 2016). Second cycle coding used Pattern coding, which involved grouping, reorganizing, and reconfiguring the data's details to further develop categories, themes, and concepts into an arrangement of shorter and more select list of broader themes (Saldaña, 2016). Both first and second cycle coding processes used a combination of manual and electronic coding in the form of Microsoft Excel®, QSR International NVivo 12® software, and transcription services.

3.4.2 First and Second Cycle Coding Analysis

The analysis of first and second cycle coding was done as part of the phenomenological reduction to refining and deriving "a textural description of the meanings and essences of the phenomenon" (Moustaka, 1994, p. 34). Analysis involved integrating the textual descriptions of each research participant into a group of more broad textual descriptions and then determining the potential amount of themes from the collected data (Moustakas, 1994). The final analysis consisted of determining Individual Textural descriptions, Individual Structural Textural descriptions, Composite descriptions, and the Synthesis of Textural and Structural Meanings and Essences (Moustakas, 1994). The analysis of Individual Textural descriptions referred to each study participant's account of the phenomenon, with Individual Structural descriptions framing the context each participant's account, and then followed by Composite descriptions that describe the common experiences shared by each participant (Moustakas, 1994). This portion of the final analysis ultimately provided the essence of participants' lived experiences and allow for research analysis to arrive at meaning (Moustakas, 1994).

4. Results

Question 1 – Why Have Organizational Leaders Implemented AI in their Organizations?

According to participant data, organizational leaders implemented AI in their organizations with the goal of organizational efficiency, as a response to external forces, and out of a desire to innovate for competitive advantage. Leaders intended AI integration to aid in pragmatically managing complex business systems, streamlining their organization's operations, and reducing costs in a rapid fashion. Organizational leaders also implemented AI as a response to peer pressure from the market, competitors, and industry investors. Other leaders implemented AI out of a sincere desire to innovate and transform their organizations in order to develop automation for competitive advantage.

Question 2 – How Have Leaders Developed AI Technology Within their Organizations?

As evidenced by participant data, organizational leaders developed AI technology through a multitude of methods that depend on contextual conditions, organizational flexibility, and level of preparation. Contextual conditions included planned efforts that evolved over the course of the AI implementation, large-scale organization-wide efforts, small-scale pilot endeavors, ad hoc, gradually, and implementation represented by disparate unconnected projects. Some leaders depended on their organization's flexibility in forming and executing plans to integrate AI technology in their organizations. Other leaders' AI implementation efforts were characterized by their organization's level of preparation, which resulted in varying degrees of success or failure, but with lessons to learn from, invariably.

The participant data revealed that AI implementations caused strong emotions, both positive and negative, that centered on what AI implementation may mean personally and corporately for the organization. Participant sentiment after AI implementation still maintained strong emotions but evolved into characterizations of enthusiasm and pessimism based on their organizational experience, which led to more refined beliefs about how to move forward with their organization's AI implementation efforts. Additionally, leaders and subordinates began to realize how AI implementation could change the organization's internal power balance, which can further the increase of tension and anxiety.

Question 3 – What Attributes of Leadership have been Identified and Desired in the management of AI Technology?

According to participant data, the attributes of leadership in the management of AI technology that are desired, included themes of organizational alignment, path-goal leadership theory, and expectation symmetry. Having all levels of the organization aligned in the same direction may significantly aid in the management of AI technology. Attributes of path-goal leadership theory were represented by participant codes of providing support, clarifying paths, removing obstacles, supportive leadership style, and achievement orientation. In addition, leaders identified AI program expectations having consistency with the organization's reality as a desired attribute for organizational leadership.

Participant data also showed that entrepreneurial leadership, communication, and effective incentive systems enhance their organization's AI program. Entrepreneurial leadership provided the vision, perseverance, education, and environment for growth necessary for integrating new AI technology. Communication supported necessary discussion, motivation, and anxiety reduction needed in organizational environments. Effective incentive systems delivered funding, motivation, obstacle removal, and anxiety reduction attributes required for effective management of AI technology.

Question 4 – What Impact has AI had in the Effective Leadership of Organizations?

As evidenced by participant data, the impact of AI in the effective leadership of organizations is considerable though that impact has been characterized by positive and negative elements. While some leaders saw increased organizational performance and the development of learning climates that supported their AI initiatives, other leaders experienced negative outcomes and missed opportunities. The introduction of AI programs revealed great potential for automation and social connectedness within organizations, but also cynical perspectives about the effectiveness of the technology. In addition, fear of the unknown, unrealistic leadership expectations, lack of funding, neglect of other divisions of the organization, and anxiety over change tempered promising organizational productivity, efficiencies, and customer satisfaction increases that advanced effective leadership of organizations.

Question 5 – How has Organizational Leadership Practice Changed due to the Application of AI Technology?

According to participant data, the application of AI technology has appreciably changed how organizational leadership is practiced. Due to the unique ability of AI to create value and competitive separation for organizations, leaders exhibited keen interest in making the technology a greater part of their organization's present and future. However, data revealed that the technology's largely unknown potential could cause debilitating organizational tension centered on fear. This fear stemmed from the removal of the human component within the organization, which instigated the building of barriers for self-preservation and struggles for power and control. Leaders recognized that new organizational issues relating to AI involve building the technology but also focusing on the human side of the organization in a new form of human and machine collaboration that incorporates the best of each to perform at higher levels of productivity, efficiency, and fulfillment.

Question 6 – How will Organizational Leadership Collaborate with AI Technology in the Future?

As evidenced by participant data, organizational leadership will collaborate in the future through significantly increased human compatibility with the goal of increased organizational performance. There seems little doubt that AI will develop to become more pervasive in organizational environments, help to transition to higher levels of automation, and assist in making better decisions. However, the data shows that AI's increased role will focus on improving the interaction with and benefit for humanity.

5. Discussion

AI has seemingly advanced to the point that its potential to transform organizational systems and leadership practice is widely recognized (Daugherty & Wilson, 2018). However, as Schwab (2016) has stated, there remains a large gap between the great need for leadership and relative lack of it in AI environments. In addition, Schwab asserted that a lack of capacity for reconceptualizing organizational, business, cultural, and political systems to account for humanity's future with AI exists as a major obstacle for not just moving the technology along but advancing organizations and society as a whole. With those obstacles in mind, based on the results of data collected from participants, this study concludes that the nature of leadership in AI environments revolves around the concepts of organizational flexibility and human alignment and compatibility.

a. Organizational Flexibility

Madhani (2010) depicted organizational flexibility as the "main capability that enables organizations to face environmental fluctuations, as it makes them responsive to change" (p. 1). By establishing organizational flexibility, leaders may more easily adopt critical changes, like integrating AI technology, that are required to maintain competitiveness in dynamic and rapidly moving environments. Huber (2004) surmised that, "in the future, top managers will be able to carry out change actions effectively and before disaster overcomes them only if they have created firms well suited to the increased dynamism, complexity, and competitiveness of future business environments" (p. 7). The study's results underscore Huber's (2004) assertion that organizations that can adapt to meet the growing complexity and turbulence of modern organizational settings have significantly greater capability to sustain growth and survive in the future.

Participant data revealed that many within organizations are risk averse and will not respond to change without sufficient stimulus. Those in the organization who are risk averse, especially to automation programs that may involve the reality or perception of phasing out jobs, will need leaders to provide motivation in the form of communicating vision, defining goals, clarifying paths, and properly incentivizing actions that align with the organization's direction. Oster (2011) posited that personnel resistant to change may become organizational antibodies "who are determined to slow or eliminate innovation or change" (p. 229), and that "typically, the more radical the innovation and the more it challenges the historical status quo, the more numerous and stronger are the antibodies" (p. 229). Oster recommended that organizations intending to lead change must integrate organizational antibodies as useful elements of the change or remove them from the organization altogether. This management of organizational antibodies aligns with the study's participant data that emphasized leadership direct personnel for greater organizational flexibility to more quickly respond to the changes that characterize the incorporation of AI technology.

b. Human Compatibility

Participant data also revealed that collaboration with AI technology should include greater emphasis on its compatibility with humanity. While popular press communicates a future world dominated by AI that involves automating people out of employment and flippantly destroying their way of life, research data reveals that the human element of the organization remains the most important. Participant

10 provided a powerful and articulate representation of the human compatibility theme by noting:

> the hardest part of all this is the human side of the equation…and if your strategy is wrong with those relationships, you're not doing anything with AI…and I think that's probably the pivot point. The fulcrum between success and failure is how well organizations deal with the human component…And so I don't ever think we're going to get to the state where the company is run by an algorithm or AI technology. Maybe I'm wrong, but I don't know if the powers that be in an organization would be interested in turning this technology back on themselves and their jobs…And so, using the AI systems for their strengths, and only their strengths, and having serve the human so that the human can best use their strength. I really feel like that's the winning combination. And because our world is so chaotic and if we build AI systems that are so optimized…and I really feel like we don't need to try to replace the greatest neural network that evolution ever created with the most novel technology that's come out this year.

Russell (2019) asserted that to truly make AI compatible with humanity, its definition should be revised from the traditional "Machines are intelligent to the extent that their actions can be expected to achieve their objectives" to the more human focused "Machines are beneficial to the extent that their actions can be expected to achieve our (humanity's) objectives" (p. 9), thereby creating a more sustainable future. This definition aligns with participant data that recognizes humanity as being of the greatest importance in the human and machine collaborative equation. According to the data, AI programs should primarily focus on human concerns and augment human capabilities rather than dismiss these elements and terminate the relationship. Instead of creating the present atmospheres of tension and resentment, leaders should design AI technology to make it more harmonious with humanity in an interdependent and reciprocally beneficial relationship.

c. Limitations of the Study

Several limitations to this study exist and relate to sampling issues and researcher reflexivity. One of the study's sampling issues involves selectivity bias that is inherent in the purposeful sampling method (Patton, 2015). Though no bias is intended, purposeful sampling lacks the indiscriminate nature of random sampling and may introduce a degree of selectivity bias. Another sampling issue includes the limited diversity of the sample. While research was performed without consideration for demographic segments relating to gender, race, or income level, and only focused on AI experience, the sample of 10 included eight men and only two women without a single person of color participating in the study. This lack of gender and racial diversity may have introduced a lack of diverse perspective that could have revealed a more accurate, broad, and deeper insight.

Researcher reflexivity, or systematic self-awareness, remains a persistent limitation within qualitative inquiry. Agar (1980) noted that researcher bias will always exist but needs clarification of what kinds of researcher bias exists and how they are recognized. Throughout the study, every effort was made to systematically attend to meaning making and knowledge construction through consultation and direction from knowledgeable academicians and scientists. Still, even with the best efforts, there remains the possibility of researcher bias in the form of hidden beliefs, ideals, values, perspectives, expectations, and assumptions.

d. Recommendations for Future Research

Considering that this research is one of the first to explore the relationship between organizational leadership and AI technology, there exists opportunities to explore other aspects of the relationship that could expand and deepen the body of knowledge about the subject. Future research should qualitatively examine the lived experiences of a sample with more representation from female co-researchers and a diversity of ethnicities to determine if there exists any difference in results. Also, future research may want to focus on a broadened or narrowed range of industries, organizations, and geographies to examine. For instance, future research may explore the nature of leadership in AI environments broadened to also include academia, healthcare, utilities, and agriculture industries or just focus on one of the many available industries and geographies to determine differences or unique characteristics.

In addition, while additional qualitative research is recommended and there exists ample room for it, future research could also include quantitative methods as well. The relationship between organizational leadership and AI technology needs a quantitative method to generate numbered data that can then be transformed into usable statistics for quantifying behaviors, values, attitudes, opinions, actions, and other variables. An instrument may then be created to validly and reliably measure the nature of leadership in AI environments and operationalize, describe, and assess leader perceptions about the subject.

6. Conclusion

The goal of this study was to explore the nature of leadership in organizations that have endeavored to integrate AI technology in their organizations. The results indicated that organizational leaders should reconceptualize how they intend to work with AI, adapt to its unique organizational characteristics, and reconsider how AI may harmoniously and seamlessly benefit mankind. The results of the research may now be used to inform the organizational leadership and AI communities about how to lead organizations that desire to leverage AI technology or have a greater desire to understand the relationship between organizational leadership and AI technology.

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