FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

MOVING TOWARDS A HIGHER ADOPTION RATE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNOLOGIES: WHAT ARE THE FACTORS CONTRIBUTING TO THE PERCEPTION OF US FIRM ORGANIZATIONAL READINESS IN ADOPTING ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) TECHNOLOGIES

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

by

Kevin Dwayne Brown

2024

To: Dean William G. Hardin
College of Business

This dissertation, written by Kevin Dwayne Brown, and entitled Moving Towards A Higher Adoption Rate of Artificial Intelligence Technologies: What Are The Factors Contributing To The Perception of US Firm Organizational Readiness In Adopting Artificial Intelligence (AI) and Machine Learning (ML) Technologies, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Hemang Subramanian

Arijit Sengupta

Robert Rodriguez

George Marakas
Major Professor

Date of Defense: May 23, 2024

The dissertation of Kevin Dwayne Brown is approved.

Dean William G. Hardin
College of Business

Andrés G. Gil
Senior Vice President for Research and Economic Development and Dean of the University Graduate School

Florida International University, 2024

DEDICATION

This research is dedicated to all business leaders, theorists, applied researchers and technologists who find the adoption and utilization of Artificial Intelligence and Machine Learning as fascinating as I do. It is my hope that this research contributes to the business domain and sheds light on the importance of understanding and embracing these technologies rather than fearing them. We technologist and newly trained researchers have the responsibility to lead the charge in the development of new opportunities to help our customers develop new insights, processes, and services to increase revenues.

ACKNOWLEDGMENTS

This research would not be possible without the support of my wife, children, family, and friends. Thank you all for allowing me to pursue my lifelong dream of earning my Doctorate Degree. For my family, I especially thank you for your support over the past 3 years of missing family gatherings, birthdays, and other important family events. It is my hope that I will make you proud of my efforts as I attempt to create additional knowledge in this new world of Artificial Intelligence and Machine Learning.

I must thank my FIU professors, FIU administrative team, my cohort and others who have been my support structure without which this work would not be possible.

I want to extend a special thanks to my dissertation committee chair, Dr. George Marakas, for his patience, toughness, understanding and guidance as I completed this research study through one of the most difficult times of my life.

ABSTRACT OF THE DISSERTATION

Moving Towards A Higher Adoption Rate of Artificial Intelligence Technologies: What Are The Factors Contributing To The Perception of US Firm Organizational Readiness In Adopting Artificial Intelligence (AI) and Machine Learning (ML) Technologies

by

Kevin Dwayne Brown

Florida International University, 2024

Miami, Florida

Professor George Marakas, Major Professor

As we enter the era of widespread Artificial Intelligence (AI) and Machine Learning (ML) technology adoption, businesses, and individuals, regardless of size, are being overwhelmed with invitations to adopt and incorporate these advanced technology constructs into their daily operations. Before any individual or entity can truly embrace AI or ML, they first must have a thorough understanding of the technology and their firms' position on adoption.

The primary purpose of this research is to help firms assess and understand their perceived readiness to adopt AI and other advanced technologies. It also serves as a reference framework for the future development of a measurement instrument to help firms with adoption readiness assessments. This research is more organizational behavior centered and sits at the intersection of Organizational Behavior, Change Management and Technology Adoption.

This research study is an extension to several well-known theories and technology adoption frameworks including Theory of Diffusion of Innovations (DOI) (Firm Level) (Rogers, 1995), Theory of Planned Behavior (TPB) (Ajzen, 1991), Technology Adoption Model2 (TAM2) (Individual Level) (Morris, Davis, & Davis, 2003), Organizational Readiness for Change Theory (Weiner B. J., 2009) and others. This study extends the aforementioned theories and frameworks by infusing a modern approach to include firm level factors of leadership and employee attitudes, cultural constraints, competitive needs, and digital and transformation management intensity.

This study is timely because it can serve as a deterrent to prevent companies from attempting to adopt AI and other advanced technologies without a strategic roadmap.

Several well-known failures of AI technology implementations have been disclosed that resulted in significant financial loss and reputation damage to companies including IBM, Amazon, Microsoft, and Apple (Lexalytics,). Many of these failures followed similar patterns and failed primarily due to a lack of organizational level cohesiveness to a solid adoption framework.

Lastly, this study determined that Strategic Agility, Knowledge Absorption Capacity, Data Driven Decision Making Capabilities, Competitive Need/ Advantage, Digital Intensity and Transformation Management Intensity were factors that influenced a firm's perception of AI and ML technology adoption readiness.

Table of Contents

CHAPTER PAGE

LIST OF TABLES

LIST OF FIGURES

TABLE PAGE

INTRODUCTION

Problem Statement

Many scholars and industry experts agree that we as a global economy are well into what is termed the Fourth Industrial Revolution. Table 1 below outlines five Industrial Revolutions, according to the Regenesys Business School (School, 2020). Each Industrial Revolution has two components. The first is the creation of new technology – for example, the invention of the steam engine. The second is a change in production brought about by the technology – for example, the introduction and utilization of the automated production and assembly lines. The Fourth Industrial Revolution, also known as the Age of Digitization, is defined as the development of Robotics, AI, the Internet of Things (IoT), Genetic Engineering, Quantum Computing, Augmented and Virtual Reality and is believed to have started in the year 2000, immediately following the .com boom and bust of the late 1990’s. The term “The Fourth Industrial Revolution” was first credited to Klaus Schwab, the founder of the World Economic Forum during a meeting in Davos Switzerland in 2016.

Figure 1: Industrial Revolutions

1st Industrial Revolution	2nd Industrial Revolution	3rd Industrial Revolution	4th Industrial Revolution	5th Industrial Revolution
Mechanisation	Electrification	Automation and Globalisation	Digitalisation	Personalisation
Occurred during the 18th and 18th centuries, mainly in Europe and North America	From the late 1800s to the start of the First World War	The digital revolution occurred around the 1980s	Start of the 21st century	2nd decade of the 21st century
Steam engines replacing horse and human power	Production of steel, electricity and combustion engines.	Computers, digitisation and the internet,	AI, robotics, IoT, blockchain and crypto.	Innovation purpose and inclusivity.
Introduction of mechanical production facilities driven by water and steam power	Division of labour and mass production, enabled by electricity.	Automation of production through electronic and IT systems	Robotics, artificial intelligence, augmented reality, virtual reality	Deep, multi-level cooperation between people and machines. Consciousness.

I propose that we are entering the early stages of the Fifth Industrial Revolution, characterized by profound and intricate collaboration between humans, machines, and awareness, as defined by (School, 2020). In the Article – The Fifth Industrial Revolution: where mind meets machine (Noack, 2021), the author makes the case that revolution thrives and operates in the background due to advanced technologies including the internet and cloud or computing platforms. These advanced technologies allow for devices connectivity and less personalized engagement with the background computing platforms. These platforms include Internet of Things (IoT) that connect other devices like smart appliances, autonomous vehicles, and others (MARJANI, 2017). The Fifth Industrial Revolution will make the connection between human and machine much closer and more seamless by using brain-computer interfaces to replace our current connectivity through our smart devices. It is because of this seamless connectivity that in comparison to the first Three Industrial Revolutions, both the Fourth and Fifth Industrial Revolutions will have the greatest positive impact on the daily lives of individuals and the financials of business consumers in the history of our planet.

The proliferation and adoption of Artificial Intelligence, Machine Learning and other Advanced Analytics technology constructs over the past 15 years has had some of the most profound impacts on the profitability and productivity of some of the world's largest companies. For many businesses, such as Microsoft, AWS, FedEx, Wal-Mart and many others, the adoption of these advanced technologies has taken off like a rocket. By allowing consumers and businesses to complete tasks ranging from the mundane to the most complex with relative ease and with improved accuracy, efficiency and effectiveness, the need to understand the motivators for adopting and utilizing these constructs is of critical importance to the continued proliferation of these advanced technologies and related applications.

Although many entities show interest in AI and ML technologies, the question of whether firms are prepared to adopt these advanced technology constructs is often overlooked at the firm level. Given the more recent focus on large language models available for use via webservice, this research will help companies improve their perception of readiness to adopt AI/ ML technologies.

Significance of the Problem

The potential for US Business consumers to take advantage of these epic advances in the utilization of AI brings to light key questions related to technology preparedness and adoption proclivities. Many industries are experiencing an explosion in the need to take advantage of these advanced technologies, however the growing demand for highly skilled professionals could have a negative or slowing effect on the usage of advanced analytics capabilities. Workforce and shortages of highly skilled technology labor has been identified as one of the most important factors in the continued adoption of these advanced technology constructs (Will Markow, 2017).

The pace of innovation is driving many US Businesses to reshape their business models and go to market strategies to utilize the advances in Data Science, and advanced technologies (Neha Soni, 2019). The desire to infuse Artificial Intelligence into the various business domains can have a direct positive impact on existing business operations and can also be the catalyst for the creation of new products and services. This pace of innovation can also provide a reciprocating effect and help drive the development of a comprehensive AI adoption strategy for the US Business consumer.

Companies that are looking to create new products and services may be ideal candidates to consider the capabilities of utilizing AI and ML. Products and services such as Facial Recognition, Speech-To-Text and Digital Assistance like Siri, Google Assistant and Cortana were some of the more well-known core AI and ML products and services. What we are seeing now is that many more products and services are being developed and created utilizing these initial services. In the theory of the growth of the firm, the argument is made that as soon as physical resources are purchased externally for their known services and become part of a company, the range of services they are capable of yielding starts to change. (Penrose, 1959)

Research Gap

AI/ ML technologies are being developed at a much more rapid pace than any other technology construct in history. As such, traditional adoption models may not support the needs of organizations in today's rapidly changing business environments. Organizations must have a framework that can be used to measure firm -level readiness to adopt technology constructs that are more adaptative. In addition, this framework needs to allow for faster and more robust assessment of firm readiness based on key variables conducive for the adoption of these newer, more disruptive technologies.

From Five-Factor model personality traits (Tim Barnett, et al) (Tim Barnett, 2015) suggests "Further research involving employees may provide additional insights into how personality impacts intentions to use, as well as perceived and actual us. This research study includes investigating how personality impacts perception of readiness to adopt Artificial Intelligence and Machine Learning constructs for US Firms.

Research Questions

In order for US business consumers to continue leveraging these technological advancements, we must have a baseline understanding of the motivations for companies to perceive their readiness in adopting these technologies This study is focused on providing answers to the following question: **What are the factors contributing to the perception of organizational readiness in adopting Artificial Intelligence and Machine Learning technologies for US firms?**

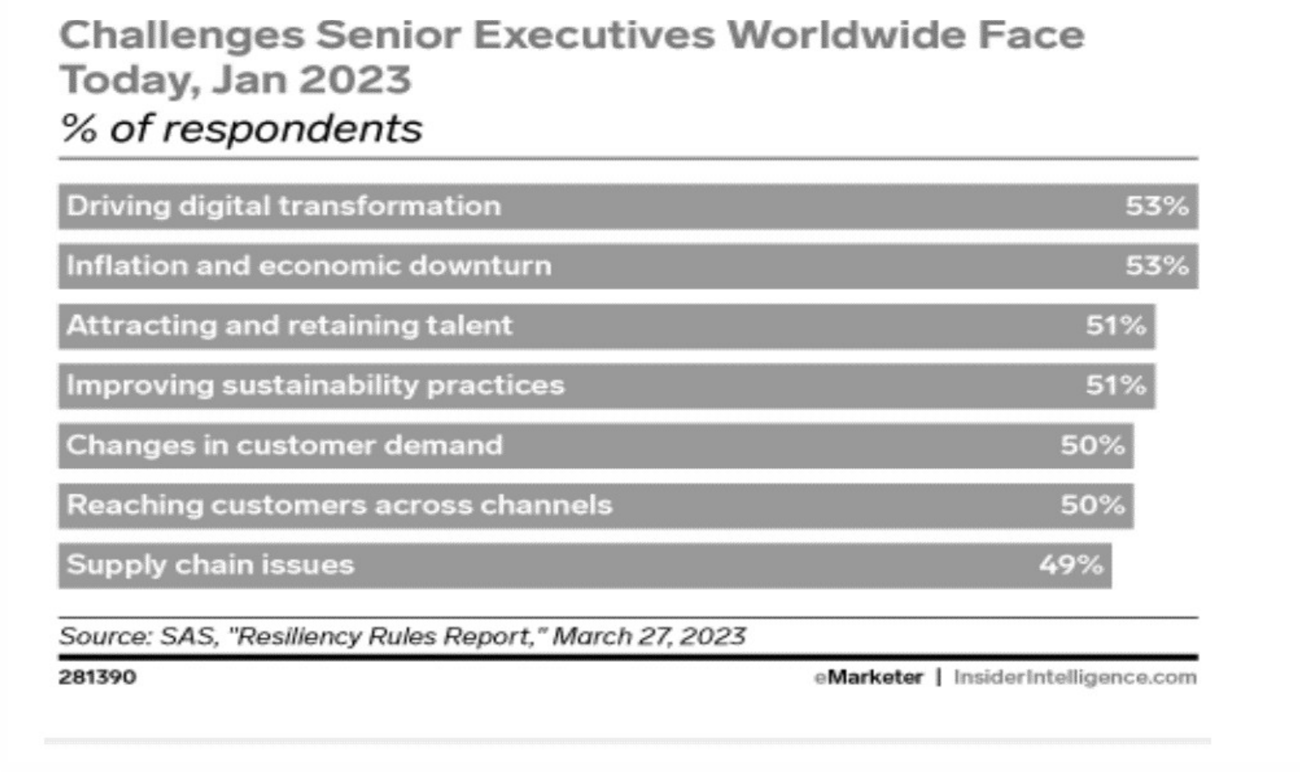
This research study is centered on understanding the perception of organizational readiness in adopting Artificial Intelligence (AI) and Machine Learning (ML) technology constructs and understanding the potential impact on US Businesses. The fundamental purpose of this study is to better understand at a more granular level firm readiness and to identify the drivers that will influence the adoption of aforementioned advanced technology constructs for American business consumers.

Research Contributions

Understanding why business users and consumers are willing to adopt advanced analytical tools and software across multiple industry sectors, will be an extremely lucrative opportunity for manufacturers, distributors, technology consultants and industry and technology solution providers. Additionally, there has been a tremendous uptick in the number of AI-First companies whose focus is on establishing AI/ ML and other advanced technology constructs as viable solution platforms. Companies like Abacus.AI, Landing.AI and many others have been created over the past 8 years and have been extremely profitable in helping companies educate, empower, and implement Advanced Analytics platforms and solutions that have led to increased profitability and capital markets investment returns never before seen in this country.

One of the most important challenges senior business executives face is driving and managing digital transformation across their respective organizations (Intelligence, 2023). In this analyst report outlined in Figure 2, 53% of the respondents listed driving digital transformation as being their number one challenge. Given the rapid development and release of Artificial Intelligence and Machine Learning tools and capabilities, many executives are desperate to grasp and understand technologies that can help them in their digital transformation journey.

Figure 2: Senior Executive Challenges



The widespread accessibility of data has led to growing need for a new class of professionals with the expertise in data analysis, ML and AI (Will Markow, 2017). Burning Glass, a human-capital analytics firm projected that by 2020 the number of positions for data and analytics talent in the United States will increase by 364,000 openings to 2,720,000. To address the talent gap, both workforce development and higher education need to expand their focus beyond just data scientists. They should aim to cultivate skills for various roles such as data product developer, data engineer, data privacy and security specialist, and data governance and lifecycle expert. This broader approach will contribute to narrowing the talent gap.

Data is the constant that will have the greatest impact on all careers. Academia is not exempt and needs to ensure data literacy for all students regardless of major or field. (Will Markow, 2017)

Figure 3: Future Jobs Survey 2018, World Economic Forum

Stable Roles	New Roles	Redundant Roles
Managing Directors and Chief Executives	Data Analysts and Scientists*	Data Entry Clerks
General and Operations Managers*	AI and Machine Learning Specialists	Accounting, Bookkeeping and Payroll Clerks
Software and Applications Developers and Analysts*	General and Operations Managers*	Administrative and Executive Secretaries
Data Analysts and Scientists*	Big Data Specialists	Assembly and Factory Workers
Sales and Marketing Professionals*	Digital Transformation Specialists	Client Information and Customer Service Workers*
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	Sales and Marketing Professionals*	Business Services and Administration Managers
Human Resources Specialists	New Technology Specialists	Accountants and Auditors
Financial and Investment Advisers	Organizational Development Specialists*	Material-Recording and Stock-Keeping Clerks
Database and Network Professionals	Software and Applications Developers and Analysts*	General and Operations Managers*
Supply Chain and Logistics Specialists	Information Technology Services	Postal Service Clerks
Risk Management Specialists	Process Automation Specialists	Financial Analysts
Information Security Analysts*	Innovation Professionals	Cashiers and Ticket Clerks
Management and Organization Analysts	Information Security Analysts*	Mechanics and Machinery Repairers
Electrotechnology Engineers	Ecommerce and Social Media Specialists	Telemarketers
Organizational Development Specialists*	User Experience and Human-Machine Interaction Designers	Electronics and Telecommunications Installers and Repairers
Chemical Processing Plant Operators	Training and Development Specialists	Bank Tellers and Related Clerks
University and Higher Education Teachers	Robotics Specialists and Engineers	Car, Van and Motorcycle Drivers
Compliance Officers	People and Culture Specialists	Sales and Purchasing Agents and Brokers
Energy and Petroleum Engineers	Client Information and Customer Service Workers*	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
Robotics Specialists and Engineers	Service and Solutions Designers	Statistical, Finance and Insurance Clerks
Petroleum and Natural Gas Refining Plant Operators	Digital Marketing and Strategy Specialists	Lawyers

Source: Future of Jobs Survey 2018, World Economic Forum.

Note: Roles marked with * appear across multiple columns. This reflects the fact that they might be seeing stable or declining demand across one industry but be in demand in another.

LITERATURE REVIEW

This literature review follows a narrative approach with search strategy, where the researcher explores the impact of Artificial Intelligence and Machine Learning technologies by reviewing peer reviewed and non-peer reviewed publications and references. Existing theories, models and frameworks have been reviewed to discover if newer theories and conceptual models are needed to address the modern era of information technology adoption.

This research model aims to add to existing theories and concepts. It also borrows concepts from well-known theories including:

1. **Technology-Organization-Environment (TOE) framework (Firm Level)** (Dwivedi, Wade, & Schneberger) and (Eveland & Tornatzky, 1990)
2. **Theory of Diffusion of Innovations (DOI)** (Firm Level) (Rogers, 1995)
3. **Theory of Planned Behavior (TPB)** (Ajzen, 1991)
4. **Growth of the Firm** (Penrose, 1959)
5. **Technology Adoption Model (TAM) (Individual Level)** (Davis, Bagozzi, & Warshaw, 1989)
6. **Technology Adoption Model2 (TAM2) (Individual Level)** (Morris, Davis, & Davis, 2003)
7. **Unified Theory of Acceptance and Use of Technology (UTAUT**) – (Individual Level) (Venkatehs, 2022)

Theoretical or Practical Foundation for this Research

The potential for US Business consumers to take advantage of these epic advances in the utilization of Artificial Intelligence (AI) and Machine Learning (ML) brings to light key questions related to technology preparedness and adoption proclivities. Many industries are experiencing an explosion in the need to take advantage of these advanced technologies, however the growing demand for highly skilled professionals could have a negative or slowing effect on the usage of advanced analytics capabilities. Workforce and shortages of highly skilled technology labor has been identified as one of the most important factors in the continued adoption of these advanced technology constructs (Will Markow, 2017).

The pace of innovation is also a major factor for the increasing push for many US Businesses to reshape their business models and go to market strategies to utilize the advances in Data Science, and advanced technologies (Neha Soni, 2019). The desire to infuse Artificial Intelligence into the various business domains can have a direct positive impact on existing business operations and can also be the catalyst to create new products and services. This pace of innovation can also provide a reciprocating effect and help drive the development of a comprehensive AI adoption strategy for the US Business consumer.

Literature Review and Related References

The proliferation and adoption of Artificial Intelligence, Machine Learning and other Advanced Analytics technology constructs over the past 10 years has had some of the most profound impacts on the profitability and productivity of some of the world's largest companies. The use of these innovative technologies has soared in popularity among numerous firms, including Microsoft, AWS, FedEx, Wal-Mart, and many others.

The primary driver of these profitability, performance and operational effectiveness improvements is due to the production and analysis of exceptionally large amounts of data (MARJANI, 2017). Access to data, analytics and the insights derived from the data assets allows business users the ability to complete tasks ranging from the mundane to the most complex with relative ease and with improved accuracy, efficiency, and effectiveness. The need to understand the motivators for adopting and utilizing these constructs is of critical importance to the continued proliferation of these advanced technologies and related applications.

Defining Artificial Intelligence, Machine Learning and Algorithms

Artificial Intelligence has a number of definitions. A few of the more popular definitions are listed and summarized below:

1. "The simulation of human intelligence processes by machines, especially computer systems." (Burns E. , 2021)
2. "Intelligence demonstrated by machines, as opposed to natural intelligence displayed by animals including humans." (Wikipedia, n.d.)
3. Artificial Intelligence is a machine that can "think" (Staff, 2024)

The definition of Machine Learning also has several connotations, however at its core, Machine Learning (ML), is a method of data analysis that automates analytical model building – those needed for machines to "learn." Machine Learning is a subscience of Artificial Intelligence and can be defined as the science of causing a computer to act without being explicitly programmed. (Petersson, 2021).

An Algorithm is defined as a series of mathematical calculations or procedure for computing a function (Hartley Rogers, 1957). While the focus of this research is on AI adoption, it is important to note that many often use the definitions of AI, ML and Algorithms interchangeably, when ML and Algorithms are subsets of AI from the Computer Science discipline.

More companies are implementing AI applications into their business operations including Human Capital Resources, Finance, Cybersecurity, Customer Service, and many others. In other scenarios, companies are using AI, ML and Advanced Analytics to transform their core business operations for products or services for their consumers. For Example, General Motors (GM), went on record years ago stating that the electric cars would not become a viable product. Today, not only is GM embracing Electric Vehicle (EV) technology, but they are also using Artificial Intelligence, Machine Learning, and other technologies to transform their core product from gasoline-powered vehicles to produce Electric Vehicles to compete with companies like Tesla and Lucid. Marriott International is one of the largest hotel and hospitality companies in the world and is best known for their moderately priced hotels. With the tremendous success of new competitors in the hospitality industry, Marriott is changing its core business model to become more like Airbnb, an online marketplace for short and long-term rentals.

Over the past 10 years, we have seen a sharp increase in the incorporation of Artificial Intelligence and Machine Learning into many technologies including:

- **Artificial Intelligence as a Service (AIaaS)**, (Newlands, 2021), allows for companies to access specific AI capabilities via cloud computing.
- **Robotic process automation (RPA)**, which allows for robotics to be programmed to complete high-volume and repeatable tasks that humans may find mundane.
- **Machine or Deep Learning (ML/DL),** which enables computers to automate predictive analytics and act without programming, including supervised, unsupervised and reinforcement learning.
- **Machine/ Computer Vision**, which captures and analyses visual information using cameras and digital signal processes such as human eyesight, which can be used, for example, in signature identification and image analysis.
- **Autonomous or Self-driving cars**, which automate safe driving using computer vision, image recognition and deep learning capabilities (Burns & Laskowski, N. , 2018)

- **Healthcare,** adoption of artificial intelligence- based medical diagnosis support systems (AIMDSS) to reduce the number of misdiagnosis and patient death (Wenjuan Fan, 2018)
- **ChatGPT,** a large language model that allows for the creation of new and original content by learning from existing data.

These advanced analytical constructs are positively impacting more non- traditional industries: those in which advanced analytics were never before used or even considered. In (Leonidas Aristodemou, 2018), the authors discuss the proliferation of the use of Big Data Analytics on improved decision making in patent analytics. Intellectual Property Analytics (IPA) is a new knowledge domain that has been created to improve insight and decision making from Intellectual Property and has resulted in the creation of a multi-million-dollar industry.

CONCLUSION

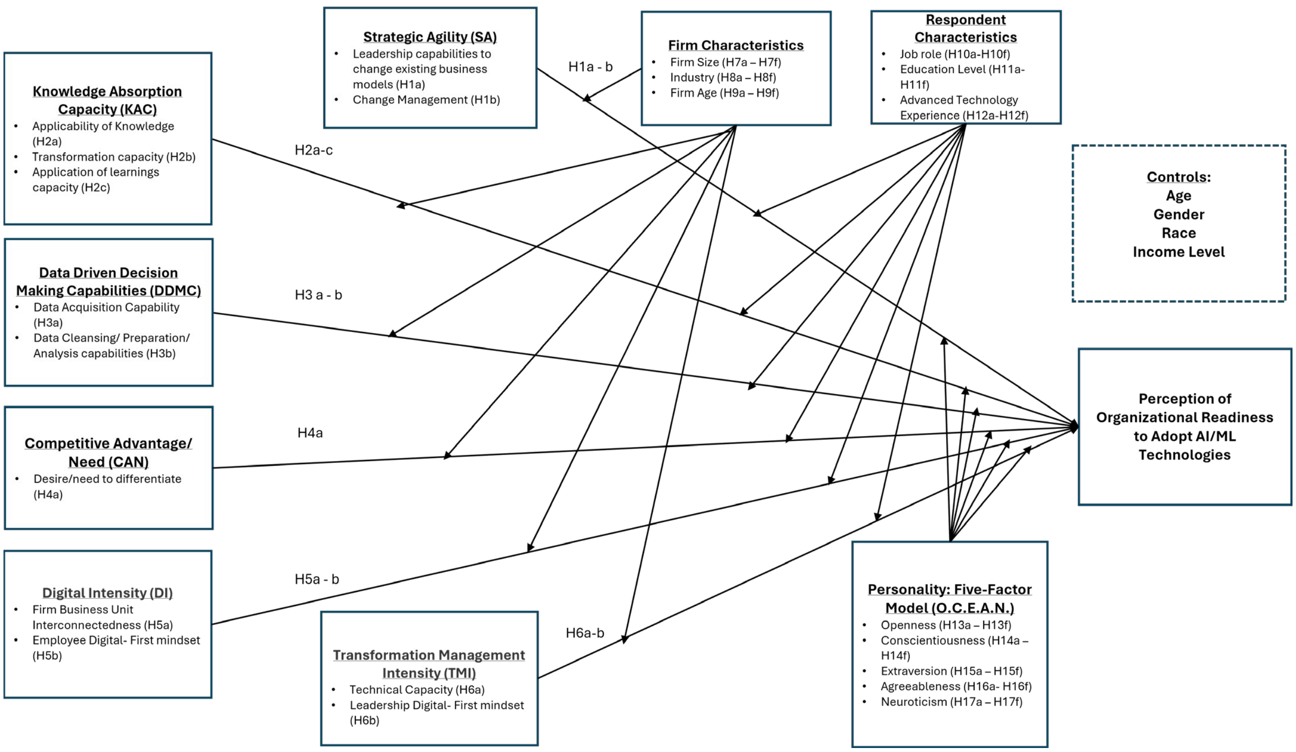
Although existing theories, models and frameworks on IT adoption have been well documented and cited, there has not been extensive research focused on adoption at the firm or organizational level. This study identifies crucial issues that need to be addressed in order for companies to fully consider their readiness to adopt advanced technologies like AI and others.

RESEARCH MODEL AND HYPOTHESES

Conceptual Model & Framework

Traditional technology acceptance models are often outdated, not focused on the firm level, or are not well-suited for more modern, fast-paced, and disruptive technologies such as Artificial Intelligence or Machine Learning. The conceptual research model presented in Figure 2 proposes a more modern theory that seeks to address modern era variables that many US companies encounter as determinants of their perceived organizational readiness and ultimate adoption intention for rapidly changing technologies.

Figure 4: Conceptual Research Model



Hypothesis and Variables

The conceptual model in Figure 2 demonstrates the factors that impact the perception of organizational readiness to adopt Artificial Intelligence and Machine Learning technologies. The independent variables hypothesize Strategic Agility (H1), Knowledge Absorption Capacity (H2), Data Driven Decision Making (H3), Firm Level Digital Intensity (H4) and Competitive Advantage/ Competitive Need (H5**)** as direct factors that drive the Perception of Organizational Readiness to Adopt AI/ML(DV). The model is a measurement model with independent variables with sub factors, moderating variables with multiple categorical variables, and a dependent variable that will be used for more accurate and focused analysis.

Information technology (IT) is now widely recognized as a key tool for boosting a firm's economic competitiveness. To maximize the impact of IT on firms' productivity, the determinants of IT adoption must be clearly understood. The adoption of the IT constructs must be firm- wide to maximize its impact. (Oliveira & Martins, 2011)

The sections below detail the model constructs and hypotheses development to support the research question and conceptual model. Table 3 below lists the Hypotheses and their definitions.

Table 1: Hypothesis Summary

Hypotheses	Mnemonic/Path	Description
H1	SA -> DV	As the firm's Strategic Agility increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H2	KAC -> DV	As the firm's Knowledge Adoption Capacity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H3	DDMC ->DV	As the firm's Data Driven Decision Making Capabilities increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H4	CAN -> DV	As the firm's Competitive Advantage or Need increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H5	DI -> DV	As the firm's Digital Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H6	TMI -> DV	As the firm's Transformation Management Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase
H7a	SA -> FS -> DV	The Firm Size will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H7b	KAC -> FS -> DV	The Firm Size will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H7c	DDMC -> FS -> DV	The Firm Size will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H7d	CAN -> FS -> DV	The Firm Size will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H7e	DI -> FS -> DV	The Firm Size will moderate the relationship between the firms Digital Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H7f	TMI -> FS -> DV	The Firm Size will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Hypotheses	Mnemonic/Path	Description
H8a	SA -> FI -> DV	The Firm Industry will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H8b	KAC -> FI -> DV	The Firm Industry will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H8c	DDMC -> FI -> DV	The Firm Industry will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H8d	CAN -> FI -> DV	The Firm Industry will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H8e	TMI -> FI -> DV	The Firm Industry will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H8f	DI -> FI -> DV	The Firm Industry will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9a	SA -> FA -> DV	The Firm Age will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9b	KAC -> FA -> DV	The Firm Age will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9c	DDMC -> FA -> DV	The Firm Age will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9d	DI -> FA -> DV	The Firm Age will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9e	CAN -> FA -> DV	The Firm Age will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H9f	TMI -> FA -> DV	The Firm Age will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10a	SA -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10b	KAC -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10c	DDMC -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10d	CAN -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10e	DI -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H10f	TMI -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Hypotheses	Mnemonic/Path	Description
H11a	SA -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H11b	KAC -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H11c	DDMC -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H11d	CAN -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H11e	DI -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H11f	TMI -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12a	SA -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12b	KAC -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12c	DDMC -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12d	CA -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12e	DI -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H12f	TMI -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13a	SA -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13b	KAC -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13c	DDMC -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13d	CA -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13e	DI -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H13f	TMI -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Hypotheses	Mnemonic/Path	Description
H14a	SA -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H14b	KAC -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H14c	DDMC -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H14d	CAN -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H14e	DI -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H14f	TMI -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15a	SA -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15b	KAC -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15c	DDMC -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15d	CAN -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15e	DI -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H15f	TMI -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16a	SA -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16b	KAC -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16c	DDMC -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16d	CAN -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16e	DI -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H16f	TMI -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Hypotheses	Mnemonic/Path	Description
H17a	SA -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H17b	KAC -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H17c	DDMC -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H17d	CAN -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H17e	DI -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies
H17f	TMI -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Strategic Agility

The ability to adapt to new developments, continuously adjust the strategic direction of the company, and devise inventive methods for generating value are all hallmarks of agility and flexibility. (Weber & Tarba, 2014). The HR Daily advisor defines the three As of agility as: anticipate, adapt, and act. (Pophal, 2019) Companies must remain strategically and organizationally agile to respond to rapid changes in market and consumer demands.

Strategic agility denotes a company's ongoing capacity to successfully alter its course of action in order to maintain its competitive advantages. (Weber & Tarba, 2014). Considering the rapid availability of AI and ML technologies to help companies remain strategically agile, the study hypothesizes:

H1: As the firm's Strategic Agility increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase

Knowledge Absorption Capacity (KAC)

Knowledge Absorption Capacity (KAC) can be defined as processes oriented toward the actual use of knowledge. (Gold, Malhotra, & Segars, 2001). This construct allows a firm to create knowledge assets that can lead to a sustainable advantage over their competitors. KAC can also be extremely valuable in developing the confidence of firm leadership and practitioners in adopting and utilizing new technologies. In this research study, we hypothesize:

H2: As the firm's Knowledge Adoption Capacity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase.

Data Driven Decision Making Capabilities (DDMC)

The main objectives for firms that adopt Data Driven Decision Making frameworks is the transformation of data into knowledge. This is enabled most effectively by the use of technology-based tools that help to support decision making by various stakeholders across the firm. (Mandinach, Honey, & Light, 2006).

As late as 2020, the successful transformation of companies becoming true data-driven organizations has been low. (Svensson & Taghavianfar, 2020) Organizations that are positioning themselves to adopt advanced technologies such as AI and ML, must make a serious and concerted effort to address any obstacles if they wish to remain competitive. This research study hypothesizes the following:

H3: As the firm's Data Driven Decision Making Capabilities increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase

Competitive Advantage or Need (CAN)

Competitive Advantage/ Need refers to attributes that enable a firm to generate goods and services more affordably and efficiently than its competitors. Firms must consider the importance and significance of being adaptable and proactive in an effort to respond to unforeseen and unpredictable changes in business environments (Worley, Williams, & Lawler III, 2014). Many firms learned the importance of being proactively agile during 2020 and 2021 during the height of the Covid 19 pandemic. Those that were proactive in providing remote working environments for their employees were able to maintain business operations with only minor reductions in productivity, while others were forced to develop entirely new operating models. As a result, we identify and test the following Hypothesis:

H4:As the firm's Competitive Advantage or Need increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase

Firm Level Digital Intensity (DI)

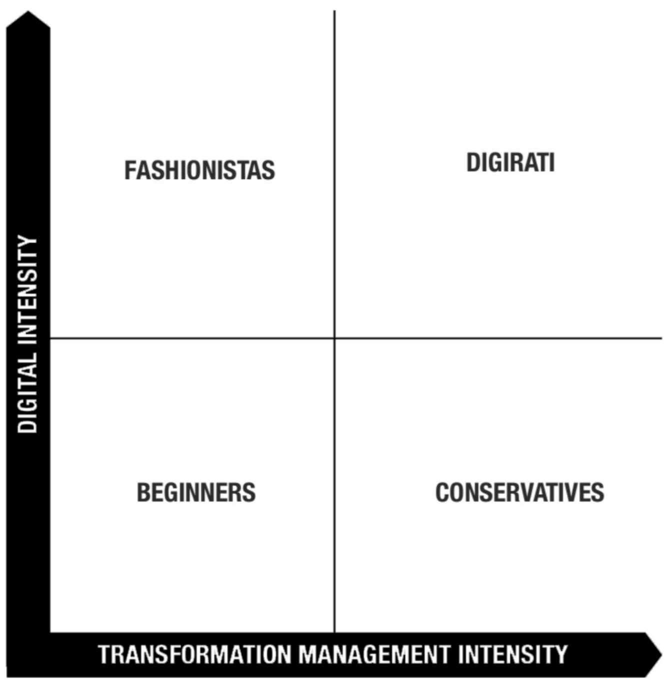
Digital Transformation has multiple definitions, however the most basic of all definitions is leveraging technology to significantly enhance the efficiency of a business. (Westerman G. C., 2011). Firm Level Digital Maturity is a combination of two domains. The first domain is called Digital Intensity (DI), which is measured at the overall firm level. Its primary goal is to measure and record processes, technologies and procedures that modify how a company operates (Wroblewski, 2018). The relationship between DI and TMI is explained in more detail in Figure 3 in section 3.2.6 Transformation Management Intensity (TMI).

H5: As the firm's Digital Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase.

Transformation Management Intensity (TMI)

Transformation Management Intensity (TMI) is the second of two domains in the Firm Level Digital Maturity model. Its primary focus is to measure the level of investment in leadership capabilities and mindset changes needed to create and implement operational and governance strategies centered on adopting new digital transformation approaches. (Wroblewski, 2018) (Westerman G. C., 2011) (Westerman & McAfee, 2012). Figure 5 is the Four Level Maturity model referenced in (Westerman & McAfee, 2012) and shows the relationship between Digital Intensity (DI) discussed in section 3.2.5 and TMI.

Figure 5: The DI and TMI Framework (Westerman & McAfee, 2012)



To illustrate the importance of the DI and TMI framework, the study hypothesizes:

H6: As the firm's Transformation Management Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase.

Perception of Organizational Readiness (DV)

The theory of Organizational Readiness for change is a firm or organizational level framework designed to categorize and measure a firm's dedication (commitment to change), and shared buy-in to effect changes (Weiner B. J., 2009). This variable is classified as a psychological construct and is said to be a leading indicator for successful implementation of complex changes in healthcare IT projects (Amatayakul, 2005) and (Weiner B. J., 2009).

This theory is also defined as the shared evaluation within an organization concerning its ability, resources, and eagerness to effectively embrace and integrate new technologies.

As the conceptual model in Figure 2 denotes, this study hypothesizes that several factors will have a moderating effect on a firm's perception of its organizational readiness. support this theory this study hypothesizes:

Moderators

Moderators affect the relationship between independent and dependent variables. They most often amplify the strength or determine the direction of the relationship between variables. For the purposes of this research study, we will investigate the following moderators and their impact on the Perception of Organizational Readiness dependent variable from the independent variables listed in section 3.2.

Moderating Effect of Firm Characteristics

Firm Characteristics can be defined as attributes of a firm that are normally under the control of the firm (Nyabaga & Wepukhulu, 2020). For the purposes of this study, they include Firm Size, Firm Industry and Firm Age. These attributes will be used in this study to investigate the following Moderating categories for their direct or indirect effect on the independent and dependent variable relationships:

1. **<u>Firm Size</u>** – the number of employees with the measurement scale ranging from 1 to over 5000
2. **<u>Industry</u>** – the economic activity the respondent's firm is associated with.
3. **<u>Firm Age</u>** – how long in years the respondent's firm has been in existence.

The following moderating hypotheses for the Firm Characteristics moderator will be interrogated in this study:

H7a: The Firm Size will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies.

H7b: The Firm Size will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies.

H7c: The Firm Size will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies.

H7d: The Firm Size will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies.

H7e: The Firm Size will moderate the relationship between the firms Digital Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies.

H7f: The Firm Size will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies moderator

H8a: The Firm Industry will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H8b: The Firm Industry will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H8c: The Firm Industry will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H8d: The Firm Industry will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H8e: The Firm Industry will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H8f: The Firm Industry will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9a: The Firm Age will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9b: The Firm Age will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9c: The Firm Age will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9d: The Firm Age will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9e: The Firm Age will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H9f: The Firm Age will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Moderating Effect of Respondent Characteristic

In this study we will investigate the following Moderating categories for their direct or indirect effect on the independent and dependent variable relationships:

1. **Job Role** – the specific job or ownership title of the respondents

2. **<u>Education Level</u>** – educational attainment level of respondents
3. **<u>Experience with Advanced Technology</u>** – a yes/ no indicator of experience level with advanced technology constructs like AI or ML.

The following moderating hypotheses for the Respondent Characteristics moderator will be interrogated in this study:

H1a: The respondent's Education Level will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H1b: The respondent's Education Level will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H1c: The respondent's Education Level will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H1d: The respondent's Education Level will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H1e: The respondent's Education Level will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H1f: The respondent's Education Level will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12a: The respondent's Advanced Technology Experience will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12b: The respondent's Advanced Technology Experience will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12c: The respondent's Advanced Technology Experience will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12d: The respondent's Advanced Technology Experience will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12e: The respondent's Advanced Technology Experience will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H12f: The respondent's Advanced Technology Experience will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Moderating Effect of the Five Factor Model of Personality

The Five Factor Model of Personality is one of the most widely used and well-known theory models that identifies and groups personality traits into five dimensions (Digman, 1990). The five factors identified in the Digman reference are Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. General definitions from Psychology Today are listed below (Today, 2024) and (Contributors, 2024):

1. Openness – indicates creativity, open-mindedness, and insightfulness
2. Conscientiousness – indicates the thoughtfulness and goal-orientation
3. Extraversion – indicates positive emotionality and high energy
4. Agreeableness – indicates general concern for and a willingness for cooperation
5. Neuroticism – defined as negative emotionality and reactive to stressful situations

Various studies have shown the influence of one or more of the five personality factors as being more influential on leadership decision-making than others. In an effort to find and potentially support this influence, we define each factor and hypothesize as follows:

Openness

H13b: The respondent's Openness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H13c: The respondent's Openness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H13d: The respondent's Openness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H13e: The respondent's Openness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H13f: The respondent's Openness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Conscientiousness

H14a: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H14b: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H14c: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H14d: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H14e: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H14f: The respondent's Conscientiousness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Extraversion

H15a: The respondent's Extraversion personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H15b: The respondent's Extraversion personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H15c: The respondent's Extraversion personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H15d: The respondent's Extraversion personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H15e: The respondent's Extraversion personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H15f: The respondent's Extraversion personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Agreeableness

H16a: The respondent's Agreeableness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H16b: The respondent's Agreeableness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H16c: The respondent's Agreeableness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H16d: The respondent's Agreeableness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H16e: The respondent's Agreeableness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H16f: The respondent's Agreeableness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Neuroticism

H17a The respondent's Neuroticism personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H17b The respondent's Neuroticism personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H17c The respondent's Neuroticism personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H17d The respondent's Neuroticism personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H17e The respondent's Neuroticism personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies

H17f The respondent's Neuroticism personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies

Control Variables and Construct Definitions

The impact on both independent and dependent variables in his study are controlled by respondent age, gender, race, and income levels. Table 2 provides a summary of all constructs used in this study.

Table 2: Construct Definitions

Construct (abbr.)	Definition (reference)
Strategic Agility (SA)	The ability to adjust to changing conditions to create value (Weber & Tarba, 2014)
Knowledge Absorption Capacity (KAC	The capacity to gather, absorb and utilize new knowledge (Gold, Malhotra, & Segars, 2001)
Data Driven Decision Making Capabilities (DDMC)	The utilization of tools and processes for transforming data into knowledge and using this knowledge to guide business decisions (Joubert, 2019)
Competitive Advantage/Need (CAN)	Characteristics or abilities that afford a firm to outperform its competitors (Porter, 1980)
Digital Intensity (DI)	Leveraging technology to significantly enhance the efficiency of a business (Westerman G. C., 2011)
Transformation Management Intensity (TMI)	Measures the level of investment in leadership capabilities and mindset changes needed to create and implement operational and governance strategies centered on adopting new digital transformation approaches (Westerman & McAfee, 2012)
Firm Characteristics (FC)	Attributes of a firm that are normally under the control of the firm (Nyabaga & Wepukhulu, 2020)
Perception of Organizational Readiness to Adopt AI/ML Technologies	Psychological construct and is said to be a leading indicator for successful implementation of complex changes in healthcare IT projects (Amatayakul, 2005) and (Weiner B. J., 2009)
Respondent Characteristics (RC)	Attributes of survey participants that often include demographic, personality, or other data points (Olson, Smyth, & Ganshert, 2019).
Five Factor Personality Model (FFM)	Theory models that identify and groups personality traits into five dimensions (Digman, 1990)
Controls	
Age	Respondent age
Gender	Respondent gender
Race	Respondent race
Income Level	Respondent income level in US dollars

METHODOLOGY

A quantitative study utilizing Pollfish and Qualtrics was performed for the main study's data collection. The survey instrument was created in Qualtrics and administered via the Pollfish survey platform. Respondents were provided access to the survey instrument after completing an adequate qualifying process. Survey participants were given a maximum time of thirty five minutes to complete the twenty two questions survey as derived from the Pilot study and analysis.

The demographic data in Table 5 was collected from four hundred respondents, of which 58% were male and 42% were female. The ages of the respondents were also captured and 9.25% were between ages 18-24, 29.25% were between ages 25-34, 45.5% were between ages 35-44 , 11.75% were between ages 45-54 and only 4.25% were aged 54 or older. Ethnicity data was captured and 3.25% self-reported as Asian, 8.75% Black, 3% Hispanic, 2% Latino, 77.25% White, 3.25% Multiracial, 1.75% Other and .75% Preferred not to say. Education attainment data was also captured. 8% of respondents were High School educated, 14.75% had completed Vocational or Technical College, 24.75% had earned University degrees and 42.50% were Post-Graduates. Income data was also captured. 7.25% reported income under $25,000, 10% between $25,000 and $49,999, 13.50% between $50,000 and $74,999, 14.50% between $75,000 and $99,000, 12.25% between $100,000 and $124,999, 23% $150,000 or more, and 2.75% preferred not to report their income.

Table 3: Main Study Demographic Data (n = 400)

Control	Response	Freq.	% of Sample
Age	18 - 24	37	9.25%
	25 - 34	117	29.25%
	35 - 44	182	45.50%
	45 - 54	47	11.75%
	54 +	17	4.25%
Race	Asian	13	3.25%
	Black	35	8.75%
	Hispanic	12	3%
	Latino	8	2%
	White	309	77.25%
	Multiracial	13	3.25%
	Other	7	1.75%
	Prefer Not To Say	3	.075%
Gender	Male	232	58%
	Female	168	42%
Income Level	Under $25,000	29	7.25%
	$25,000 to $49,999	40	10%
	$50,000 to $74,999	54	13.50%
	$75,000 to $99,999	58	14.50%
	$100,000 to $124,999	49	12.25%
	$125,000 to $149,999	67	16.75%
	$150,000 Or More	92	23%
	Prefer Not To Say	11	2.75%

Research Design

This research study utilized a quasi-experimental and cross-sectional design (Babbie, 2016). This study included a quantitative survey instrument that allowed for an interrogation and establishment of the relationships between independent, moderating, and dependent variables (Creswell & Creswell, 2018). The survey instrument was developed and delivered using Qualtrics Survey Software and was administered via web browser access and delivered via the Pollfish market research provider platform. Respondents were selected by passing a rigorous screening process controlled by the Pollfish. Qualifying questions used to select respondents were:

1. Do you have at least 1 year of experience with Artificial Intelligence?
2. Are you an employee, agent or business owner of a United States-based firm or company?

This research study was focused on exploring the research question and established hypotheses using a 4-part process. An Informed pilot was conducted for the specific purpose of validating the proposed research study. The pilot included four subject matter experts, with considerable experience utilizing Artificial Intelligence and other advanced technologies. Next, an informed pilot was conducted to validate the proposed content for the survey instrument and the conceptual model. The focused pilot study was next conducted to validate the overall research approach, survey instrument and data collection. Feedback, updates, and corrections from all pilot studies were made prior to the launch of the Main or Full Study.

Measures

The study utilized a 5-point Likert scale survey instrument used to measure all model variables. The main study survey length was twenty one questions with an average completion time of ten minutes and thirty six seconds against a target completion time of under thirty minutes. The survey instrument was developed from several theoretical sources detailed in Table 4. The full survey instrument can be found in the Appendix.

Table 4: Survey Instrument Measure

Construct (abbr.)	**ID**	**Question**	**Reference**

Strategic Agility (SA)	H1a	Senor leadership at my firm communicate and align the organization's workforce with the strategic changes required to transform existing business models	(Yukl, 2012)
	H1b	My firm plans, communicates, and executes change initiatives aimed at adopting new business models and strategies	(Cameron & Green, 2015)
	H1b	My firm identifies and addresses resistance to change when implementing new business models and strategies	(Beer & Nohria, 2016)
Knowledge Absorption Capacity (KAC)	H2c	My firm effectively aligns its existing processes, products, and strategies with the knowledge it acquires	(Teece, 2007)
	H2e	My firm promotes a culture of continuous learning and knowledge sharing among employees	(Senge, 2006)
	H2e	My firm effectively captures and utilizes feedback from employees and customers to improve its processes and products	(Brown & Eisenhardt, 1997)
Data Driven Decision Making Capabilities (DDMC)	H3a	My firm has an adequate data acquisition infrastructure for collecting necessary data for consumption by the business users.	(LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2010)
	H3a	My firm invests in technologies for effective data acquisition.	(Kambatla, Kollias, Kumar, & Grama, 2014)
	H3a	My firm effectively ensures the reliability of acquired data	(Pipino, Lee, & Yang, 2002)
	H3b	My firm adequately updates its data analysis tools and methods.	(Davenport, 2012)
	H3b	My firm has adequate capabilities for detecting and resolving data errors and inconsistencies	(Rahm & Do, 2000)

Competitive Advantage Need (CAN)	H4b	My firm does an adequate job differentiating its products and services from competitors.	(Porter, 1980)
	H4b	My firm invests in research and development to create unique offerings.	
	H4b	My firm frequently launches new or improved products and services to maintain is market differentiation.	(Ansoff, 1957)
	H4b	My firm effectively communicates its unique value proposition to its customers.	(Kapferer, 2008)
Digital Intensity (DI)	H5c	My firm's digital investments are strategically aligned with its overall business goals.	(Fitzgerald, Kruschwitz, Bonnet, & Welch, 2013)
	H5c	My firm prioritizes digital investments in strategic planning.	(Matt, Hess, & Benlian, 2015)
Transformation Management Intensity (TMI)	H6b	Firm leaders adequately participate in technical training discussions.	(Eden, 1992)
	H6b	Firm leaders often champion the adoption of new digital tools across firm business units.	(Venkatesh, Morris, Davis, & Davis, 2003)
	H6b	Firm Leadership Technical Competency at my firm is adequate for digital transformational efforts.	(Bassellier, Reich, & Benbasat, 2000)
	H6c	Firm leaders welcome open discussions on continuous learning and staying. updated with technological advancements.	(Kane, Palmer, Phillips, Kiron, & Buckley, 2016)

Information technology (IT) is now widely recognized as a key tool for boosting a firm's economic competitiveness. To maximize the impact of IT on firms' productivity, the determinants of IT adoption must be clearly understood. The adoption of the IT constructs must be firm- wide to maximize its impact. (Oliveira & Martins, 2011)

Strategic Agility

The ability to adapt to new developments, continuously adjust the strategic direction of the company, and devise inventive methods for generating value are all hallmarks of agility and flexibility. (Weber & Tarba, 2014). The HR Daily advisor defines the three As of agility as:

anticipate, adapt, and act. (Pophal, 2019) Companies must remain strategically and organizationally agile to respond to rapid changes in market and consumer demands.

Strategic agility does not refer to a single change that an organization makes, such as in response to a serious threat or emergency. Strategic agility, on the other hand, denotes a company's ongoing capacity to successfully alter its course of action in order to maintain its competitive advantages. (Weber & Tarba, 2014)

Knowledge Absorption Capacity

Knowledge Absorption Capacity (KAC) can be defined as processes oriented toward the actual use of knowledge. (Gold, Malhotra, & Segars, 2001). This construct allows a firm to create knowledge assets that can lead to a sustainable advantage over their competitors. KAC can also be extremely valuable in developing the confidence of firm leadership and practitioners in adopting and utilizing new technologies.

Data Driven Decision Making Capabilities

The main objectives for firms that adopt the Data Driven Decision Making frameworks is the transformation of data into knowledge. This is enabled most effectively by the use of technology-based tools that help to support decision making by various stakeholders across the firm. (Mandinach, Honey, & Light, 2006).

As late as 2020, the successful transformation of companies becoming true data-driven organizations has been low. (Svensson & Taghavianfar, 2020) Organizations that are positioning themselves to adopt advanced technologies such as AI and ML, must make a serious and concerted effort to address any obstacles if they wish to remain competitive.

Competitive Advantage or Competitive Need

As competition increases due to globalization, the rapid pace of technological change, changes in consumer tastes and preferences and the changing demands on business models, firms must take into consideration the importance of becoming adaptable and proactively nimble in order to respond to unforeseen or unpredictable changes in their business environments. (Worley, Williams, & Lawler III, 2014)

Firm Level Digital Intensity (DI)

Digital Transformation has multiple definitions, however the most basic of all definitions is leveraging technology to significantly enhance the efficiency of a business. (Westerman G. C., 2011). Firm Level Digital Maturity is a combination of two domains. The first domain is called Digital Intensity (DI), which is targeted at the overall firm. It focuses on capturing and measuring the processes and technologies that change how a company operates. (Westerman, 2011). Digital Intensity (DI), which focuses on capturing and measuring the processes and technologies that change how a company operates.

Transformation Management Intensity (TMI)

Transformation Management Intensity (TMI) is the second of two domains in the Firm Level Digital Maturity construct. Its primary focus in on leadership mindset changes in the development and implementation of operational and governance strategies centered on adopting new digital transformation approaches. (Wroblewski, 2018) (Westerman G. C., 2011)

Perception of Organizational Readiness

The theory of Organizational Readiness for change is defined as organizational level construct that measures an organization's shared resolve to implement or effect a change (change commitment) and their shared ability to implement change (change efficacy) (Weiner B. J., 2009). When people of an organization desire to make a change and are confident that they can make it, organizational readiness is likely to be at its maximum.

Pretest and Informed Pilot

The Pretest and Informed Pilot was conducted in August 2023 prior to the completion of a Pilot study. Four subject matter experts with extensive experience in AI and ML technology participated in the Informed Pretest in two stages. Stage one was completed with a review of the conceptual model, construct definitions, and survey instrument. Stage two was completed after incorporating feedback from the SMEs that involved updates to the survey instrument to correct wording errors. All constructs were validated during Stage two and updates improved the survey instrument validity and internal reliability.

In addition to the Pretest Study, the SMEs were provided with defense proposal feedback from the dissertation committee to provide additional support for the overall study, instrument, and internal reliability. The feedback and responses can be found in the Appendix on Table 6.

Pilot Study

A quantitative methodology was used for the informed pilot study. The Connect Cloud survey platform by Cloud Research was used to administer the data collection. The survey questions were developed and administered by Qualtrics and IBM SPSS was used to conduct analysis and validate the strength of the model constructs. One hundred fifty responses were collected and validated through data cleansing. The survey instrument initially contained one hundred thirty three questions and through factor analysis we discovered constructs that were not differentiating indicating high correlations across my survey questions that resulted in the final survey containing twenty two questions.

Figure 6: Rotated Component Matrix Factor Analysis

	1	2	3	4	5	6
DDD - Q1 (H3a)_2	.778					
DDD - Q1 (H3a)_5	.771					
DDD - Q1 (H3a)_4	.734					
DDD - Q2 (H3b)_2	.728					
DDD - Q2 (H3b)_1	.567					
TMI - Q2 (H6b)_2		.776				
TMI - Q2 (H6b)_3		.754				
TMI - Q2 (H6b)_5		.748				
TMI - Q3 (H6c)_3		.586	.532			
KAC-Q5 (H2e)_3			.755			
KAC-Q5 (H2e)_1			.643			
KAC-Q3 (H2c)_4			.594			.520
CNA - Q1 (H4b)_4				.813		
CNA - Q1 (H4b)_1				.729		
CNA - Q1 (H4b)_2				.686		
CNA - Q1 (H4b)_5				.571		
SA - Q2 (H1b)_1					.752	
SA - Q1 (H1a)_2					.704	
SA - Q2 (H1b)_3					.558	
DI - Q1 (H5a)_3						.646
DI - Q3 (H5c)_3						.631
DI - Q3 (H5c)_4						.563

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 7 iterations.

The KMO and Bartlett's Test also indicated a .922 or 92.2% sampling adequacy and a Significance/ p-value <.001. These results indicate the data collected is suitable for factor analysis. These analyses show that the constructs demonstrate reasonable validity and reliability.

Figure 7: KMO and Bartlett's Test Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.922
Bartlett's Test of Sphericity	Approx. Chi-Square	1782.345
	df	231
	Sig.	<.001

RESULTS

The calculated sample size for the study was three hundred seventy respondents based on the Qualtrics Sample Size Calculator. The confidence level of 95%, population size of ten thousand and margin of error of 5% were derived from guidance provided by (Hair, Hult, Ringle, & Sarastedt, 2017). However, to prepare for the potential for unusable data, additional responses were added for a total sample size of four hundred.

IBM SPSS was used for exploratory factor analysis (EFA) to validate the measurement model and to ensure the proper loading of survey results and to ensure discriminant validity. Cross loadings were validated during the Pilot study using the varimax rotated factor matrix with a .05 for loadings and resulted in only twenty two questions used for the survey instrument.

Regression analysis was also used to test the research hypotheses by comparing the means and grand means of the Independent, Moderating and Dependent Variables.

Using a 5 point Likert Scale to validate the proposed model using regression-based approach and four hundred respondents answered the survey questions. Respondents that failed the qualifying questions, had missing responses or data, attention check questions or completed the survey in less than 3 minutes were removed from the main study prior to analysis. After data cleansing and additional analysis, only two hundred five of the four hundred respondents' data was utilized in the survey analysis.

Hypothesis Testing and Results

Table 5 below lists the seventy two hypotheses identified in this study along with hypothesis testing results. Additional details on the results are summarized in the subsequent sections.

Table 5: Hypothesis Testing Results

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H1	SA -> DV	As the firm's Strategic Agility increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.484	7.831	<.001	S
H2	KAC -> DV	As the firm's Knowledge Adoption Capacity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.607	10.833	<.001	S
H3	DDMC ->DV	As the firm's Data Driven Decision Making Capabilities increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.705	14.082	<.001	S
H4	CAN -> DV	As the firm's Competitive Advantage or Need increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.579	10.069	<.001	S
H5	DI -> DV	As the firm's Digital Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.588	10.317	<.001	S
H6	TMI -> DV	As the firm's Transformation Management Intensity increases, their Perception of Organizational Readiness to Adopt AI/ML Technologies will increase	0.587	10.276	<.001	S
H7a	SA -> FS -> DV	The Firm Size will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness To Adopt AI/ML Technologies	0.185	2.451	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H7b	KAC -> FS -> DV	The Firm Size will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.147	2.258	<.001	S
H7c	DDMC -> FS -> DV	The Firm Size will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.027	0.433	<.001	S
H7d	CAN -> FS -> DV	The Firm Size will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.185	2.679	<.001	S
H7e	DI -> FS -> DV	The Firm Size will moderate the relationship between the firms Digital Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.105	1.452	<.001	S
H7f	TMI -> FS -> DV	The Firm Size will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.175	2.538	<.001	S
H8a	SA -> FI -> DV	The Firm Industry will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.029	0.465	<.001	S
H8b	KAC -> FI -> DV	The Firm Industry will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.061	1.081	<.001	S
H8c	DDMC -> FI -> DV	The Firm Industry will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	-0.02	-0.288	<.001	**S**
H8d	CAN -> FI -> DV	The Firm Industry will moderate the relationship between the firms Competitive Advantage or Need and their Perception	-0.01	-0.129	<.001	**S**

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
		of Organizational Readiness to Adopt AI/ML Technologies				
H8e	TMI -> FI -> DV	The Firm Industry will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.046	0.796	<.001	S
H8f	DI -> FI -> DV	The Firm Industry will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.026	0.454	<.001	S
H9a	SA -> FA -> DV	The Firm Age will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.149	1.665	<.001	S
H9b	KAC -> FA -> DV	The Firm Age will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.086	1.083	<.001	S
H9c	DDMC -> FA -> DV	The Firm Age will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.055	0.773	<.001	S
H9d	DI -> FA -> DV	The Firm Age will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	-0.01	-0.076	<.001	**S**
H9e	CAN -> FA -> DV	The Firm Age will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.109	0.012	<.001	S
H9f	TMI -> FA -> DV	The Firm Age will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.135	1.584	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H10a	SA -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.06	0.957	<.001	S
H10b	KAC -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.016	0.271	<.001	S
H10c	DDMC -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.043	0.838	<.001	S
H10d	CAN -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.059	0.998	<.001	S
H10e	DI -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.006	0.095	<.001	S
H10f	TMI -> JR -> DV	The respondent's Job Role will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.049	0.842	<.001	S
H11a	SA -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.013	1.734	<.001	S
H11b	KAC -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.109	1.684	<.001	S
H11c	DDMC -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Data Driven Decision Making Capabilities and	-0.01	-0.153	<.001	**S**

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
		their Perception of Organizational Readiness to Adopt AI/ML Technologies				
H11d	CAN -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.131	1.912	<.001	S
H11e	DI -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.093	1.34	<.001	S
H11f	TMI -> EL -> DV	The respondent's Education Level will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.083	1.201	<.001	S
H12a	SA -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.111	1.435	<.001	S
H12b	KAC -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.083	1.197	<.001	S
H12c	DDMC -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.06	0.976	<.001	S
H12d	CA -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.087	1.124	<.001	S
H12e	DI -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Digital Intensity or	0.143	2.065	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
		Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies				
H12f	TMI -> ATE -> DV	The respondent's Advanced Technology Experience will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.078	1.052	<.001	S
H13a	SA -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	1.019	8.96	<.001	S
H13b	KAC -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.759	6.947	<.001	S
H13c	DDMC -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.556	4.818	<.001	S
H13d	CA -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.862	8.052	<.001	S
H13e	DI -> FFM-OPEN -> DV	The respondent's Openness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.479	7.761	<.001	S
		The respondent's Openness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to				

H13f	TMI -> FFM-OPEN -> DV	Adopt AI/ML Technologies	0.88	7.097	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H14a	SA -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	1.013	8.943	<.001	S
H14b	KAC -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.808	7.423	<.001	S
H14c	DDMC -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.597	5.535	<.001	S
H14d	CAN -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.014	0.917	<.001	S
H14e	DI -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.835	8.171	<.001	S
H14f	TMI -> FFM-CONSC -> DV	The respondent's Conscientiousness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.833	7.501	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H15a	SA -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	1.017	9.741	<.001	S
H15b	KAC -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.802	8.055	<.001	S
H15c	DDMC -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.612	6.147	<.001	S
H15d	CAN -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.876	8.579	<.001	S
H15e	DI -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.88	7.883	<.001	S
H15f	TMI -> FFM-EXTRA -> DV	The respondent's Extraversion personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.889	7.927	<.001	S
H16a	SA -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.947	7.947	<.001	S

H16b	KAC -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.717	6.608	<.001	S
H16c	DDMC -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Data Driven Decision	0.511	4.75	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
		Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies				
H16d	CAN -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.826	7.579	<.001	S
H16e	DI -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.547	8.676	<.001	S
H16f	TMI -> FFM-AGREE -> DV	The respondent's Agreeableness personality factor will moderate the relationship between the firms Transformation Management Intensity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.78	6.217	<.001	S
H17a	SA -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Strategic Agility and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.992	8.833	<.001	S
H17b	KAC -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Knowledge Adoption Capacity and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.788	8	<.001	S
H17c	DDMC -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Data Driven Decision Making Capabilities and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.578	5.309	<.001	S
H17d	CAN -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Competitive Advantage or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.909	9.124	<.001	S

Hypotheses	Mnemonic/Path	Description	β	t- statistic	ANOVA/ P-Value	Supported/ Unsupported
H17e	DI -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Digital Intensity or Need and their Perception of Organizational Readiness to Adopt AI/ML Technologies	0.831	7.71	<.001	S
H17f	TMI -> FFM-NEURO -> DV	The respondent's Neuroticism personality factor will moderate the relationship between the firms Transformation	0.875	7.774	<.001	S

Independent Variables

Strategic Agility (SA) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.788, 8.0 and p< .001 is significant and show H1 is supported.

Knowledge Absorption Capacity (KAC) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.607, 10.833 and p< .001 is significant and show H2 is supported.

Data Driven Decision Making (DDMC) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.705, 14.082 and p< .001 s is significant and show H3 is supported.

Competitive Advantage/ Need (CAN) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.579 10.069and p< .001 show H4 is supported.

Digital Intensity (DI) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.588, 10.317 and p< .001 show that H5 is supported.

Transformation Management Intensity (TMI) has a positive impact on a firm's Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.587, 10.276 and $p < .001$ show H6 is supported

Moderating Variables

Firm Size (FS) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.185, 2.451 and $p < .001$ show H7a is supported.

Firm Size (FS) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.147, 2.258 and $p < .001$ show H7b is supported.

Firm Size (FS) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.027, 0.433 and $p < .001$ show H7c is supported.

Firm Size (FS) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.185, 2.679 and $p < .001$ show H7d is supported.

Firm Size (FS) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.105, 1.452 and $p < .001$ show H7e is supported.

Firm Size (FS) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.175, 2.538 and $p < .001$ show H7f is supported.

Firm Industry (FI) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.029, 0.465 and $p < .001$ show H8a is supported.

Firm Industry (FI) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.061, 1.081and $p < .001$ show H8b is supported.

Firm Industry (FI) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of -0.015, -0.288 and $p < .001$ show H8c supports an <u>inverse</u> relationship.

Firm Industry (FI) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of -0.01, -0.129 and $p < .001$ show H8d supports an <u>inverse</u> relationship.

Firm Industry (FI) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.046, 0.796 and $p < .001$ show H8e is supported.

Firm Industry (FI) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.026, 0.454 and $p < .001$ show H8f is supported.

Firm Age (FA) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.149, 1.665 and $p < .001$ show H9a is supported.

Firm Age (FA) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.086, 1.083 and $p < .001$ show H9b is supported.

Firm Age (FA) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.055, 0.773 and $p < .001$ show H9c is supported.

Firm Age (FA) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of -0.007, -0.076 and $p < .001$ show H9d supports an <u>inverse</u> relationship.

Firm Age (FA) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.109, 0.012 and $p < .001$ show H9e is supported.

Firm Age (FA) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.135, 1.584, and $p < .001$ show H9f is supported.

Job Role (JR) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.06, 0.957 and $p < .001$ show H10a is supported.

Job Role (JR) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.016, 0.271 and $p < .001$ show H10b is supported.

Job Role (JR) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.043, 0.838 and $p < .001$ show H10c is supported.

Job Role (JR) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.059, 0.998 and $p < .001$ show H10d is supported.

Job Role (JR) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.006, 0.095 and $p < .001$ show H10e is supported.

Job Role (JR) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.049, 0.842 and $p < .001$ show H10f is supported.

Education Level (EL) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.013, 1.734 and $p < .001$ show H11a is supported.

Education Level (EL) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.109, 1.684 and $p < .001$ show H11b is supported.

Education Level (EL) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of -0.01, -0.153 and $p < .001$ show H11c supports an <u>inverse</u> relationship.

Education Level (EL) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.131, 1.912 and $p < .001$ show H11d is supported.

Education Level (EL) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.093, 1.34 and $p < .001$ show H11e is supported.

Education Level (EL) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.083, 1.201 and $p < .001$ show H11f is supported

Advanced Technology Experience (ATE) moderates the relationship between the firm's Strategic Agility (SA) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.111, 1.435 and $p < .001$ show H12a is supported.

Advanced Technology Experience (ATE) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.083, 1.197 and $p < .001$ show H12b is supported.

Advanced Technology Experience (ATE) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.06, 0.976 and $p < .001$ show H12c is supported.

Advanced Technology Experience (ATE) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.087, 1.124 and $p < .001$ show H12d is supported.

Advanced Technology Experience (ATE) moderates the relationship between the firm's Digital Intensity (DI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.143, 2.065 and $p < .001$ show H12e is supported.

Advanced Technology Experience (ATE) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception Of Readiness to Adopt AI and ML technologies (DV). The β value, t-statistic, and p-values of 0.078, 1.052 and $p < .001$ show H12f is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Strategic Agility (SA) and their Perception of Organizational Readiness to

Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 1.019, 8.96 and $p < .001$ show H13a is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.759, 6.947 and $p < .001$ show H13b is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.556, 4.818 and $p < .001$ show H13c is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.862, 8.052 and $p < .001$ show H13d is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Digital Intensity (DI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.479, 7.761 and $p < .001$ show H13e is supported.

The respondent's Openness personality factor (FFM – OPEN) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.88, 7.097 and $p < .001$ show H13f is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Strategic Agility (SA) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 1.013, 8.943 and $p < .001$ show H14a is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Knowledge Absorption Capacity (KAC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.808, 7.423 and $p < .001$ show H14b is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Data Driven Decision Making (DDMC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.597, 5.535 and $p < .001$ show H14c is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Competitive Advantage/ Need (CAN) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.014, 0.917 and $p < .001$ show H14d is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Digital Intensity (DI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.835, 8.171 and $p < .001$ show H14e is supported.

The respondent’s Conscientiousness personality factor (FFM – CONSC) moderates the relationship between the firm’s Transformation Management Intensity (TMI) and their

Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.833, 7.501 and $p < .001$ show H14f is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Strategic Agility (SA) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 1.017, 9.741 and $p < .001$ show H15a is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.802, 8.055 and $p < .001$ show H15b is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.612, 6.147 and $p < .001$ show H15c is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.876, 8.579 and $p < .001$ show H15d is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Digital Intensity (DI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.88, 7.883 and $p < .001$ show H15e is supported.

The respondent's Extraversion personality factor (FFM – EXTRA) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.889, 7.927 and $p < .001$ show H15f is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Strategic Agility (SA) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.947, 7.947 and $p < .001$ show H16a is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.717, 6.608 and $p < .001$ show H16b is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.511, 4.75 and $p < .001$ show H16c is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.826, 7.579 and $p < .001$ show H16d is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Digital Intensity (DI) and their Perception of Organizational

Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.547, 8.676 and p< .001 show H16e is supported.

The respondent's Agreeableness personality factor (FFM – AGREE) moderates the relationship between the firm's Transformation Management Intensity (TMI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.78, 6.217 and p< .001 show H16f is supported.

The respondent's Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm's Strategic Agility (SA) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.992, 8.833 and p< .001 show H17a is supported.

The respondent's Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm's Knowledge Absorption Capacity (KAC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.788, 8.0 and p< .001 show H17b is supported.

The respondent's Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm's Data Driven Decision Making (DDMC) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.578, 5.309 and p< .001 show H17c is supported.

The respondent's Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm's Competitive Advantage/ Need (CAN) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.909, 9.124 and p< .001 show H17d is supported.

The respondent’s Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm’s Digital Intensity (DI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.831, 7.71 and $p < .001$ show H17e is supported.

The respondent’s Neuroticism personality factor (FFM – NEURO) moderates the relationship between the firm’s Transformation Management Intensity (TMI) and their Perception of Organizational Readiness to Adopt AI/ML Technologies (DV). The β value, t-statistic, and p-values of 0.875, 7.774 and $p < .001$ show H17f is supported.

DISCUSSION AND IMPLICATIONS

Discussion

In order for US business consumers to continue leveraging these technological advancements, we must have a baseline understanding of the motivations for firms to perceive their readiness in adopting advanced technologies. This study focused on using empirical survey research and statistical analysis methods to answer the question what the factors are contributing to the perception of organizational readiness in adopting Artificial Intelligence and Machine Learning technologies for US firms**.** The fundamental purpose of this study is to better understand at a more granular level firm readiness and to identify the drivers that will influence the adoption of aforementioned advanced technology constructs for American business consumers.

The conceptual model in this study is a new model that aimed to identify specific constructs not necessarily present in some of the more well-known technology adoption models and theories. The study findings provide positive statistical support for sixty eight of the seventy two relationships identified in the model that hypothesized positive impacts on firm perception of organizational readiness to adopt AI and ML technologies. The results of the analysis show that with the exception of four inverse moderating relationships, firm perception of readiness to adopt AI and ML technologies is positively correlated with firm-level factors of Strategic Agility, Knowledge Absorption Capacity, Data Driven Decision Making Capabilities, Competitive Advantage/ Need, Digital Intensity and Transformation Management Intensity.

Hypothesis Analysis

The research tested seventy two hypothesis to identify the relationship and impact of six firm-level constructs on the dependent variable as identified in the conceptual model. The findings were surprising in that all but four of the identified hypotheses showed positive support. The inversely supported hypotheses were moderating hypotheses and identified that Firm Industry had an inverse impact on the relationship between Data Driven Decision Making and Firm Perception of Readiness to Adopt AI and ML. Firm Industry also had an inverse moderating effect on the relationship between Competitive Advantage and Firm Perception of Readiness to Adopt AI and ML. Firm Age also proved to have an inverse moderating effect on the relationship between Competitive Advantage and Firm Perception of Readiness to Adopt AI and ML. Lastly, Education Level had an inverse moderating effect on the relationship between Data Driven Decision Making and Firm Perception of Readiness to Adopt AI and ML.

The research surmises that the inverse moderating effect shown in four of the hypotheses tested could be due to response cross loadings or calculation errors. Additional testing will be needed for more detailed analysis and conclusions.

Implications

Theoretical Implications

This study was conducted to contribute to and extend existing literature on technology adoption by employing applied research and deep industry expertise and experiences. This study aimed at providing a baseline model and analysis for a future framework to help firms better understand and measure their readiness for advanced technology adoption.

The theory of Organizational Readiness for change is defined as organizational level construct that measures an organization's shared resolve to implement or effect a change (change commitment) and their shared ability to implement change (change efficacy) (Weiner B. J., 2009). Additionally, when people of an organization desire to make a change and are confident that they can make it, organizational readiness is likely to be at its maximum. The theory of Organizational Readiness is also defined as a psychological construct and is said to be a leading indicator for successful implementation of complex changes in healthcare IT projects. (Amatayakul, 2005) and (Weiner B. J., 2009)

One of the main obstacles to the successful adoption of AI is reported to be the shortage of expertise and abilities in data science among current employees (Ipsos Belgium, 2020). This study purports to extend this literature by adding the organizational level construct of firm readiness as another critical success factor for successful AI adoption practices.

Practical Implications

As early as 2022, we have seen a steady disruption in the consulting services firm revenues due to the impact and use of AI in performing data processing and analysis workflows (Kaplan, Soren, 2023). Companies are utilizing internal resources undergirded by Generative AI in addition to smaller, more focused strategy organizations to help improve their operations and derive additional insights from their data assets.

This study was aimed at developing a modernized conceptual and theoretical approach to interrogate existing technology adoption literature for relevance measuring advanced technologies such as AI and ML. Additionally, this study can be used as a baseline conceptual model for development of an adoption framework to help firms better understand and measure their readiness for advanced technology adoption. The ability to develop new measurement frameworks and monetize them as a service could be an extremely lucrative business opportunity for the near future.

Limitations

This study and related analysis relied on the self-reported results of the survey respondents and the willingness of the participants to share open and honest feedback. One factor that could have a direct impact on the survey data gathering, analysis and readout could be the respondents experience level with the aforementioned advanced technology platforms, tools, and software. Another factor that could limit the study accuracy is the size of the company or firm of the respondent. More often than not, larger firms have shown themselves to have more experienced and engaged professionals, particularly with respect to new and emerging technologies.

This study began with a one hundred and thirty three questionnaire. Several rounds of factor analysis revealed a remarkably high degree of correlations and cross-loadings. In order to establish discriminant and convergent validity, the survey instrument used in the full study was reduced to a questionnaire that contained less than 10% of the original questionnaire. Additional research should be completed to further validate the constructs and survey instrument identified and utilized in this study.

The majority of the constructs measured in this study were developed from extending existing literature and from the professional experiences of the researcher. This could in effect introduce unintentional biases such as affinity or conformity bias. Future studies are recommended to minimize this potential.

The personality of the respondent could have different moderating effects, depending upon the mood and mind state of the respondent at the time of data collection. In addition, more research is needed to determine how firm level factors are impacted by moderators at the individual level.

There is an active debate in psychology and academic research on the importance and value of significance and alpha levels as indicators of statistical significance (Aidley, 2019). Guidance provided by the American Statistical Association shares six principles on the statistical significance of p-values. The most impactful observation that could have the most direct impact on this and future studies that utilize p-values as a measure of evidence states that p-values alone are not good measures of the strength of a hypothesis. In the context of this study, EFA, p-values, along with t-statistics and beta values were used together to demonstrate the strength of tested hypothesis.

Future Studies

This study attempted to create a more contemporary theoretical and conceptual framework as an extension of existing theories for analyzing the literature on technology adoption and determining the firm-level perception of readiness to adopt advanced technologies like AI and ML. The researchers aim was to structure this study to be used as a baseline conceptual model for development of an adoption framework to help firms better understand and measure their readiness for advanced technology adoption.

A European enterprise survey on the use of technologies based on AI conducted by Ipsos and the International Centre for Innovation, Technology and Education presented a list of internal obstacles to the adoption of AI firms reported during the survey. The cost of adoption, difficulty of hiring new skilled staff and the lack of skills of existing staff were shown to be the most relevant (Ipsos Belgium, 2020). Future studies to extend this research could include analysis of the theory of firm readiness to adopt AI to determine if it would also be listed as one of the most relevant barriers.

CONCLUSIONS

This study was aimed at developing a modernized conceptual and theoretical approach to interrogate existing technology adoption literature for relevance measuring advanced technologies such as AI and ML. Additionally, this study can be used as a baseline conceptual model for development of an adoption framework to help firms better understand and measure their readiness for advanced technology adoption.

Utilizing CFA, EFA and Regression Analysis, the researcher concluded that all constructs were proven to have a positive or inverse relationship with the firm’s perception of readiness to adopt AI and ML technologies. As today’s firms scramble to prepare for the adoption of AI technologies like Generative AI and other large language models, having a solid understanding of the drivers for AI adoption could present an opportunity for the monetization of this research for financial gain.

LIST OF REFERENCES

Aggarwal, N. (2021). The Norms of Algorithmic Credit Scoring. *The Cambridge Law Journal*, 42-73.

Agresti, A. (2018). *Statistical Methods for the Social Sciences (5th Edition).* Pearson.

Aidley, D. (2019). *Introducing Quantitative Methods - A Practical Guide.* MacMillan international higher education.

Ajay Agrawal, J. G. (2019). The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. In U. o. Press, *The Economics of Artificial Intelligence* (pp. 115 - 148). Chicago: University of Chicago Press.

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Process*, 179-211.

Alexandros Bousdekis, k. L. (2021). A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. *MDPI*. Retrieved from https://doi.org/10.3390/electronics10070828

Amatayakul, M. (2005). EHR? Assess readiness first: there's no denying interest in electronic health records is increasing. *Healthcare Financial Management (Vol. 59, Issue 5)*, 112+.

Ansoff, I. H. (1957). Strategies for Diversification. *Harvard Business Review*, 85+.

Babbie, E. (2016). The Ethics and Politics of Social Research. In E. Babbie, *The Practice of Social Research* (pp. 62 - 85). Cengage Learning.

Bassellier, G., Reich, B. H., & Benbasat, I. (2000). *Information Technology Competence of Business Managers: A definition and Research Model.*

Beer, M., & Nohria, N. (2016, May-June 2000). Cracking the Code of. *Harvard Business Review*, pp. 15-23.

Bilal Alhayani, H. J. (2021). Effectiveness of artificial intelligence techniques against cyber security risks apply of IT industry. *Materials Today*.

Brian K. Boyd, E. R.-E. (1998). Research Notes and Communications: A Measurement Model of Strategic Planning. *Strategic Management Journal, 19*, 181 - 192.

Brown, S. L., & Eisenhardt, K. (1997). The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations. *Administrative Science Quarterly*, 1-34.

Burns, E. (2021, August). *http://searchenterpriseai.com* . Retrieved from http://searchdesign.ai

Burns, E., & Laskowski, N. . (2018). Artificial Intelligence in AI in IT Tools Promises Better, Faster and Stronger Ops. *TechTarget*.

Caliendo, M., & Kopeinig, S. (2008). SOME PRACTICAL GUIDANCE FOR THE IMPLEMENTATION OF PROPENSITY SCORE MATCHING. *Journal of Economic Surveys*, 199-215.

Cameron, E., & Green, M. (2015). *Making Sense of Change Management.* Kogan Page.

Chiao, V. (2019). Fairness, accountability, and transparency: notes on algorithmic decision-making in criminal justice. *International Journal of Law in Context*, 126-139.

Contributors, C. W. (2024). *https://www.crystalknows.com/big-five*. Retrieved from Crystal : https://www.crystalknows.com/big-five/conscientiousness

Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative and Mixed Methods Approaches.* Sage Publications.

Davenport, T. H. (2012). How "Big Data" is Different. *MITSloan Management Review*, 22+.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 982-1003. doi: https://doi.org/10.1287/mnsc.35.8.982

Dawes, R. M. (1979). The Robust Beauty of Improper Linear Modelsin Decision Making. *American Psychologist, 34*(7), 571-582. Retrieved from https://doi.org/10.1037/0003-066x.34.7.571

Digman, J. M. (1990). Personality Structure: Emergence Of The Five-Factor Model. *Annual Review of Psychology*, pp. 417-440.

Dwivedi, Y. K., Wade, M. R., & Schneberger, S. L. (n.d.). *Information Systems Theory: Explaining and Predicting Our Digital Society, Vol.1* (Vol. Integrated Series in Information Systems 28). Springer.

Eden, D. (1992). Leadership and expectations: Pygmalion effects and other self-fulfilling prophecies in organizations. *The Leadership Quarterly*, 271-305.

Eveland, J., & Tornatzky, L. (1990). Technological Innovation as a Process. In *The Processes of Technological Innovation* (pp. 27-50). Lexington Books.

Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2013). *Embracing Digital Technology: A new Strategic Imperative.* MIT Sloan Management Review .

George Westerman, D. B. (2012, November 20). *RESEARCH HIGHLIGHT: The Advantages of Digital Maturity.* Retrieved from MIT Sloan Management Review: https://sloanreview.mit.edu/article/the-advantages-of-digital-maturity/

Gold, A. H., Malhotra, A., & Segars, A. H. (2001, January 09). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information Systems*, 185-214. doi: https://doi.org/10.1080/07421222.2001.11045669

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarastedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* Sage Publications.

Hartley Rogers, J. (1957). Theory of recursive functions and effective computability. Volume 1. *The Journal of Symbolic Logic, 1*, 1-15.

Hastie, R., & Dawes, R. M. (2009). *Rational choice in an uncertain world: The psychology of judgment and decision making.* (2nd, Ed.) Sage Publications.

Hirsbrunner, S. F. (2021). *A New Science for Future.* Transcript Verlag.

Iain M. Cockburn, R. H. (2019). The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. In J. G. A. Agrawal, *The Economics of Artificial Intelligence* (pp. 115-148). Chicago: University of Chicago Press.

Intelligence, I. (2023). *Resiliency Rules Report.* Insider Intelligence and eMarketer. Retrieved from https://www.insiderintelligence.com/

Ipsos Belgium. (2020). *European enterprise survey on the use of technologies based on artificial intelligence.* Brussels: Ipsos Belgium.

Ivy Liu, A. A. (2005). The Analysis of Ordered Categorical Data: An Overview and a Survey of Recent Developments. *Sociedad de Estad,{stica e [.,vestigaci6n Operativa*, 1-73.

Jason Dana, R. T. (2006). In Defense of Clinical Judgment...and Mechanical Prediction. *Journal of Behavioral Decision Making, 19*, 413-428. doi:10.1002/bdm.537

Joubert, S. (2019, August 22). *Data-Driven Decision Making: A Primer for Beginners.* Retrieved from Northeastern University Graduate Programs: https://graduate.northeastern.edu/resources/data-driven-decision- making/#:~:text=Data %2Ddriven%20decision%20making%20(or,aims%20to%20be%20 data%2Ddriven.)

Kambatla, K., Kollias, G., Kumar, V., & Grama, A. (2014). Trends in big data analytics. *Journal of Parallel and Distributed Computing*, 74-77.

Kane, G. C., Palmer, D., Phillips, A. N., Kiron, D., & Buckley, N. (2016). *Aligning the Organization for Its Digital Future.* MITSloan Management Review.

Kapferer, J. N. (2008). *Kapferer, J. N. (2008). The New Strategic Brand Management: Creating and Sustaining Brand Equity Long Term.* . Kogan Page Publishers.

Kaplan, Soren. (2023, March 31). *How A.I. Will Disrupt the Consulting Industry - Here's what consultants can do*. Retrieved from How A.I. Will Disrupt the Consulting Industry - Here's what consultants can do: https://www.inc.com/soren-kaplan/artificial-intelligence-ai-will-disrupt-consulting-industry.html

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2010, December 21). *Big Data, Analytics and the Path From Insights to Value.* Retrieved from MIT Sloan Management Review : https://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/

Leonidas Aristodemou, F. T. (2018). The state-of-the-art on Intellectual Property Analytics (IPA): A literature review on artificial intelligence, machine learning and deep learning methods for analyzing intellectual property (IP) data. *Elsevier*, 37-51.

Lim, A. G. (2023, July 10). *Big Five Personality Traits: The 5-Factor Model Of Personality.* Retrieved from Simply Psychology: https://www.simplypsychology.org/big-five-personality.html

Mandinach, E. B., Honey, M., & Light, D. (2006). A Theoretical Framework for Data-Driven Decision Making. *AERA.* San Francisco.

Mani, C. (2020, October 20). *Forbes Technology Council.* Retrieved from How Is Big Data Analytics Using Machine Learning?: https://www.forbes.com/sites/forbestechcouncil/2020/10/20/how-is-big-data-analytics-using-machine-learning/?sh=42a92bb071d2

MARJANI, M. (2017). Big IoT Data Analytics: Architecture,. *IEEE Access*, 5247 - 5261.

Matt, C., Hess, T., & Benlian, A. (2015). Digital Transformation Strategies. *Business & Information Systems Engineering*, 339-343.

Ming-Hui Huang, R. R. (2019). The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). *California Management Review*, pp. 43-65.

Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *Management Information Systems (MIS) Quarterly*, 425-478.

Naik, K. (2019, November 26). *AI VS ML VS DL VS Data Science*. Retrieved from YouTube: https://www.youtube.com/watch?v=k2P_pHQDlp0

Neha Soni, E. K. (2019, May 3). Impact of Artificial Intelligence on Businesses: from Research, Innovation, Market Deployment to Future Shifts in Business Models. *Journal of Business Research - Elsevier*, 1-38.

Newlands, G. (2021, January - June). Lifting the curtain: Strategic visibility of human labour in AI-as-a-Service . *Big Data & Society*, pp. 1-14.

Noack, P. (2021, December 12). *The National News*. Retrieved from https://www.thenationalnews.com/opinion/comment/the-fifth-industrial-revolution-where-mind-meets-machine-1.1061280: https://www.thenationalnews.com/opinion/comment/the-fifth-industrial-revolution-where-mind-meets-machine-1.1061280

Nyabaga, R. M., & Wepukhulu, J. M. (2020). Effect of Firm Characteristics on Financial Performance of. *International Journal of Economics and Financial*, 255-262.

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *The Electronic Journal Information Systems Evaluation, 14*(1), 110-121. Retrieved from https://academic-publishing.org/index.php/ejise

Olson, K., Smyth, J. D., & Ganshert, A. (2019). The Effects of Respondent and Question Characteristics on Respondent Answering Behaviors in Telephone Interviews. *Journal of Survey Statistics and Methodology* , Volume 7, 275–308.

Penrose, E. (1959). *The Theory of the Growth of the Firm - 4th Edition.* New York: Oxford University Press.

Petersson, D. (2021, June 28). *AI vs. machine learning vs. deep learning: Key differences*. Retrieved from https://searchenterpriseai.techtarget.com/tip/AI-vs-machine-learning-vs-deep-learning-Key- differences? _gl=1*igm83h*_ga*OTMzOTY2MDg1LjE2MzkzMDA0OTg.*_ga_TQKE4 GS5P9*MTYzOTMwMDQ5Ny4xLjEuMTYzOTMwMDY0NS4w&_ga=2.71863889.37 6462134.1639300498-933966085.163930049: https://searchenterpriseai.techtarget.com/tip/AI-vs-machine-learning-vs-deep-learning-Key- differences? _gl=1*igm83h*_ga*OTMzOTY2MDg1LjE2MzkzMDA0OTg.*_ga_TQKE4 GS5P9*MTYzOTMwMDQ5Ny4xLjEuMTYzOTMwMDY0NS4w&_ga=2.71863889.37 6462134.1639300498-933966085.163930049

Pipino, L. L., Lee, Y. W., & Yang, R. Y. (2002). Data Quality Assessment. *Communications of the ACM*, 211+.

Pophal, L. G. (2019, August 19). *HR Daily Advisor.* Retrieved from HR Daily Advisor: https://hrdailyadvisor.blr.com/2019/08/19/the-3-as-of-business- agility/#:~:text=As %20part%20of%20the%20discussion,comes%20to%20the%20three% 20A's.

Porter, M. E. (1980). *Competitive Strategy - Techniques for Analyzing Industries and Competitors* . New York, New York: Simon & Schuster, Inc. .

Rahm, E., & Do, H. H. (2000). *Data Cleaning: Problems and Current Approaches.* Bulletin of the IEEE Computer Society Technical Committee on Data Engineering.

Roccas, S., Sagiv, L., Schwartz, S. H., & Kanafo, A. (2002). The big five personality factors and personal values. *Personality and Social Psychology, 28*(6), 789-801.

Rogers, E. (1995). *Diffusion of Innovations.* New York: The Free Press.

Sarah Giest, A. S. (2020). For good measure': data gaps in a big data world. *Policy Sciences*, 559-569.

School, R. B. (2020, September 8). *https://insights.regenesys.net/the-fifth-industrial-revolution-5ir/*. Retrieved from RegInsights: https://insights.regenesys.net/the-fifth-industrial-revolution-5ir/

Senge, P. M. (2006). *The Fifth Discipline: The Art & Practice of the Learning Organization.* New York, New York: Crown Business.

SpriggHR. (2021, November 22). *What is Strategic Agility?* Retrieved from SpriggHR: https://sprigghr.com/blog/leaders/what-is-strategic- agility/#:~:text=Strategic%20agility %20refers%20to%20a,to%20maintain%20strong%20 strategic%20agility.

Srivastava, S. C., Chandra, S., & Shirish, A. (2015). Technostress creators and job outcomes: theorizing the moderating influence of personality traits. *Information Systems Journal*, 355-401.

Staff, C. (2024, April 1). *Coursera*. Retrieved from Coursera: https://www.coursera.org/articles/ai-vs-deep-learning-vs-machine-learning-beginners-guide

Svensson, R. B., & Taghavianfar, M. (2020). Toward Becoming a Data-Driven Organization: Challenges and Benefits. *Research Challenges in Information Science, 14th International Conference, RCIS 2020. LNBIP 385*, pp. 4-19. Limassol, Cyprus : RCIS. doi:https://link.springer.com/chapter/10.1007/978-3-030-50316-1_1

Teece, D. J. (2007). Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strategic Management Journal*, 1319-1350.

Tim Barnett, A. W. (2015). Five-factormodelpersonalitytraitsaspredictors ofperceivedandactualusageoftechnology. *European Journal of Information Systems, 24*(4), 374-390. doi:https://www.tandfonline.com/action/showCitFormats?doi=10.1057/ejis.2014.10

Today, P. (2024). Retrieved from Psychology Today: https://www.psychologytoday.com/us/basics/

Venkatehs, V. (2022). Adoption and use of AI tools: a research agenda grounded. *Annals of Operations Research*, 641-652. Retrieved from https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unifed View. *MIS Quarterly*, 425-478.

Weber, Y., & Tarba, S. Y. (2014). Strategic Agility: A State-of-The-Art introduction to the special section on strategic agility. *California Management Review, 56*(3).

Weiner, B. J. (2009, October). A theory of organizational readiness for change. *Implementation Science*. Retrieved from http://www.implementationscience.com/content/4/1/67

Weiner, B. J. (2009). A Theory of Organizational Readiness for Change. *Implementation Science*, 4:67.

Wenjuan Fan, J. L. (2018, March 19). Investigating the impacting factors for the healthcare. *Springer Science + Business Media (Part of Springer Nature 2018)*, pp. 567-592.

Westerman, G. C. (2011). *Digital Transformation: A roadmap for billion-dollar organizations. MIT Center for digital business and Capgemini consulting, .* MIT Center for digital business and Capgemini Consulting.

Westerman, G., & McAfee, A. (2012). *The Digital Advantage: How Digital Leaders Outperform Their Peers in Every Industry.* MIT Center for Digital Business.

Wikipedia. (n.d.). *https://en.wikipedia.org/wiki/Artificial_intelligence*. Retrieved from Wikipedia.

Will Markow, S. B. (2017). *The Quant Crunch - How the Demand For Data Science Skills Is Disrupting the Job Market.* Burning Glass Technologies.

Worley, C. G., Williams, T., & Lawler III, E. E. (2014). The Agility Factor: Building Adaptable Organizations for Superior Performance. Jossey-Bass (Wiley).

Wroblewski, J. B. (2018, June). Digitization and Firm Performance: Are Digitally Mature Firms Outperforming Their Peers? Peer-Reviewed Masters Thesis. (D. H.--.-L. Management, Ed.)

Yaakov Weber, S. Y. (2014). Strategic Agility: A State of the Art Introduction to the Special Section on Strategic Agility. California Management Review, Vol. 56, No. 3 .

Yukl, G. (2012). Leadership in Organizations. Pearson.

Zhang, L.-f. (2006). Thinking styles and the big five personality traits revisited. Elsevier, 1177- 1187.

APPENDICES

Table 6: Defense Proposal Feedback and Researcher Response

Defense Proposal Feedback	Researcher Response
Am I testing for employee resistance to AI and ML?	Not for this study. This is an important aspect, but not for this dependent variable with regard to my planned respondents. This is definitely a factor to be considered for my future research on this topic.
What Types of AI/ ML am I targeting for this research? You should consider focusing on AI types: AGI, ANI and ASI or ML types: Simple to Predictive, Deep Learning or Prescriptive.	For this study I am focusing on the organization readiness regardless of the type of AI or ML technology. This is definitely an important distinction given the proliferation of GenAI and Cloud based ML solutions. I will consider this for my future research topics.

VITA

KEVIN DWAYNE BROWN

Born in Cleveland, Ohio

1987-1992	BBA Management Savannah State University Savannah, Georgia
1994-1996	BBA Accounting Georgia State University Atlanta, Georgia
2009-2011	MBA Finance University of Dallas Irving, Texas
2008	The Open Group Architecture (TOGAF) Enterprise Architecture 8 Certification
2015	FINRA Series 6: Investment Company and Variable Contracts Products Representative
2019	Microsoft Certified: Dynamics 365 Fundamentals Certification
2019	Microsoft 365 Certified: Fundamental
2019	Microsoft Certified:

	Azure Fundamentals
2020	Microsoft Open Hack: IoT Gateway Operations
2021	Data Science For All, Data Science Fellow (DS4A) Correlation One New York, New York
2021	Data Science For All/ Empowerment 2.0 Honors Certification
2021	Social/ Behavioral Human Research Certification
2022	Data Science For All, Data Science Fellow (DS4A), Data Engineering – Inaugural Fellow Correlation One New York, New York
2022	Social and Behavioral Responsible Conduct of Research Course Certification
2021-2024	Doctoral Candidate, Doctorate in Business Administration (DBA) Florida International University Miami, Florida

2023	Artificial Intelligence and Machine Learning Postdoc Certification - Foundations in AI, Machine Learning, Deep Learning, in Business Applications University of Texas/Great Learnings Austin, Texas
1996-1998	Finance Management Associate (MAPS) NationsBank/ Bank of America Charlotte, North Carolina
1998-2007	Consultant, I/T Architect, Senior I/T Architect IBM Dallas, Texas
2008-2012	Associate Director American General (AIG) Dallas, Texas
2012-2012	Customer Program Manager HP Dallas, Texas
2012-2014	Senior Program Manager Think Finance Fort Worth, Texas
2014-2014	Senior Solutions Manager MoneyGram International Frisco, Texas
2014-2015	Principal Systems Program Manager and Product Owner AT&T Plano, Texas
2015 – Current	Senior Data Solutions Architect, Senior Cloud Architect, Senior Technology Strategist, Chief Customer Digital Officer Microsoft Irving, Texas

PUBLICATIONS AND PRESENTATIONS

2021	Correlation One, Data Science For All, Research Thesis and Findings, New York, New York