5-2-2021

Industry 4.0 Technology: A Cross-Industry View of Adoption, Usage and COVID-19 Effects

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doi: https://doi.org/10.57709/24163480

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Industry 4.0 Technology: A Cross-Industry View of Adoption, Usage, and Covid-19 Effects

by

Dawn Gatling Gregory

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Executive Doctorate in Business

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2021

ACCEPTANCE

This dissertation was prepared under the direction of the *DAWN GATLING GREGORY* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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DEDICATION

I dedicate my dissertation to my husband, Sam, whose unwavering sacrifice is highly revered. Your endless love and encouragement brought me peace and calm. Your support served as my foundation throughout this journey. I am forever grateful and blessed to have you by my side.

I also dedicate this work to my sons, Daniel and Samuel. Thank you for bringing laughter and joy into my life. Daniel, thank you for your patience and understanding when this pursuit stole me away from you so many nights. Please know, I did this for you, my sons. May my achievement inspire you, as you have inspired me.

My achievement is also dedicated to the many foster children I have been blessed to care for and those yet to come. Go confidently in the direction of your dreams, and you will achieve success. This is especially for Karayah, my dear daughter; you are forever in my heart.

I further dedicate this paper to my parents, Donald Gatling and Patricia Edgerton, who have helped me in all things, big and small. I thank you for instilling in me the love of learning. I thank my mother for provoking me to set high bars, and I am eternally thankful for my father's support to hurdle over each one.

I am fortunate for the encouragement and prayers of so many friends and family: Pamela Victim, Anitra Moreland Lewis, Conredge Lewis, Erica Warren, Andrae Warren, Tinuke Solomon, Yolonda Bell, Johnny Bell, Jean Jackson, Al Jackson, Geraurd Moreland, Sherndina Moreland, Lucy Smith, Sheila Alston, and Derrick Grissom.

In loving memory of my sister Tara Jackson, cousin Darrel Smith and godmother Deborah Pearmon, may I be a beacon of love for others as you each have been to me.

ACKNOWLEDGEMENTS

First, I thank my Almighty God and Lord and Savior, Jesus Christ, for blessing me beyond anything I could think or ask.

I am grateful to my committee members, who were more than generous with their expertise and precious time. A special thanks to Dr. Denish Shah, my committee chairman, for his countless hours of reflecting, reading, encouraging, and most of all, patience throughout the entire process. Thank you, Dr. Donthu and Dr. Cheng, for agreeing to serve on my committee and your invaluable feedback.

I would like to acknowledge and thank Dr. Mandy Swygart-Hobaugh and Jeremy Walker for their insights and responsive support during my countless hours of analysis. Special thanks go to Dr. Lars Mathiassen, Dr. Louis Grabowski, Jorge Vallejos, Stephanie Black, and other administrators and staff at the J. Mack Robinson School of Business for their ongoing assistance and attentiveness.

I must acknowledge Audria King, Ossie Gaines, III., Tina Wilson, and Jonna Blount. Their excitement and willingness to be supportive teammates and to provide feedback, made the completion of this research an enjoyable experience. Audria, I will never forget the many late-night calls, encouraging messages, and steadfast accountability. I owe you a massive debt of gratitude, and I am blessed to call you a friend.

Finally, I would like to thank my cohort, professors, and graduate assistants who enriched my academic career. I exit this program with lifetime colleagues and friends. Thank you all.

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LIST OF ABBREVIATIONS

List of Operationalized Terms Abbreviations

3D	3D Printing
4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
AR/VR/MR	Augmented Reality/Virtual Reality/Mixed Reality
AUTO	Autonomous/Automation Technology
BIG	Big Data
BLOCK	Blockchain
CC	Cloud computing
COVID-19	Coronavirus 2019
CX	Customer Experience
CYBER	Cybersecurity
I4.0	Industry 4.0
IoT	Internet of Things
NANO	Nanotechnology
TAM	Technology Acceptance Model
TOE	Technological–Organizational–Environmental Framework

ABSTRACT

Industry 4.0 Technology: A Cross-Industry View of Adoption, Usage, and Covid-19 Effects

by

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August 2021

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Major Academic Unit: Executive Doctorate in Business Administration

Industry 4.0 technology (I4.0) is inescapable. It transforms the way businesses and customers interact and revolutionizes how organizations produce goods and services (SAP Insights, 2020). It requires a level of agility that many organizations do not possess. Defending against disruptive business models is no longer enough. Organizations must be agile to optimize assets and resources in response to adversity. In March 2020, the coronavirus (COVID-19) pandemic ushered a devastating blow to the U.S. economy and job market with pervasive shocks that continue to be a business threat. In response, many organizations are accelerating automation, digitization, and communication capabilities to close the gap and connect with customers.

This dissertation examined the cross-industry adoption of the nine most common Industry 4.0 technologies: big data, artificial intelligence, cloud computing, the internet of things, cybersecurity, 3-D printing, autonomous technology, augmented reality, and blockchain. This descriptive study explored factors of I4.0 adoption across industries and organizational sizes during a national pandemic.

The study sought to reveal “what” factors contributed to the adoption of Industry 4.0, “what” industry patterns exist, “what” effect COVID-19 had on these concepts. A quantitative method was used to examine the relationship between factors. An online survey was administered to a Qualtrics panel of 520 business owners and executives to capture perceptions, knowledge, and insights. A binary logistic regression analysis was performed.

The results of this study inform a cross-industry framework of I4.0 technology adoption, which includes contributing factors. The findings also showed the influence and impact of COVID-19 on the adoption of Industry 4.0 technologies.

INDEX WORDS: Industry 4.0, I4.0, I40, Technology Adoption, Industry Adoption, United States, COVID-19, Artificial Intelligence, AI, Blockchain, Cloud Computing, Nanotechnology, 3D Printing, Cybersecurity, Augmented Reality, Mixed Reality, Virtual Reality, AR, MR, VR, Big Data, Autonomous Technology, Internet-of Things, IoT, Cyber-Physical Systems, CPS

I INTRODUCTION

Organizations in the United States face surmounting business challenges, ranging from global competition, rapid technological advancements, and higher customer expectations. The environmental pressures that stem from dynamic transformations, real-time demands, and the influx of data everywhere place organizational forces that must be balanced. Leaders often turn to technological advances for help to adapt, compete, or survive. The coronavirus global pandemic shocked the world in early 2020 and hit United States businesses hard as the country struggled to impede the spread of COVID-19. Faced with the double impact on economics and health well-being, organizational leaders must respond to regulatory impositions, social distancing, and in some cases, operational restrictions and supply chain constraints.

Many organizations made swift shifts to remote, contactless, frictionless work environments and customer experiences. The acceleration of Industry 4.0 (digital) technologies has commenced. Organizations are forced to make strategic decisions about Industry 4.0 adoption, requiring leaders to navigate uncertainty and unfamiliarity. This research study seeks to understand the perceptions, behaviors, and conditions around this phenomenon.

This research study's introduction provides further insight into the background, research objectives, study rationale, method, and structure for the remaining paper.

I.1 Background

Industry 4.0 technology and the digital world it creates are inescapable. It transforms the way organizations worldwide do business and produce goods or services (SAP Insights, 2020, p. 1). I4.0 integrates software, hardware, at times, biological applications (D. Perez Perales, 2018). Industry 4.0 (I4.0) power harnesses automation, digitization, and communication (Kelly, 2019) to drive efficiency, speed, and performance. Industry 4.0 is enabled by innovation, research, and education, while its execution is motivated by competition. I4.0 transforms the nature of production and consumption and reshapes the competitive landscape toward shared success (Lambin, 2014). Now much more than a concept or a marketing moniker, Industry 4.0 is the business gold standard for the digital network economy.

Organizations face a daily barrage of industry and economic stressors that threaten their success and performance. The fast-paced emergence of new technologies exacerbates the issue. Traditional markets constrained the competitive landscape to industry-specific, geographical areas, and time-bound operations. The entrance of Industry 4.0 and its digital capabilities expand the conventional boundaries by connecting markets across the world. The market demands investment in technology, but many organizations struggle to embrace the paradigm shift. Even more, companies muddle to identify and select the right technologies that foster resilience and agility (Gartner, 2020).

Germany introduced the concept of Industry 4.0 as part of the country's "High-Tech Strategy 2020," a ten-point plan established nearly ten years ago. According to Anja Karliczek, the German Federal Minister of Education and Research, the strategy envisions a symbiotic future where social equity, environmental systems, and technology transform the Deutsche economy and way of life. Nations around the globe have begun to adopt similar visions. Since the inception of Industry 4.0, more than 65% of German businesses have adopted Industry 4.0 technologies to realize 20% market growth (German Federal Government, 2020). Germany's success indicates a massive movement across all industries towards I4.0 adoption. The World Economic Forum's 2025 Industry 4.0 market projections exceed $3 trillion in generated economic value.

To capitalize on this opportunity, organizations in the United States must accelerate the acceptance of Industry 4.0 technologies. Their success will require implementing impactful technologies that drive objectives and goals. However, the emergence of new technologies outpaces an organization's capability to adjust (Forrester Research, 2020), as it requires a level of flexibility that most have not achieved or know how to do so. Defending against disruptive business models is no longer enough. Organizations must be agile enough to leverage existing assets and resources in response to adversity. They must also be equally adaptive to activate new protocols, capacities, and partnerships swiftly. This adoption requires a continual pulse on current state activities and a heightened sense of market conditions. Unfortunately, today's dynamic market requires organizations to adjust with such rapidity that while many entities attempt to muddle through the complexity and ambiguity of Industry 4.0, most ultimately risk failure.

Industry 4.0 includes a diverse set of elements that facilitate connectivity, interoperability, and automation. Examples of these components include (Lu, 2017; Vaidya et al., 2018):

- sensors
- fraud detection technologies
- on-demand availability
- data visualization
- location detection technologies
- wearables
- human-machine interfaces

Vertical and horizontal integration and communication across components are essential for an Industry 4.0 strategy. The internet of things facilitates data sharing between people, devices, and infrastructure. Data sharing between people, devices, and infrastructure is enabled through the internet of things. The overall interoperability of this technical system creates a loop for multi-directional information exchanges. These aspects highlight the nature of complexity practitioners face during implementation and the clarity researchers must elucidate. Thus, simplifying this context will help organizational leaders and primary academic investigators in their Industry 4.0 quests.

As an emergent field of research, there are a plethora of Industry 4.0 academic literature focused on implementation (Araújo Cordeiro et al., 2019), country-specific capabilities (Trento et al., 2018), barriers to implementation (Raj et al., 2020), manufacturing and supply chain (Raut et al., 2020), readiness assessments (Sony et al., 2020), sustainability (Bai, 2020) (Kamble et al., 2018), and technology-specific acceptance (Masood et al., 2019). One study identifies 13 distinct research domains (Wagire et al., 2019), yet "despite the increasing devotion of academia and practitioners, the research field around Industry 4.0 remains fragmented and spotty" (Osterrieder et al., 2020, p. 1). The literature inconsistently defines Industry 4.0 and its core technologies, adding to the confusion and complications of this topic. Extant literature calls for a more comprehensive view of Industry 4.0 as a strategy and its foundational set of technologies (Haseeb et al., 2019); a couple of examples are listed below.

Table I.1: Industry 4.0 Technology Definitions

Industry 4.0 Technology Definition	Resource
An intelligent network centered around smart products based on enabled communication.	(Ercan Oztemel, 2019)
Innovation across production, organizations, and the product supply chain.	(Hermann et al., 2015)

For United States' organizations to ratify Industry 4.0 as a strategy and unreservedly use its associated technologies, a holistic view and understanding are required to assess and apply this system across diverse industries, business structures, and organizational sizes. Researchers and practitioners alike would benefit from this level of insight to advance further investigation and operation. This descriptive study explores factors of I4.0 adoption across industries and organizational sizes. The study seeks to reveal "what" factors contribute to the adoption of Industry 4.0, "what" benefits avail as a result, "what" industry patterns exist, "what" differs between them, and "what" effect COVID-19 has on these concepts.

I.2 Context

A 2019 Forrester Research report signaled the criticality of Industry 4.0 adoption for business survival. This report persuaded organizations to embrace digital capabilities to improve operations and customer experiences (Forrester Research, 2020). Unbeknownst to the Forrester authors, their letter was foreboding, as March 2020 ushered devastating business impacts resulting from the coronavirus (COVID-19) global pandemic. Businesses in the United States suffered another gloomy fate in April 2020, as 42 States imposed varying regulations that forced the closure of non-essential businesses and ordered strict social distancing measures.

In June, over 45 million Americans had filed unemployment claims (Kochhar, 2020; Lambert, 2020). The daily death tolls continued to soar through the summer, reaching a daily record of 77,000 deaths in one day across the U.S. (John's Hopkins University, 2020). By October, over 100 corporations filed bankruptcy (Tucker, 2020), 80,000 small businesses permanently closed their doors, and thousands more struggled to stay afloat (Kochhar, 2020). When November 2020 arrived, America began to experience another uptick in the infection rate, exceeding 100,000 new cases daily. In nearly nine months, the coronavirus claimed 239,00 souls and infected an additional 10 million Americans (John's Hopkins University, 2020).

Since June 2020, America has felt the long-lasting and devasting blows to its healthcare system, job market, and the overall economy. Within the onset of political battles, states across the nation were left to their counsel as to whether shutdowns would be implemented. This left a patchwork effect of job loss, work availability, and cascading business impacts. Across several months and a presidential election, the United States began developing and distributing vaccines. With the political pressure to perform, President Biden committed to making vaccines widely available. With each push of production, the nation began to slowly re-open. While schools and many office firms remained remote, businesses that survived the first year now have a story to tell. It is within this context; this study evaluates the role of Industry 4.0 technologies. The below timeline highlights a few key COVID-19 milestones in the United States.

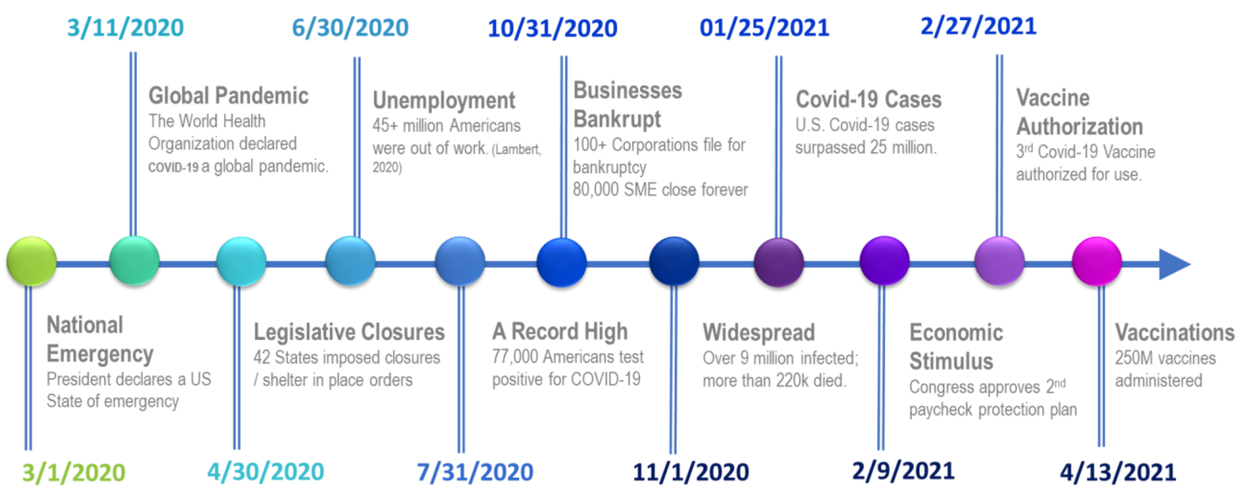


Figure I.1: U.S. COVID-19 milestones

COVID-19 issued widespread destruction to the United States' business community and job market (Kochhar, 2020). Non-profit organizations experienced abrupt shortages in volunteers and dwindling donations. At the same time, for-profit entities saw various disturbances, the extent of which correlated closely to the industry sector and product mix. Common effects in the business community were lost income, supplier interruptions, workforce shortages, and changes to operating business models (BLS, 2020; Goasduff, 2020; Kochhar, 2020; Thau, 2020). Few entities were spared the undesirable costs of the pandemic. In response to COVID-19 (Trump, 2020) and the country's economic woes, the U.S. Congress issued the Coronavirus Aid, Relief, and Economic Security (CARES) ACT. This $2.2 trillion stimulus package primarily provides financial benefits to businesses and unemployed workers. Additionally, the United States Chamber of Commerce developed business resources, as shown in the image below.

The pervasive shocks to organizations continue to be a business threat. Faced with proximity guidelines and a skeleton employee crew, some organizations have turned to technology to close the gap and connect with customers (Goasduff, 2020). Social distancing measures accelerated work-from-home, e-commerce, and contactless business models (Thau, 2020). "For many professionals, technology has been a lifeline during the pandemic, enabling them to be productive while stuck at home" (Mims, 2020, p. 1). However, when offering business preparedness tips, The U.S. Chamber of Commerce did not recognize technology as a possible tool for recovery, see image below. Others in the business community recognize the correlation between technology adoption and post-pandemic business survival.

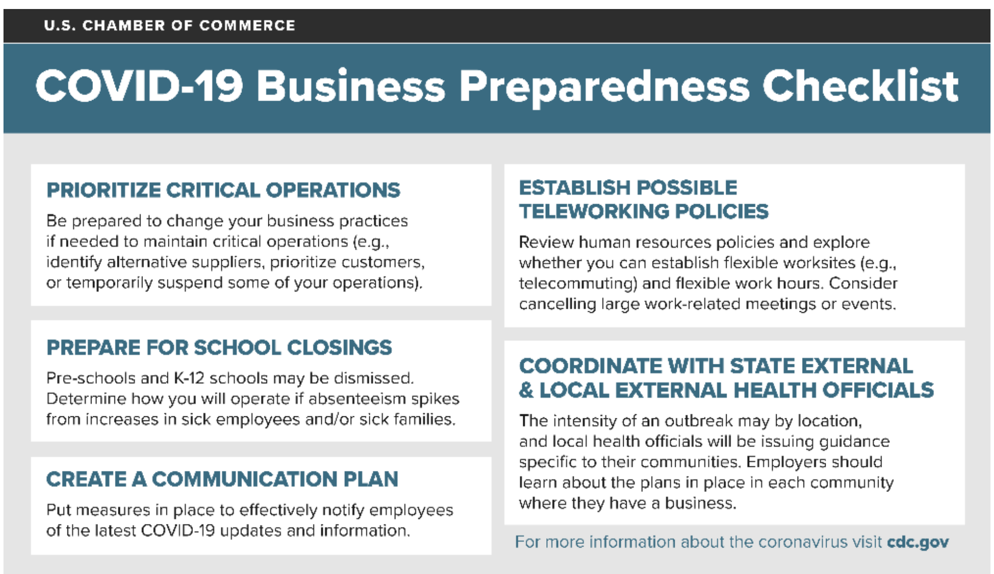


Figure I.2: U.S. Chamber of commerce coviD-19 Business Message

McKinsey Digital, Inc. projects the adoption of Industry 4.0 (digital) technologies, such as artificial intelligence (A.I.), which will be the business out of COVID-19 (Baig et al., 2020).

The report directs organizations to advance technology capabilities selectively and dissuades readers from a holistic view of Industry 4.0. The information fails to offer organizations a viable method of answering "what" technology will accelerate "what" objective with "what" level of achievement. This omission further demonstrates the practitioner's need for a simplified yet comprehensive view of Industry 4.0 technologies and their industry-specific value. The table below identifies the industry potential for broad adoption of Industry 4.0.

Figure I.3:Potential industry adoption of I4.0

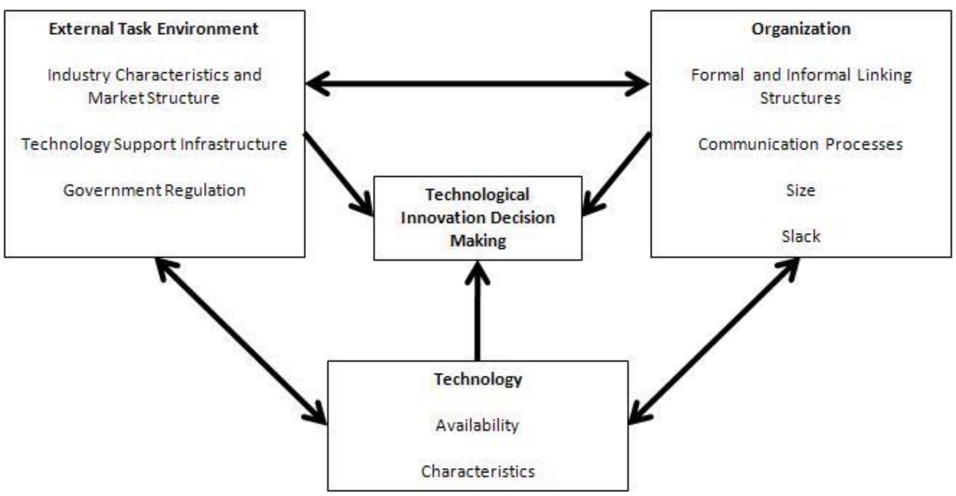
The unprecedented conditions of COVID-19 offer a novel context to research the adoption and use of Industry 4.0 technologies. The persistent business failure has a catastrophic effect on the nation's economy, and it is necessary to reverse this trend. Studies investigate technology adoption, but few have explored the range of Industry 4.0 technologies across multiple industries. Even fewer have explored these constructs through a quantitative method in the context of a global health crisis, specifically COVID-19. Extant research calls for the holistic study of Industry 4.0 technologies (Nazarov et al., 2020; Smuts et al., 2020) as a comprehensive technology system. Additionally, the intersection of Industry 4.0 technology and the COVID-19 adversity is void in the academic literature. A study of the diversity of Industry 4.0 technology implementation across diverse business sectors will reveal acceptance patterns toward developing an accelerated I4.0 industry adoption model and strategy.

I.3 Theoretical Framework

Technology acceptance theories abound (Mokgohloa et al., 2019), but few address adoptions at the firm level. Extensive research has examined and validated the adoption of various information technologies (Gangwar et al., 2014a). Those are still advancing (P. C. Lai, 2017). The Technology Acceptance Model (TAM) is one of the most cited adoption theories (King et al., 2006), as well as its descendants: TAM 2, TAM3, Unified Theory of Acceptance and Use of Technology (UAUT), and UAUT2. Adoption theories evolved, as they tested various external variables on perception (Davis, 1986), behavioral intention (Davis, Bogozzi & Warshaw, 1989), attitude toward use (Vankatesh & Davis, 1996), explanatory powers (Venkatesh & Davis, 1996), performance and effort expectancy (Venkatesh, Morris, Davis & Davis, 2003). Across this evolutionary journey, models tested for validity and reliability under voluntary and compulsory adoption scenarios (Vankatesh &Davis, 1996) as well as parsimonious structure (Venaktesh, Morris, Davis & Davis (2003). TAM and its offspring explain the technology adoption of individuals. This study will use the Technological-Organizational-Environmental (TOE) Framework as a proven and popularly leveraged model to examine technology adoption within an organization (Arpaci et al., 2012). The TOE comprises three dimensions (technological, organizational, and environmental) that align with 1) the Industry 4.0

technological foreground, 2) the industry traits of the organization, and 3) the contextual background of a global pandemic environment.

Industry 4.0 technology adoption is a process by which a user becomes aware of innovation, decides about the technology, alters behavior by using the invention, and then communicates and socializing the experience across an ecosystem (Rogers, 2003). Prior research has narrowly explored a singular technology (Gibbs & Kraemer, 2004) or industry (Efrat, 2020). While some studies have encompassed a suite of technologies (Lee & Shim, 2007), little is understood about Industry 4.0 technology adoption across diverse business sectors. Consequently, industries outside of manufacturing have little adoption reference to inform their decisions. To understand the Industry 4.0 technology adoption behaviors across sectors, this study uniquely examines adoption across twelve business sectors in the United States.



(Rocco DePietro, 1990)

Figure I.4: Technological Organizational Environmental Framework

I.4 Problem Statement

The magnitude of the coronavirus pandemic issued a double-pronged impact on the lives and livelihoods of Americans. Millions face health concerns, while millions more face unemployment. The U.S. Gross Domestic Product (GDP) dropped beyond 32%, while 76% of small businesses, which account for 44% of GDP, were profoundly impacted. The devastation in the United States compares to the Great Depression and the 1819 Flu Pandemic. According to the U.S. Chamber of Commerce, above half of the U.S. population has increased use of e-commerce since the start of the coronavirus pandemic. The unprecedented nature of the COVID-19 pandemic offers a unique background to research the adoption of Industry 4.0 Technology.

Recent Industry 4.0 technology research topics are e-maintenance (Aboelmaged, 2014), blockchain (Raut et al., 2020), cloud computing (Carcary et al., 2014), green technology (Su et al.), and e-supply chain, amongst others. While the literature explores specific industries, little is known about Industry 4.0 adoption across diverse business sectors, especially those not manufacturing or supply chain oriented. A comprehensive view of the Industry 4.0 technology suite and the simultaneous study across technology classifications is absent from the literature. “Technology can help make society more resilient in the face of pandemic and other threats” (World Economic Forum, 2020). However, for many businesses, the questions remain, “what technology, for what purpose, and for what outcome?” Answers to these questions motive this research. As such, this descriptive study will investigate the promotive factors of adoption, industry acceptance rates, and benefits of Industry 4.0 technologies during COVID-19.

I.5 Purpose of the Study

The purpose of this descriptive quantitative study is to understand the United States’ industry patterns of Industry 4.0 technology adoption, derive associated organizational traits, and discover differences between a variety of business sectors and sizes. This study will formulate a cross-industry view of promotive factors of technology adoption towards the facilitation of a contemporary business solution. The findings of this research will be extrapolated and transferred to the business and academic communities of practice to inform the decision-making process of Industry 4.0 technology adoption.

I.6 Research Inquiry

This research is an exploratory quantitative study that will deploy descriptive statistical analysis to understand this phenomenon. Variables are uncontrolled and will not be influenced, rather observed. Therefore, no formal hypotheses were presented; instead, descriptive relationships were explored based on extant literature.

A recent McKinsey report listed several I4.0 adoption benefits: improved productivity, global scale enablement, shorter lead times, and fewer downtimes. Some companies may seek these outcomes, but they may not be applicable across all businesses. The below model will be used to examine relationships between variables. As organizations seek to clarify the need and benefits of Industry 4.0 technologies, the below questions guided this study.

Research Questions (RQ)

RQ1: What Industry 4.0 technologies do business industries adopt?

RQ2: What factors contribute to the adoption of I4.0 technologies?

RQ3: What is the effect of COVID-19 on I4.0 technology adoption across industries?

I.7 Research Rationale

This empirical study investigates the complexity of Industry 4.0 adoption. Twelve diverse industries were examined through an online survey deployed to a Qualtrics panel of small and mid-sized business owners and executives at larger firms.

This empirical study will pursue a quantitative method and deploy an online survey through a Qualtrics panel of small and mid-sized business owners and executives at larger firms across diverse industries. The degree of industry adoption of ten unique industry 4.0 technologies were explored. Additionally, several characteristics that survey respondents identified as most applicable to their sector were also investigated. The numerous factors examined in this study highlight the potential ambiguity business leaders face when deciding which Industry 4.0 technology to deploy.

I.8 Summary

This descriptive quantitative research study will examine Industry 4.0 technology adoption perceptions and use across multiple industries through a Qualtrics survey panel of SME and large corporations' business leaders. The remainder of this paper is organized as follows:

Chapter 2: Literature Review - The emerging literature reviews Industry 4.0 Technology Adoption and extant body of knowledge. This chapter will provide a brief history of the evolution of industrial revolutions and associated technologies. Further, this chapter will elaborate on the core technology pillars contained within the Industry 4.0 system. A brief synthesis of prior studies on I4.0 technologies' adoptions and the role of adversity on the adoption rate will be discussed. The literature review will reveal gaps in the Industry 4.0 body of knowledge, specifically, its adoption across diverse trades.

The Technological – Organizational – Environmental (TOE) framework and application examples for advanced innovation acceptance and use will be explained. This chapter also describes the framework's constructs, associated variables, and contextual references from prior studies. A brief overview of other technology acceptance models will be identified as justification for the TOE mode's appropriateness. Further, gaps in the literature will surface to confirm this research opportunity.

The unit of analysis is the firm-level of technology adoption. The Technological-

Organizational-Environmental Framework (Rocco DePietro, 1990), often erroneously attributed to Tornatzky and Fleischer, explaining how contextual factors influence complex technology adoption, was developed by Rocco DePietro, Edith Wiarda, and Mitchell Fleischer. The literature shows that a commonly cited seminal article erroneously referenced Tornatzky and Fleischer as authors of the chapter instead of editors. Subsequent researchers followed this example. Seminal research suggests that firm adoption examination must include the perspectives of organizational tasks and the firm’s characteristics (Chau et al., 1997). The TOE Framework is an appropriate lens to evaluate this study as descriptive factor variables will include organizational traits and strategic activities related to Industry 4.0 acceptance and use.

Chapter 3: Research Methodology – In this chapter, an explanation for a quantitative study describes the research approach and methodology. As a descriptive study, the study’s objective seeks to answer “what” questions appropriate for quantitative research. This research study explores various industries’ characteristics, adaptive behaviors, and the use of Industry 4.0 technologies, and the effects of COVID-19 on these concepts. The data collected will be statistically analyzed to reveal patterns. The data will identify what is occurring, not how or why; there are no dependent or independent variables, only uncontrolled variables.

This section describes the data collection and analysis strategy. The study uses data collected from an online survey panel of 500 business owners and executives across different industries and organizational sizes. Additionally, this section describes the used for this study and the models that address the research question. A list of description inquiries is presented since this study omits hypotheses and propositions. Additionally, a brief statement conveys the expected contributions and limitations of this study.

This research study will provide insights for both practitioners and researchers.

For the practitioner:

- The research will reveal patterns of Industry 4.0 adoption by different industrial classifications.
- The research will reveal a standardized set of adoption factors across ten Industry 4.0 technology pillars.
- The research will provide insights into the development of an industry-level I4.0 adoption model.

For the researcher:

- The study will contribute to a holistic view of Industry 4.0 technologies, specifically their adoption.
- The study will advance the application of the TOE framework toward future I4.0 research
- The study will serve as seminal research on Industry 4.0 adoption across U.S. industries.

II CHAPTER 2: LITERATURE REVIEW

II.1 Literature Review Protocols

The Georgia State University Library was leveraged to access the ABI/Inform Collection, Web of Science Collection database, and Business Source Complete.

The following search terms were used: "Industry 4.0" and "Industry 4.0 Techn*." The keywords were placed in quotations as the word ‘industry’ drew many diverse and unrelated results. Industrie 4.0 was constrained as a search term as it refers to Germany's national strategy or the name of the digital technology suite upon which the system is founded.

An abbreviated systematic literature review was conducted. Articles were first sourced from the Business Source Complete and Google Scholar. While there are slight nuances between each database and the search conventions, the screening protocol was consistent across both environments. There were 27 results initially sourced through Business Source Complete and only 45 articles from Google Scholar. Figure 1 depicts the literature research process flow.

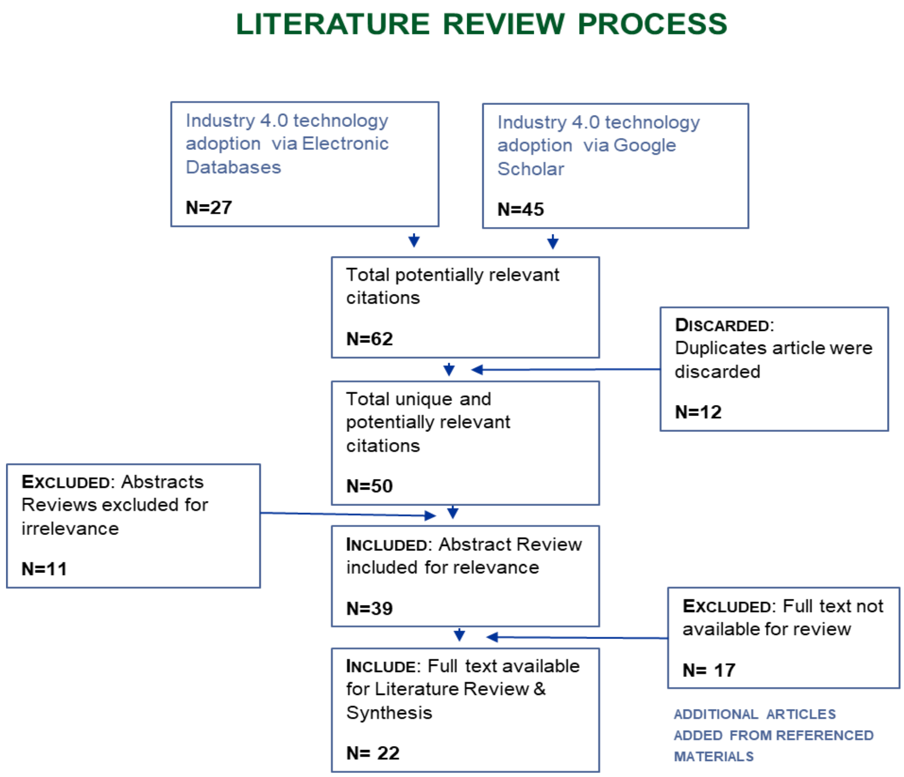


Figure II.1: Literature Review Process

Technology is an essential business tool that drives growth, profitability, and competition. The reliance on technology correlates to organizational performance and efficiency (Dalenogare et al., 2018). A recent General Electric Digital (2020) report indicated $18.5 trillion in Industry 4.0 economic value. In August 2020, the United States Federal Government announced a $1 billion commitment to Industry 4.0 technology research (Trump, 2020), which models the importance of these advanced innovations. Over 86% of respondents to a recent Forbes survey indicate positive financial gains from their Industry 4.0 investments (Gangwar et al., 2014b). Complexity and dynamism (Piccarozzi et al., 2018) of this fast-paced market challenge today's organizations.

Placed now in the context of the coronavirus (COVID-19) global pandemic, organizations face even greater pressure to embrace technology in a pivot towards e-commerce, automated processes, and contactless interactions. Besides, they must also contend with staff shortages and dwindling resources (Goasduff, 2020). It is essential to understand which Industry 4.0 technologies contribute to achieving organizational goals and strategies, the factors that promote adoption, and the industrial differences. Navigating the wealth of information, varying perspectives, and the high complexity of Industry 4.0 is a difficult feat but a necessity for business survival.

Industry 4.0 literature is relatively young, but there is already a wealth of research on this topic. Three themes primarily represent the extant body of knowledge. The first theme is Industry 4.0 technologies. While most authors agree on nine core technology pillars, the research varies in selecting innovative solutions (Gokalp et al., 2016; Hung et al., 2019). Research explores specific Industry 4.0 technologies, primarily in the context of manufacturing. The body of research explores various aspects of technology (Wagire et al., 2019). Many studies focus on implementation (Araújo Cordeiro et al., 2019) in introducing new technology. Others examine the challenges of execution. A few outliers explore conceptual models about the association of I4.0 to human factors (Mikulić, 2018), and another investigates the circular economy (Chauhan et al., 2020).

The second theme concentrates on national-level adoption and implementation. Several countries have adopted Germany's digital strategy, while others have created their unique naming convention. For example, Italy mirrors Germany and names its strategy Industrie 4.0. The United States calls its strategy the Advanced Manufacturing National Program Office (AMNPO). Each study is unique as national agendas, politics, and economics (Musawa et al., 2012) are prominent actors in developing an Industry 4.0 strategy and technology adoption.

The third stream of literature evolves around small businesses in manufacturing or as suppliers to a more massive manufacturing chain (Carcary et al., 2014; Musawa et al., 2012;

Sivathanu, 2019). While these studies are often insightful, their synthesis is challenging. These studies are "n" of 1 and present research topics with high levels of specificity that generalizability outside the national context is problematic. For example, one study explored Irish cloud adoption (Carcary et al., 2014), another researched the internet of things in Indian auto-manufacturing (Sivathanu, 2019), while yet another studied creative innovation in Malaysian manufacturing (Parvin Hosseini et al., 2014). One may consider clustered emerging markets for further contextual insight; however, the nuance is significant that comparison may prove unfruitful. For this reason, and the singular focus on U.S.-based companies, this paper provides only a cursory discussion of international adoption.

The remainder of this section will provide a summation of Industry 4.0 and the preceding industrial revolutions. Select Industry 4.0 technology pillars are discussed, along with international agendas and the case for small businesses. The theoretical framework concludes this section with a justification for using the Technological-Organizational-Environmental (TOE) Framework for examining firm-level technology adoption.

II.2 Industry Formation and Evolution

The first industrial (mechanical) revolution introduced to water and steam-powered machines to replace manual and animal labor between approximately 1790 and 1840. Steam-powered vacuum pumps untethered humanity from the burden of tirelessly hauling water buckets out of dangerous coal mines (Lira, 2001). Before the cotton gin's invention, slave labor extracted cotton seeds from the bolls by hand, then painstakingly separated and baled the cotton fibers (Schur, n.d.). This invention hastened cotton production and the need for more slaves to cultivate it. Additionally, horses and mules no longer walked endless circles turning mills to process sugarcane (Hinshaw, 2017). Instead, they were replaced by a revolutionary invention called the watermill. Ironmaking, machine tools, and the waterwheel were other innovations during this time of textile manufacturing.

Similarly, the second industrial (technological) revolution, estimated between 1870 and 1914, was marked using novel solutions, such as electricity and the internal combustion engine. Before introducing electricity, cooking was restricted to open fires, fireplaces, or wood-burning stove-tops. Refrigeration relied on ice and an icebox. Modern-day luxuries such as indoor heating, lighting, and cooking were limited before the introduction of electricity. These power sources led to the development of the engine, turbine, railroad, and telegraph. The telegraph's invention is of interest as an earlier system of disparate technologies (Mokyr, 1998). Submarine and transatlantic cables carried messages underwater but were dependent upon protective sheathing, insulation, and signal distortion solutions, according to Mokyr (1998), who goes on to identify that the electric impulse transmission and signal reverberator were also essential. The integrated system's strength is as strong as the individual components, which nods to an early distributed system. Mass manufacturing demonstrated the economies of scale of production, as the textile industry grew.

When the third (digital) industrial revolution began in 1969, the first personal computer was invented, although there is some debate in the literature about the actual date (Greenwood, 1997). This period is also commonly known as the digital age or information age. Manufacturing began slowly transitioning to digital technologies. Greenwood (1997) described this era as one of the incremental yet continual innovative advances. He emphasized that new technologies require differentiated skills and a favorable role in technology adoption (Greenwood, 1997). This scenario is exemplified by the consumers who produce their music videos and post them on YouTube. Before this period, Facebook, Uber, Airbnb, and YouTube platforms did not exist. There was no shared economy, but the emerging consumer-to-consumer distributed model enabled smaller organizations to join production efforts (Rifkin, 2015). By 2005, near the conclusion of this era, artificial intelligence, drones, and the internet of things abound while early advancements in additive manufacturing (three-dimensional printing) were introduced (Salesforce, n.d.).

In 2010 Industry 4.0 was born. The fourth industrial revolution began on the premise of cyber-physical systems (CPS) and the advancement of information communication technologies (ICT) that enabled messaging within and between systems. Technology and automation built the foundational platform for intelligent manufacturing. This fourth revolution uniquely synergizes disparate innovations to yield widely transformational opportunities. Industry 4.0 was an inflection point for Germany that sparked an international industrial revolution. Industrial revolutions demark significant transformations in the way people work and the way products are made.

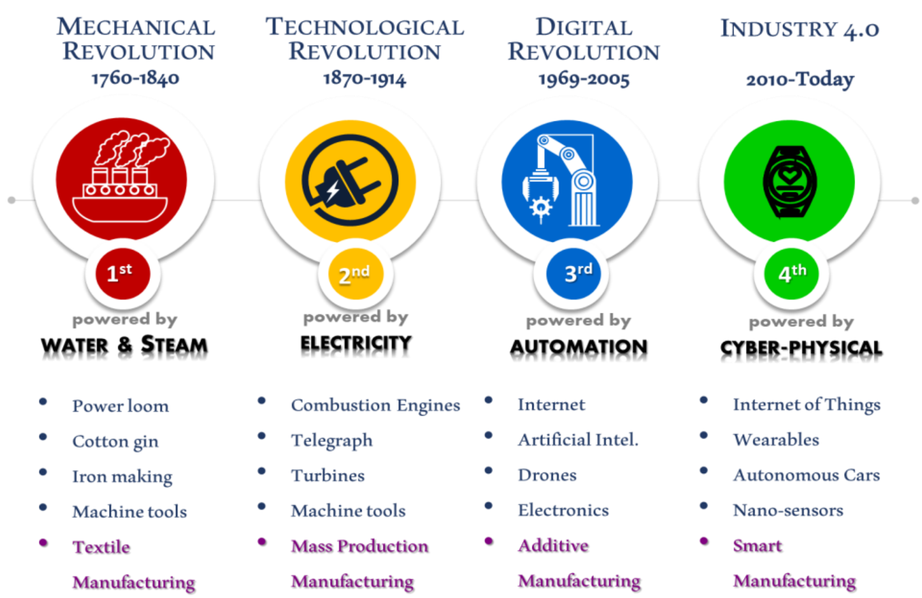


Figure II.2: Industrial Revolutions

Emerging in the marketplace are digital twins, chatbots, moreover, the horizon shoes glimpses of flying cars and the quantum internet (MIT Technology Review, 2020).

Until Industry 4.0, the gap between industrial revolutions spanned closer to 100 years. However, just over 40 years separate the digital revolution from Industry 4.0, and only five years separate the end of the digital era and the start of the cyber-physical era. Hence, both academicians and business leaders acknowledge the acceleration in technological advancements, as transformational inventions are produced in rapid succession like no time before. Industry 4.0 leverages digital era innovations and integrates them with software and information communication technology to create a distributed technology system. The integration across and between technology types, geographical locations, and software platforms is the key distinguishing factor of Industry 4.0. Swift developments in Industry 4.0 technologies create another layer of complexity in a time when businesses already face increased market pressure. What will organizations do?

II.3 Industry 4.0

In 2011, when Henning Kagermann coined the term Industrie 4.0 at the Hanover Fair (German Ministry of Education and Research, 2010), it was one of ten federally sponsored strategic initiatives in Germany’s High-Tech Strategy 2020 (H. Kagermann et al., 2013), intended to bolster Germany’s competitive stance. On the heel of a global financial market crash, Germany, like many other nations, faced an economic and financial crisis (German Ministry of Education and Research, 2010). According to this dilemma, the country turned to research and technology to stimulate economic growth, competition and protect citizens' social well-being, according to the German Federal Government (2010). The future-focused strategic plan addressed: business and science synergy, technology promotion, diffusion of innovation, research, and development, and workforce funding (H. Kagermann et al., 2013).

The German government modeled the behavior it sought to encourage and created a consortium of 19 thought-leaders from the science and business fields. Germany also paired the Ministry of Education and Research and the Ministry of Economic Affairs to collaborate and lead the Industrie 4.0 efforts. This partnered leadership brought together often disparate schools of thought and exemplified the heart and spirit of this required fusion. This group proposed overarching requirements if Germany truly wanted to succeed in delivering this agenda (German Federal Ministry of Education and Research 2020). Some of those requirements elevated attention to a tax system that fostered innovation and entrepreneurs. In contrast, others included cultivating broad acceptance of innovation, educating and training the next generation workforce, and reprioritizing funds (German Ministry of Education and Research, 2010), all in support of the ten initiatives the multi-disciplinary team put forth. The Federal Ministries demonstrated belief in the plan by setting aside over €200 million to fund the initiatives (H. Kagermann et al., 2013).

As one of ten initiatives, Industry 4.0 did not stand alone, nor was it intended to be an all-encompassing singular solution (German Federal Ministry of Education and Research, 2020; German Ministry of Education and Research, 2010). It was part of a broader context that incorporated unified strategies, tactical plans, and measures, along with enablers and performance criteria (Klitou et al., 2017).

Germany is strategically advancing the following initiatives:

- e-commerce
- mobility
- health longevity
- disease prevention & nutrition
- personalized medicine
- smart energy

- renewable energy (biofuels)
- carbon neutrality
- Industrie 4.0

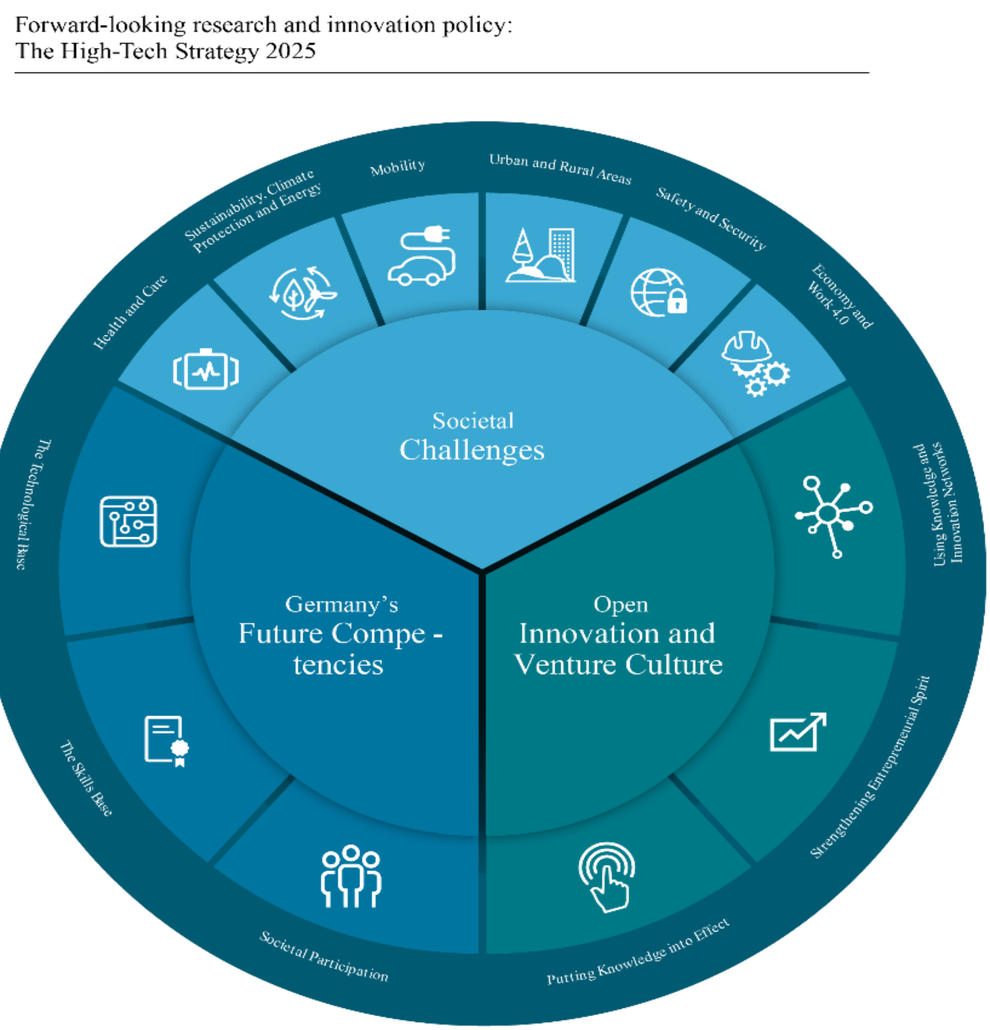


Figure II.3: Germany's High-Tech Strategy Initiatives

Research, education, and sustainability initiatives form an intricate web of systems interdependent upon one another for success. These intricately woven initiatives together created a web of systems that are interdependent upon one another for success. The synergistic focus of Germany's High-Tech Strategy is to improve the quality of life for its residents across a comprehensive platform of initiatives. Since its inception, Germany has seen a 20% overall market growth with over 65% Industry 4.0 adoption rate across all German organizations (German Federal Government, 2020). The overwhelming success of High-Tech Strategy 2020 has led to two renewals, High-Tech Strategy 2025, and most recently 2030 Vision for Industrie 4.0, which advances similar initiatives (German Federal Ministry of Education and Research, 2020). Three fundamental considerations underpin the strategy: autonomy, interoperability, and sustainability.

Establishing a solid understanding of Germany's strategic intention and deployment plans is essential for researchers and practitioners. Much of the early literature centers on implementing Industry 4.0 as both a strategy and the aggregate technologies modeled closely to the original German intentions. As other nations adopted similar concepts, the moniker Industry 4.0 remained relatively constant, while the technologies became increasingly striated. Today, most discussants offer only a cursory glance into the rich history and foundation of Industry 4.0 (Juras et al., 2020), missing critical elements that enable and promote successful implementation.

II.4 Industry 4.0 Technology

Industry 4.0 is more than a strategy. It is an aggregation of technologies, enablers, and governing principles. Many initiatives overlook the strategic vision of I4.0 and jump to implement technologies without a well-thought plan (Alok et al., 2020). One of the key Industry 4.0 principles is interoperability, enabling computer systems to exchange, respond, and act up information from other devices, technologies, systems, software, and equipment or machines. The second principle, an underlying enabler of Industry 4.0 technology, is the horizontal and vertical integrations across the value stream and throughout the system. The third principle is connectivity and communication that allow for interactions between people, devices, machines, and infrastructure. Each of these enablers facilitates optimal system functionality and is a requirement of Industry 4.0 technologies.

There are disagreements on the constitutional pillars of Industry 4.0; the number ranges from 9-12, with few outliers reaching 14 technologies. Simulation and horizontal & Vertical Integration are commonly listed as an Industry 4.0 technology pillar; they were omitted from this study as they are not technologies per se but functions or interactions of one or more technologies. Simulation is the visual or graphical representation of mathematical models and statistical tools used to depict a product behavior or a process. Horizontal and vertical integration are protocols that enable data-sharing across the entire organization (value stream and internal functions), customers, employees, equipment and infrastructure, and supply chain.

Most studies examine singular technologies or focus on the key enablers: the internet of things, big data, artificial intelligence, and cloud computing. The literature focuses on the implementation of ways to overcome challenges to adoption. Studies explore the application of these technologies primarily in manufacturing with a growing interest in sustainability. Other topics centered on successful implementation and ways to overcome challenges. I4.0 promises to revolutionize machinery, the underlying digital communication process, and the interactions with people, infrastructure, machines, and devices.

Table II.1: Literature Review of Industry 4.0 Technologies

Author	Big data Analytics	Cloud Computing	Augmented Reality	Blockchain	Artificial Intelligence	Autonomous / Automation	Cyber Security	3D Printing	Internet of Things	Biotechnology	Information Communication Technology	Energy capture & storage
Briggs et al. 2019	X	X	X	X	X	X	X					
Molino et al, 2020	X					X		X	X			
Nica, 2019	X		X	X	X	X		X	X			
Segura et al .,2018	X		X	X	X	X		X	X			
Nilekani & Walker, 2009		X				X	X	X	X	X		X
Haseeb, et al., 2019	X	X	X				X	X	X		X	
Buchi, et al., 2020	X	X	X			X	X	X	X	X		X
Butt, J., 2020	X	X	X			X	X	X	X			
Oztemel & Gursev, 2020	X	X	X		X	X	X		X		X	
Alcacer & Machado 2019	X	X	X			X	X	X	X			
Forbes, 2020	X	X			X			X	X		X	

There is little agreement on the core Industry 4.0 technologies, as depicted in Table 2. The ten technologies most agreed upon in the literature are: big data, artificial intelligence (AI), cloud computing (CC), blockchain, internet of things (IoT), cybersecurity, 3-D printing, autonomous/automation technology, augmented/virtual/mixed reality (AR/VR/MR), and nanotechnology.

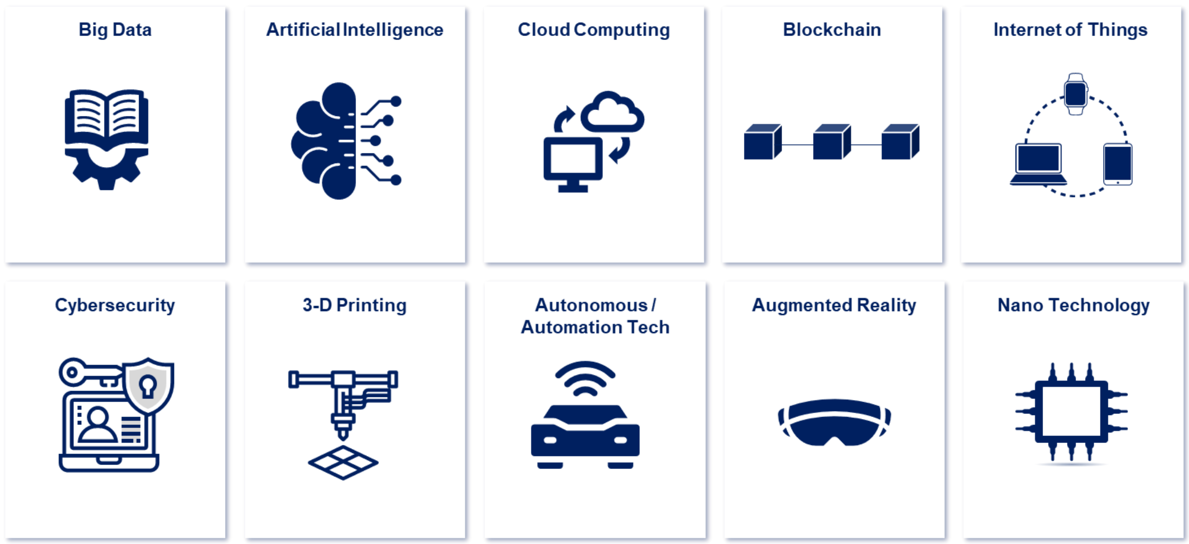


Figure II.4:Industry 4.0 Technology Pillars

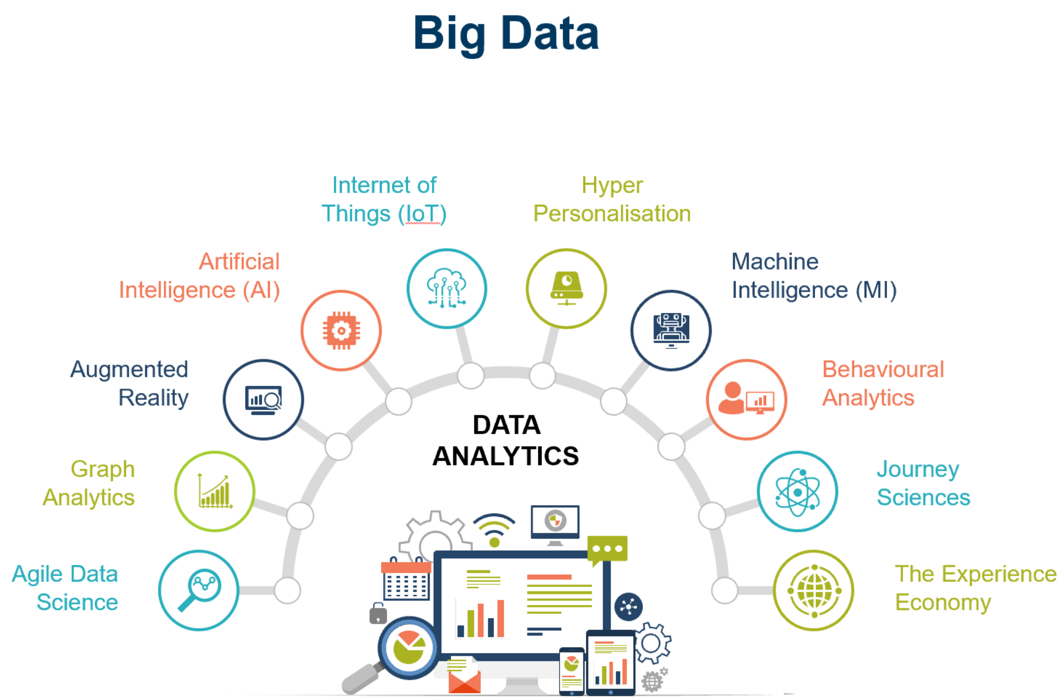
"The benefits of Industrie 4.0 will only unfold with a clever combination of these technologies. Still, many companies are unaware of the road leading to the identification and successful combination of Industrie 4.0 solution approaches" (Anderl et al., 2016, p. 7).

II.4.1 *Big Data & Analytics (BD&A)*

Industrial data is captured from various information sources such as sensors, electronics, manufacturing machines, and software. As organizations gather richer data from more diverse resources, this information's aggregation is called big data. When this voluminous information is extracted, collected, and synthesized, this is called big data analytics.

Big data and analytics adoption in context Industry 4.0 are still an emerging area of research. The information exchange between system components generates large volumes of data that require extraction, collection, and analysis. Typical significant data challenges arise from the volume and speed at which various information types are collected (L. D. Xu et al., 2019). There are three broadly accepted classifications of data types: structured, unstructured, and semi-structured, which offer aggregation, integration, and analytical challenges (Rehman et al., 2019). Due to the nature and characteristics of the data, artificial intelligence is often used to process and extract patterns from amassed information. Business leaders leverage big data to inform decisions regarding operational performance and customer demands. A large data set is valuable for the assortment of decisions it can inform and the infinite number of patterns identified from it. The patterns bring richer meaning to a business condition and illuminate a better understanding.

Big data analytics is the process of extracting actionable insights and patterns from large data sets (G. Li et al., 2019). The literature segments themes around information processing analytics, smart factory, services, and cyber-physical infrastructure data (G. Li et al., 2019). The latter is closely associated with the Internet of Things, which is inherently a substantial data source. Big data and analytics cannot be explored without the technology that processes it (Gokalp et al., 2016); thus, distributed computing (Yin, 2015) is most often referenced along with distributed business models.



Source: Slide Team

Figure II.5: Big Data Sources

The literature integrates with other topics, including logistics and supply chain (Y. Lai et al., 2018) and other organizational issues (G. Li et al., 2019; Maroufkhani et al., 2020; Yin, 2015), such as business intelligence. The image above provides examples of big data sources. The big data emphasis in the Industry 4.0 literature is less about adopting big data, per se, as it examines the conceptual implementation of new business models and distributed tools for data management and processing. Business practitioners call for more effective use of big data tools and identify a lack of enterprise skills. Some identified the underutilization of big data tools due to high levels of complexity (Gokalp et al., 2016). (German Federal Ministry of Education and Research, 2020).

The World Economic Forum (2016) reported a quarter of all industry leaders see big data and analytics as a motivating factor of technology adoption. This metric offers an interesting perspective in relationship to Industry 4.0 technology adoption. However, some variables lead to big data and analytics adoption. It is difficult to assess a core list of significant big data adoption variables as research studies selectively evaluate discriminate factors. The adoption variable selections are influenced by country, industry, and technological platforms (Kamarulzaman et al., 2019). Examples of significant adoption factors for big data and analytics are listed in the below table.

Table II.2: Selection of Big Data Adoption Factors

Adoption Factors	Industry	Reference
	Technological Context	
Perceived benefits Complexity Technology resources Big data quality & Integration	Malaysia: • Manufacturing • Logistics • Supply Chain Management	Yadegaridehkordi et al., 2018
Perceived Benefits	Asia -Pacific • Business intelligence tools	(Sun et al., 2018)
Technology Resources	Asia-Pacific • Business Intelligence tools	(Sun et al., 2018)
	Organizational Context	
Partner’s pressure Government support & policy Competitive pressure	Malaysia: • Manufacturing • Logistics • Supply Chain Management	Yadegaridehkordi et al., 2018
Firm Size	Asia -Pacific • Business intelligence tools	(Sun et al., 2018)
	Environmental Context	
Management support Human resources capability Perceived costs Change efficiency	Malaysia: • Manufacturing • Logistics • Supply Chain Management	Yadegaridehkordi et al., 2018

The generated insights from big data are either descriptive (what), diagnostics (why), predictive (possibilities), or prescriptive (recommendations) (Rehman et al., 2019). Descriptive analytics reveal the current or past state of activities but offer little context into why these factors exist. A further diagnostic analysis is required to understand why a condition prevails. A diagnostic study connects variables and begins to clarify the relationships between them. However, proactive measures are empowered by predictive analysis that forecasts the possibility of a future occurrence. While not widely embraced, prescriptive analytics assumes reliability and validity on the predictive analysis and suggests a course of action.

II.4.2 *Cloud Computing*

The cloud is an optimal storage capacity for such large volumes of material, but the computing capabilities go much further. Cloud computing enables Platform as a Service (PaaS), Software as a Service (SaaS), and Infrastructure as a Services (IaaS) (Lian et al., 2014). Within the SaaS model, there are four deployments to consider: private, public, community, and hybrid. Each model offers access levels by individual or community group. These three are the most popular business models, but others are: Function-as-a-Service, also referred to as Serverless computing (Aceto, Persico., et al., 2020). These models are considered utility computing, as the solution typically includes computational power and data storage to simplify operations (Aceto, Persico., et al., 2020). Technology resources and capacity issues are reduced in cloud computing, as managers no longer need to manage this operation. The business model reduces costs based on usage or subscriptions, with no upfront costs (Aceto, Persico, et al., 2020).

More industry leaders believe cloud computing and cellular communications are the biggest drivers of technology change (World Economic Forum, 2016). Cloud computing adoption factors center around communication between the data center and the end component, specifically bandwidth, latency connectivity, and availability. Cloud computing, like big data, does not stand alone. Cloud computing is closely associated with the Internet of Things (IoT) in the literature. As large volumes of data are collected, the cloud becomes the ideal locale (Pop, 2016) to load and process machine insights, customer data, and marketing efforts. The cloud provides business managers with greater scalability and responsiveness, supporting agile operations (Pop, 2016). Other industry cloud computing applications (Aceto, Persico, et al., 2020; Kiranmayee, 2015; Su et al., 2012) are highlighted in the image below.

The results of one study showed the mediating and direct Technology Acceptance Model (TAM) – Technological-Organizational-Environmental (TOE) Framework (TAM-TOE) provided more substantial explanatory power for cloud computing adoption than TAM and TOE Frameworks individually (Gangwar, 2016). The intention factors of managerial decision-making for cloud computing adoption are best explained using direct TAM-TOE in information technology, manufacturing, and finance sectors, according to Gangwar (2016).

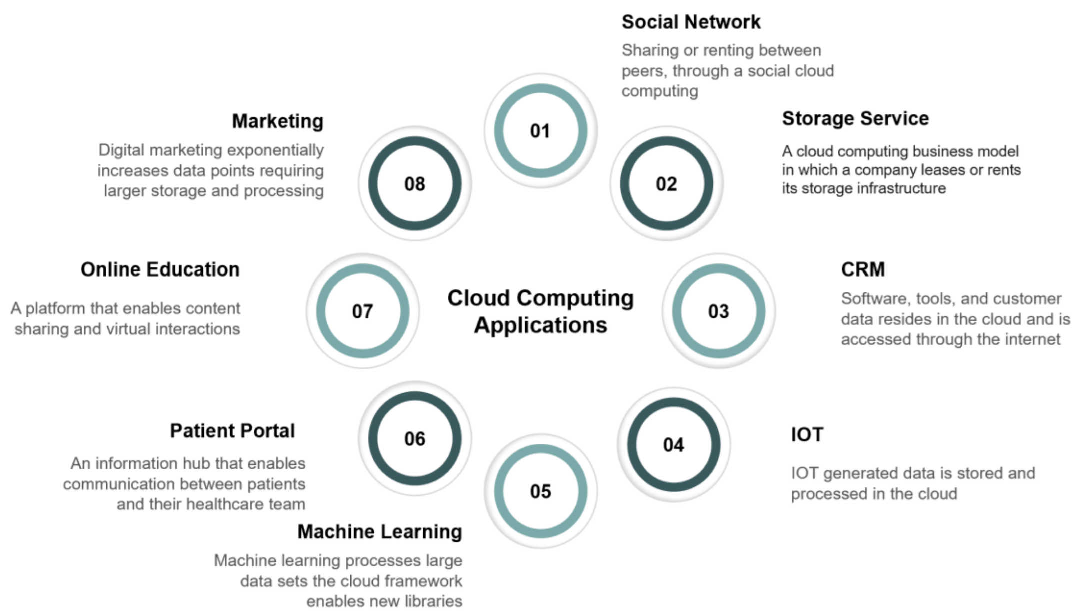


Figure II.6:Cloud Computing Applications

Source: this Author, graphics from Slide Team

II.4.3 *Artificial Intelligence (AI)*

Artificial intelligence uses computers to perform tasks that customarily required human intellect (Casalaina et al., 2018). It is also defined as studying intelligent behavior through computer automation's theoretical lens (Holland, 1992). AI and machine learning address problems and data from multiple dimensions, which allow for a broader spectrum of analysis.

AI may assume a variety of roles within the Industry 4.0 context. Artificial Intelligence tasks may include speech recognition, decision-making, and visual perception. However, the power of AI extends beyond human-like capabilities. AI can process large volumes of data, demonstrate strong computational power, and connect to endless possibilities through the Internet of Things. Much of the existing literature conceptualizes the integration and application of AI. Like many other Industry 4.0 pillars, the adoption of specific testing and exploration is still evolving.

What is clear is the practical use of artificial intelligence in manufacturing and other business settings (Alsheibani et al., 2018). Artificial intelligence can mimic a machine's function, learn and evolve (machine learning), sense the environment, and diagnose and repair its software (Lehman-Wilzig, 1981). Lehman-Wilzig alludes to the development of emotional AI, which is rapidly emerging.

AI does not stand alone in the world of I4.0, as it closely integrates with sensors and other frontline technologies to collect big data and communicates through a cyber-physical system powered by the Internet of Things. Cybersecurity must also be integrated into the solution to safeguard the information flow. Collectively, this AI network is the intellect that makes physical products smart. Artificial intelligence can extrapolate patterns and insights from large volumes of structured and unstructured data sources. While AI's performance is a comparative measure of human standards, its computational ability shows that it will exceed human capabilities.

The artificial intelligence market is projected to reach $60 billion by 2025, according to Berkeley ExecEd (2020). Human factors and IT infrastructure resources significantly contribute to the adoption of technology innovation (Liao et al., 2017).

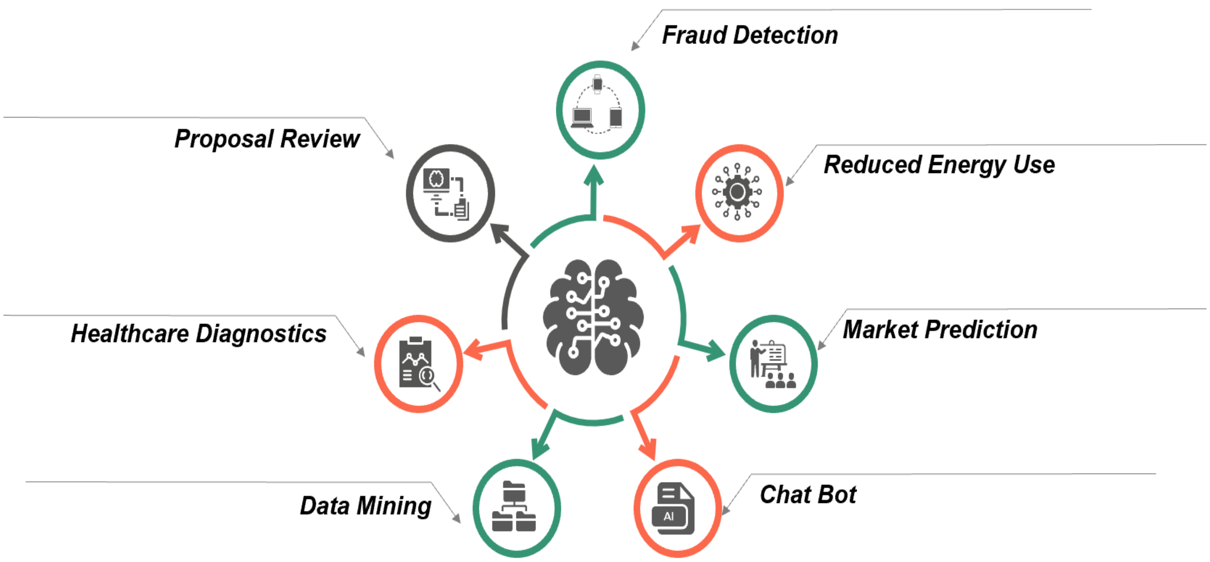


Figure II.7: Applications of Artificial Intelligence

II.4.4 *The Internet of Things*

The internet of things (IoT) and the industrial internet of things (IIoT) differ by their respective target customer groups. IoT is typically geared towards consumers, whereas IIoT focuses on industries(General Electric Digital, 2020). They both leverage devices, ICT, and big data to drive value. Sourcing high volumes of data from diverse sources afford leaders with insights otherwise not likely. The literature trend explores digital products and solutions as an innovative service (Suppatvech et al., 2019). The main classifications of service in this context are either functional operations focused or strategically based on the Internet of Things is used in the organization (Suppatvech et al., 2019).

In manufacturing, the Internet of Things focuses not on consumer products but industrial equipment, sensor, and other devices. These Industry 4.0 components capture real-time data and are part of a closed feedback loop, which communicates to a distribution center. The expected number of connected devices will reach 34 billion this year (Suppatvech et al., 2019). With this expansive capability, organizations can explore many options to align with their industry and entity.

Table II.3: Internet of Things Adoption Variables

Adoption Factors	Reference
Technological Context	
Technology Infrastructure	(Whitmore et al., 2014)
Technology Integration	(Chan et al., 2013)
It Expertise	(X. Xu, 2014)
Organizational Context	
Expected Benefits	(Bandyopadhyay et al., 2011)
Top Management Support	(Jedermann et al., 2008)
Environmental Context	
Government Policy	(Chan et al., 2013)
Government Industry	(A.Bassi et al., 2008)
Competitive Pressure	(Leminen et al., 2012)

II.5 Global Adoption

More than 50% of organizational leaders identify their deficiency in understanding disruptive models as the chief barrier to transformation, based on a World Economic Forum (2016) survey. Resource constraints, investor pressures, and a disconnect between staffing and innovation plans closely trail the barriers mentioned above (World Economic Forum, 2016); as Industry 4.0 spreads worldwide, the strategic motives, associated technologies, and societal benefits changed. The same holds for the challenges to acceptance (Raj et al., 2020), as these vary by nation.

Table II.4: International Government Adoption of Industry 4.0

Country	Plan	Focus Area	Year
United States	Advanced Manufacturing Partnership (AMP) Advanced Manufacturing National Program Office (AMNPO)	"Smart Manufacturing Innovation Institution	2011 2012
France	La Nouvelle France Industrielle Previously callede "*Industrie du future.*"	Job creation Revitalization of local industry	2013
United Kingdom	Future of Manufacturing	High-value manufacturing.	2013
European Commission	Factories of the Future (FoF)	Public-private partnership (PPP)	2017
Italy	Industria 4.0	Supported by the Italian Ministry of Economic Development	2017
South Korea	Innovation of Manufacturing 3.0 Plan	Domestic manufacturing and innovation strategies	2014
China	Made in China 2025 (MIC)	Focus on ten industries	2015
Japan	Super Smart Society	Improvement of all aspects of society	2015
Singapore	Research, Innovation, and Enterprise 2020 Plan	Advanced manufacturing the engineering	2016
Germany	Industrie 4.0	Comprehensive and holistic 15-year program	2011

Source: This Author

II.5.1 *Germany – Industrie 4.0*

One nation's vision for "an intelligently networked industry…[where] companies, their workforce, trade unions, associations, science, and politics have set out together to make this vision a reality" (BMBF), 2010), evolved to be the gold standard for the world, and is equally becoming a formidable economic opportunity.

Germany's ability to energize stakeholders from diverse backgrounds and industries is the model other countries seek to adopt or leverage when creating their own. Thematically consistent across the literature is the resounding position of Germany as an international collaborator (((BMBF), 2010; German Federal Ministry of Education and Research, 2020; Klitou et al., 2017). However, the literature also clarifies Germany's motivating interest is to distinguish itself as the world leader of Industry 4.0 ((Buxmann et al., 2011; Hemming Kagermann et al., 2016). Germany ingeniously cultivates international collaboration ((BMBF), 2010) then leverages the insights, weaknesses, and opportunities it collects (Hemming Kagermann et al., 2016) from partnering countries for opportunistic gains. This approach aligns with Germany's intent to safeguard its manufacturing industry and position the nation for long-term competitiveness (Hermann et al., 2016).

Anderl et al. (2016) offer practical guidelines for small businesses in Germany to embrace Industry 4.0 to pursue product development or production of Industry 4.0 technologies. The "Guideline Industrie 4.0 for SME" extends an opportunity for small and mid-sized businesses to connect into the broader national ecosystem and informs them how best to do so. Their guide target explicitly companies that sit inside the value-stream domain of manufacturing, such as engineering. Germany's strategy broadly focuses beyond manufacturing and remains prominent on opportunities for SMEs outside of manufacturing.

Small and mid-sized organizations account for 90% of Europe's business market; an overwhelming majority of Industry 4.0 technologies center around larger corporations (Masood et al., 2020). Unaffordability and the lack of awareness are the two most significant deterrents for SME adoption of Industry 4.0. When Industry 4.0 technology options improve functional plasticity, productivity, and competitiveness, adoption rates are higher (Masood et al., 2020).

II.5.2 *United States - Advanced Manufacturing Partnership*

The United States (U.S.) government has not fully adopted Industry 4.0 as other nations. Compared to Germany, the United States pales compared to an overarching goal to better society, envisioned by Industrie 4.0. President Barak Obama imitated the Advanced Manufacturing Partnership, a consortium of business and academia experts. The name alludes to the primary focus of this group. Unlike Germany, the U.S, the strategy is not explicitly clear and does not appear to bolster the workforce skillset or narrow the digital exclusion gaps (Liao et al., 2017). More rapid and public advancements are not driven by the Federal Government but by private sector for-profit businesses. General Electric (G.E.) created the marketing term Industrial Internet of Things (IIoT), in 2012 (General Electric Digital, 2020), as its U.S. agenda to compete with Germany's Industry 4.0. General Electric went on to find the Industrial Internet Consortium (IIC) (Buxmann et al., 2011) along with AT & T, Cisco, IBM, and Intel to lead the national agenda around standardization and coordination (Mariani et al., 2019).

Industry 4.0 is growing in popularity in the U.S. but is not widely known as the Internet of Things (IoT). This may be partly because Americans envelop I4.0 within the conceptual framework of the Internet of Things (Buxmann et al., 2011). The lack of federally driven incentives offers little support for broad awareness. G.E. estimated the IoT market to reach $225 million this year alone, which may be enough of an incentive to attract new entrants in the United States.

G.E. established a digital division to elevate and centralize digital capabilities at the core of its operations (G.E. General Electric Digital, 2020). Previously known for its products and six sigma efficiency, G.E. is rebranding itself to be the best industrial digital platform and producer. By facilitating these discussions, G.E. is positioned to mold the industry and catapult its products and services to be early market front-runners. It leaves to question if this approach "epitomizes investment-specific technological progress” (Greenwood, 1997, p. 4)?

Research surveys indicate organizations allotted approximately 11% of the overall IT or R&D budget on digital transformation (Daecher, (2019). There are mixed views on Industry 4.0 benefits (Daecher, (2019). Literature indicates that while leaders identify Industry 4.0 (digital transformation) as a strategic priority, their financial commitment waivers and their clarity wane as the complexity of I40 is revealed. Insight into the I4.0 benefits is heavily skewed towards manufacturing (Daecher, (2019), thus offering little insight into the Industry 4.0 organization’s diverse spectrum. Noted manufacturing benefits are productivity, lower maintenance cost, accident reduction, and increased resource availability. The common barriers include an incomplete feedback loop that does not accommodate inbound data from connected assets to inform decision-making.

Company adoption of I4.0 in the United States is driven by several factors related to increased workforce production and better operational performance. Frontline employees are not engaged in decision-making, which is counter-intuitive to the interconnective and inclusive nature of Industry 4.0 (Daecher, (2019). This omission indicates that many U.S. organizations are not infusing an Industry 4.0 strategy into their organization’s fabric. Instead, they are adopting selective technologies in pursuit of capitalistic-driven goals. Hence, much of the early literature concentrates on the implementation of technology and concepts to overcome barriers.

Among the most common issues in the U.S. (Daecher, (2019) are as follows:

- U.S. companies do not fully adopt Industry 4.0 as a strategy.
- There is a disconnect between leadership and the frontlines.
- Leaders take for granted the specialized skill required for digital transformation; thus, training and education are assumed to be enough when they are not
- There are few industry players, and the national agenda is controlled by a few organizations that have maintained a tight network of strategic partners.

Discussions about cross-industry adoption of I4.0 are restrictive, only accounting for manufacturing, metals, mining, utilities (oil, gas & power). Other industries that are tangentially associated include aerospace, defense, automobiles, chemicals, and specialty materials. There is growing evidence in the literature of interests towards the latter domains. However, there are advancements in other industries that receive little attention. Robots are used by some of the nation's largest companies. Both in the retail sector, Walmart and Amazon leverage robots in the delivery process (Gordon, 2020). Robots such as these manage rudimentary tasks, freeing human resources to manage high-level tasks and complex issues. Small business adoption of these technologies may be cost-prohibitive for now, but that may change soon (Gordon, 2020).

The collection of big data through the internet of things allows organizations to offer uber customization and personalization of products and services. Customers leverage the end device of their choice, whether a wearable, a car, a house, or neighbor sensors that provide healthcare alerts to asthmatics. The consumer chooses when, where, and how they engage with a business. This choice offers the ultimate consumer control while businesses are afforded near real-time insights that form patterns of behaviors, preferences, and sentiments (Gordon, 2020). During the COVID-19 pandemic, this type of engagement provides excellent continuity for business-to-consumer communication. When in-person meetings were interrupted by social distancing guidelines, the internet of things offered another way to stay connected. According to PRNewswire, by 2030, it is estimated there will be over 20 billion connected devices valued at $1.5 trillion.

Companies in the U.S. Industrial Internet Consortium (IIC) express that they offer opportunities across all industries and sectors but fail to clarify how they are accomplished (General Electric Digital, 2020). However, General Electric Digital (2020) illuminates that the target industries for IIC partnerships have critical operations, such as hospitals; and manufacturers, where system failures could result in death, injury, or severe risk. G.E. intentionally excludes consumer-based industries, which may benefit from Industry 4.0 adoption or production.

II.5.3 *International Adoption*

Many factors determine international adoption. One of significance is the leading industry, historically centered around a nation's national resources. For example, the adoption of cloud computing in Taiwanese healthcare settings is determined by relative advantage, top management support, firm size, competitive pressure, and trading partner pressure (Lian et al., 2014). In France, the adoption of Industry 4.0 is inhibited by barriers to entry, such as high investments, unavailable resources, and unsuccessful transformation plans (Alok et al., 2020).

II.6 Adversity & Technology Adoption

The coronavirus pandemic has catapulted technology adoption into the business headlines as small businesses in the United States face dire conditions. A unique perspective of this opportunity can be correlated from one study that proposed a digital maturation model to strengthen the firm's resiliency (Syed et al., 2020). Syed et al. (2020) suggest leveling the competitive playing field for small and mid-sized organizations through digital adoption. They argue against the current marginalization of SMEs in terms of Industry 4.0 innovations. The proposal offers an alternative option to develop these firms' digital maturity to higher corporate levels, paving the way for organizational resilience (Syed et al., 2020).

The researchers express the importance of small and mid-sized businesses understanding and appreciating technology as an invaluable business resource but acquiesce that the process of enlightenment can be arduous (Syed et al., 2020). The authors' aligned critical value streams with solutions technologies to develop a stair-step technology adoption model. Similarly, this research strives to offer a framework for Industry 4.0 technology adoption across industries and firm sizes.

II.7 Research Gaps

There are three thematic research gaps:

- Industry & Sector Interests:
  - According to the European Commission's (Digital Transformation Monitoring) Strengths-Weaknesses-Opportunities-Threats (SWOT) analysis, the more important opportunity and a threat to Industry 4.0 are:
  - "International cooperation opportunities and transferability of I40 platform."
  - "Balancing between different industrial and sectoral interests" (Klitou et al., 2017, p. 5)
- Organizational Size
  - Industry-specific awareness has been limited to small and mid-sized enterprises.
  - Raising attention and awareness for SMEs on the importance of Industry 4.0 transformation (Kagermann et al., (2016) takes a narrow view of cross-industry opportunities and research.
  - Industry 4.0 has rarely been viewed across all firm sizes within a singular study.
- Adoption Variables
  - Several studies have leveraged the TOE framework to examine individual Industry 4.0 technologies (Hsu & Yeh, 2017)
  - It has rarely been viewed as a composite suite of technology.

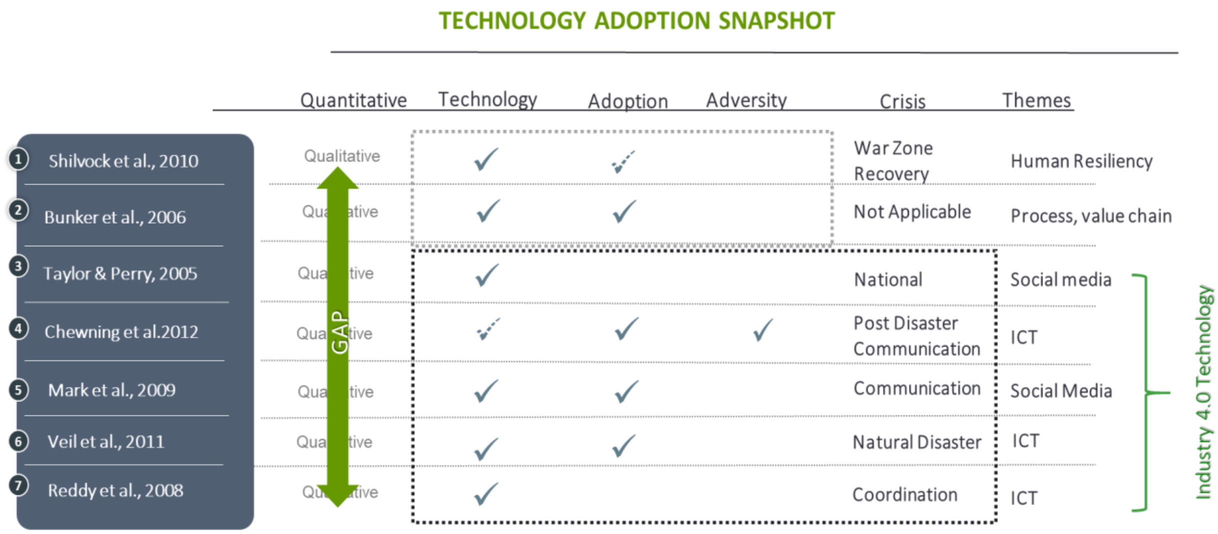


Figure II.8: Literature Review Gaps

While extant research investigates technology adoption, few have explored composite Industry 4.0 factors across multiple industries. Even fewer have examined these constructs through a quantitative method in the context of a global health crisis, specifically COVID-19.

II.8 Technological-Organizational-Environmental (TOE) Framework

This study aims to model an adoption hierarchy of Industry 4.0 technologies that facilitate broader industry adoption. Fierce economic stressors caused by the lingering COVID-19 outbreak; Industry 4.0 adoption may help businesses adapt today while transforming for tomorrow. Extant literature yields factors for the adoption of Industry 4.0 technology but fails to provide a step-by-step technology adoption model.

As many U.S. businesses tighten their financial affairs, guidance on which technologies and which order to adapt them to foster resiliency will be helpful. A structural framework will be developed and analyzed to help business leaders and owners understand, identify, and deploy Industry 4.0 technologies across multiple industries sectors, including products, services, and non-profits. The TOE Framework has been leveraged by numerous studies to explore the adoption of various Industry 4.0 technologies, as reflected in Table 2.5.

Table II.5 I4.0 Adoption Studies Using the TOE Framework

Industry 4.0 Technology	Reference
Augmented reality	(Striccoli et al., 2015)
Big Data & Analytics	(Verma, 2017)
3D Printing	(Dujovne et al., 2014)
Cloud Computing	(Low et al., 2011)
Internet of Things	(Hsu et al., 2017)
Artificial Intelligence	(Liao et al., 2017)
Blockchain	(Clohessy et al., 2019)
Cybersecurity	(Wallace et al., 2018)
Autonomous Vehicles	(Burcher et al., 2018)

Adapted from (Liao et al., 2017)

There were limitations to the Technological-Organizational-Environmental Framework. The TOE framework did not provide causal or predictive relationships; thus, another statistical technique would have been required to offer more in-depth conclusions (Lee et al., 2015), as assumptions of linearity, normality, and independence between factors may not be met (Hsu et al., 2017). This framework, however, was appropriately selected for this study as it intended to explore relationships between variables and not substantiate the origin of the relationship nor forecast when the connection would occur in the future.

III CHAPTER 3: METHODOLOGY

III.1 Research Design

This quantitative research deployed an online perception survey to investigate the adoption and use of various Industry 4.0 technologies across diverse business sectors. This descriptive study explored factors of I4.0 adoption across industries and organizational sizes. The study sought to reveal “what” factors contribute to the adoption of Industry 4.0, “what” benefits avail as a result, “what” industry patterns exist, “what” differs between them, and “what” effect COVID-19 has on these concepts. The industry-level of adoption is the unit of analysis. The research approach leverages deductive reasoning.

III.2 Data Collection

Surveys were distributed online via a Qualtrics panel of 500 business executives and owners in the United States. The research panel was opened to all gender representations, industries, organizational structures, and sizes to capture a broad view of Industry 4.0 technology adoption across the nation. The survey collected descriptive information about the firm’s characteristics (size, age, industry, etc.) to categorize the results. The survey questions are framed around the TOE model, highlighting the contextual themes of organization, environment, and technology.

III.2.1 *Survey Development*

This quantitative research deployed an online perception survey to investigate the adoption and use of various Industry 4.0 technologies across diverse business sectors. This descriptive study explored factors of I4.0 adoption across industries and organizational sizes. The research sought to uncover elements that contributed to the adoption of Industry 4.0, their value, the patterns around these relationships, and to discover the effect COVID-19 had on these concepts. The firm-level of adoption was the unit of analysis. The research approach leveraged deductive reasoning.

Table III.1: Survey Development

Variable *(significant factors from literature)*	**Reference**
Technological	
Perceived Usefulness (PU1)	(Verma, 2017)
Perceived Usefulness (PU2)	(Soon et al., 2016); (Park et al., 2015); (Sun et al., 2016)
Perceived Usefulness (PU3)	(Brock and Khan, 2017); (Shin, 2016); (Kang and Kim, 2015)
Industry	(Iacovou et al, 1995) (Sun et al, 2016)
Organizational	
I4.0 Business Strategy Orientation	(Sun et al., 2016)
Organizational Size	(Liao et al., 2017; Rogers, 1995) (Sun et al., 2016)
Environment	
Market Pressure (COVID-19)	(Yang, 2015)

III.2.2 *Research participants*

Participants were sourced through a Qualtrics, Inc. panel, leveraging the company's proprietary database established on the following screening criteria:

1. Research participants had to be business owners or executives who managed, developed, approved or reviewed their organization's digital technology budget, strategy, adoption, and use.

2. Business owners and business executives had to be eighteen (18) years of age or older.

3. Participants were required to have worked in the United States and had consistently

owned/been employed with the same organization since 2019.

4. Business owners and executives across all sectors were welcomed to participate.

Qualtrics invited participants to complete the online survey developed by this researcher through the Qualtrics survey platform. Customer identification and personal information were not collected, and Qualtrics did not disclose this information to the researcher.

As indicated above, participants who did not meet the screening criteria as a required panel demographic will be screened out of the survey. Participants could choose to opt out of participation at any time for any reason. The research consent form had been agreed upon for participants to complete the online survey.

III.2.3 *Sample Size*

The target sample size of the Qualtrics panel is 500 survey participants. Only respondents who complete the entire survey will be included in the total number of 500 survey participants: 250 small business owners and 250 business executives. The sample size was thus selected to meet targeted 95% confidence levels and 5% error margins across diverse business industries, sectors, and sizes within the United States. This sample size does not expose human subjects to any potential unnecessary risks.

III.3 Data Description

This research conducted a survey questionnaire to business owners and business executives in the United States. When aggregated by such, respondents across industries served as the unit of analysis, which is the industry level. The online survey comprised a targeted sample of 12 sectors, as described in the table below.

Table III.2: Industry List

Industry
Manufacturing
Agriculture
Entertainment, Leisure & Arts
Financial Services
Construction
Public Services
Healthcare
Information Technology
Business Services
Professional Services
Retail/Wholesale
Transportation

The below respondent demographic table provides the sample representation of this study, which included owners (51%), C-suite executives (24%), senior vice-presidents and vice-presidents (5.6%), and directors (19.6%). The respondents had varying leadership responsibilities pertaining to Industry 4.0 technologies, which consisted of management (67%), development (35%), authorization (52%), and review (31%). Additionally, over 75% had six or more of experience with their current employer or company. Survey participants' functional and technical roles indicate their depth of experience and knowledge of industry 4.0 technologies, strategic objectives, financial implication, and other evaluative factors. Organizations were characterized as either small (less than 500 employees), 52.3% of the organizations, or large (500 plus employees), representing 48% of all firms. In terms of annual revenue, 39% of large organizations reported over $20M, and 57% of small firms reported earnings between $100,000 and $9 million for the fiscal year 2019, compared to the fiscal year 2020. Thus, respondents characterized a dispersed industry representation and organizational variety.

Table 3.3 Demographics of respondents

Position	Frequency	Percentage
Owner	263	50.6
C-Suite/Executive	126	24.2
Senior/Vice President	29	5.6
Director	102	19.6
Functional Departments	Frequency	Percentage
Administrative, including law	111	21.3
Finance/Economics/Insurance	43	8.3
Human Resources	20	3.8
Information Management	168	32.3
Innovation	6	1.2
Management/Leadership	111	21.3
Operations	36	6.9
Public Relations/Affairs	2	.4
Sale & Marketing	23	4.4
Current employment years	Frequency	Percentage
2-5 years	177	34.0
6-10 years	210	40.4
>10 years	133	25.6
Industry 4.0 technology role	Frequency	Percentage
Manage	342	65.8
Develop	182	35.0
Approve/Authorize	269	51.7
Review	161	31.0
Firm Size	Frequency	Percentage
Small (<500)	272	52.3
Large (500+)	248	47.7
Firm Maturity	Frequency	Percentage
2-3 years	47	9.0
4-5 years	105	20.2
6-9 years	115	22.1
10+ years	253	48.7
Annual gross revenue (FY19)	Frequency	Percentage
>$100,000	72	13.8
$100,000 - $499,000	59	11.3
$500,000 - $999,000	54	10.4
$1M - $4.9 M	69	13.3
$5M - $9.9M	67	12.9
$10M - $14.9M	36	6.9
$15M - $19.9M	13	2.5
$20M - $49.9M	45	8.7
$50M - $499M	51	9.8
$500M - $999M	28	5.4
$1B+	26	5.0

III.4 Data Analysis

Data was exported from the Qualtrics platform into the IBM SPSS software platform. The data were then recoded to structure the data for analysis. Quantitative methods were used to remove outliers, invalid and poor-quality records. A poor-quality survey was determined when nonsensical data was entered into a text field (i.e., good and nice, as the industry identifier). Data files were assigned numerical values to order each record. There were 520 resulting surveys in the dataset used for analysis.

III.4.1 *Data management*

The survey will collect participants' opinions, behaviors, perceptions, and knowledge from survey participants. The survey will leverage a Likert-type scale. The data collected will be descriptive, and the statistical analysis will follow both descriptive and inferential procedures using IBM SPSS Statistics software.

The data will be stored securely via password-protected files and laptop devices. The survey data will not contain personally identifiable information. No personally identifiable information will be shared in the event of any future publication or presentation.

The estimated target sample size was calculated based on United States Census Bureau data for the total number of firms and business establishments in the United States, based on a 95% confidence level and a z-score of 1.96 (5% margin of error). According to the United States Census Bureau 2017 SUSB Annual Data Tables by Industry dataset, there were 5,996,900 firms and 7,860,674 establishments in the United States. This number also accommodates representatives across diverse industries within the sample to maintain confidence levels and margins of error for sample sub-sets based on the North American Industry Classification System (NAICS).

III.4.2 *Descriptive Exploration*

As the intent of this research was to answer "what" factors and conditions exist, there was no formal hypothesis. Rather a descriptive depiction, as reflected in the image below, prescribed the theoretical basis from which the factors are viewed. The descriptive characterization of adoption factors also identifies connections between variables. Frequencies and percentages were calculated for respondent demographic information, organizational characteristics, and the remaining descriptive (independent) variable.

III.4.3 *Statistical Analysis*

A binary logistic regression best analyzes relationships between a dichotomous independent variable and a dichotomous dependent variable. (Peng et al., 2002). A binary logistic regression was conducted to evaluate the relationship between strategic objectives, technology enablement, industry, firm size, COVID-19, and company-wide adoption and no-adoption. The complex logistic regression equation was constructed as follows: logit $(Y = 1n\left(\frac{\pi}{\pi-1}\right) = \propto + \beta_1 X_1 + \beta_2 X_2$, where π = probability and

X1=x1, X2=x2. ,= $\frac{e^{\propto + B_1 + x_1 + B_2 x_2}}{1 + e^{\propto + B_1 + x_1 + B_2 x_2}}$ where the π= probability of an event occurrence, α is the Y-intercept, and βs are regression coefficients, while X's represent the set of predictors under observation.

For research questions 1,2 and 3 (What Industry 4.0 technologies do business industries adopt? What factors contribute to the industry-level adoption of I4.0 technologies? What is the effect of COVID-19 on I4.0 technology adoption?), a binary logistic regression analysis was performed to assess the contributions of various technological, organizational, and environmental factors in the adoption of industry 4.0 technologies (autonomous, cloud computing, big data, cybersecurity, artificial intelligence, blockchain, internet of things, 3D printing, augmented reality, nanotechnology).

Demographic (independent) variables were entered into each block as follows:

Block One: Industry

Block Two: strategic objectives

Block Three: technology enablement

Block Four: organizational size

Block Five: COVID-19 accelerator

The following analyses were also conducted to test for reliability, validity, and sensitivity: Omnibus tests of model coefficients, model summary, Hosmer and Lemeshow test, classification table (percent concordant), and casewise; see the appendix for detailed analysis. The logistic regression overcomes the assumption violations of homoskedasticity, linearity, and normality of ordinary least squares (Menard, 2002). Linear regression can be used for a continuous independent variable and a dichotomous dependent variable, producing two parallel lines (representing the dichotomous outcomes). Ordinary least squares regression analysis does not easily explain the results. Thus, the logistic regression model explains dichotomous, categorical, and nominal independent variables and dichotomous dependent variables. Information technology was the largest represented industry, accounting for over 30% of all survey respondents. Information technology was thus excluded from the binary logistic regression analysis and set as the reference group.

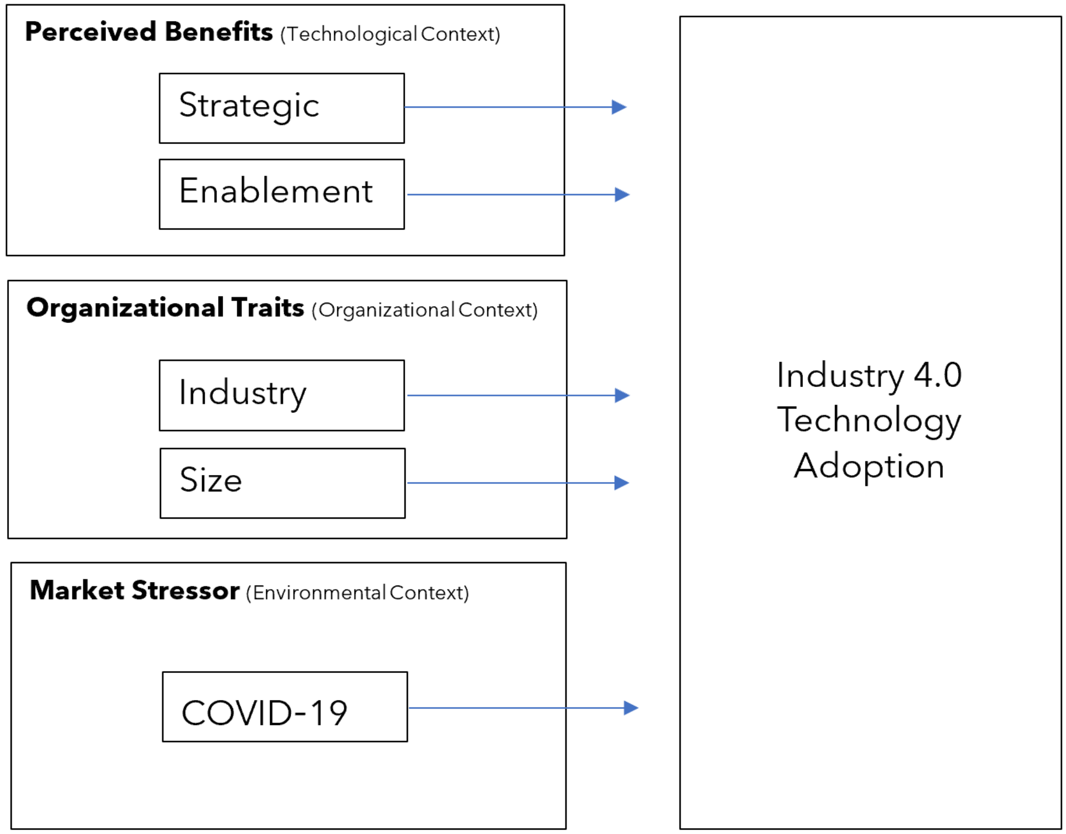


Figure III.1:Depiction of Adoptive Factor Descriptives

III.4.4 *Perceived Benefits: Technological Context*

Perceived benefit is defined as the individual perception that the usage of a specific Industry 4.0 technology helps an organization or the particular user (Pearson et al., 2005). Contextually, perceived usefulness in this study referred to defined strategic objectives and the degree to which Industry 4.0 technologies enabled a quick response to threats and opportunities induced by COVID-19.

III.4.5 *Strategic Objectives*

Organizations use Industry 4.0 technologies for different reasons. For this study, the strategic objective was defined as why an organization adopted and used an Industry 4.0 technology. In prior studies, competitive advantage, cost reduction (Press, 2016). increased revenue, improved efficiency (Curran & Purcel, 2017) have been significant adoption factors of advanced technologies. According to Iacovou et al. (2013), strategy is an indirect effect, and examples include customer services and stakeholder relationships (Kuan et al., 2001). As such, the following descriptive analysis was proposed:

(D_1): An examination of the relationship between the strategic objective of Industry 4.0 Technology and the adoption of Industry 4.0 technology was explored.

III.4.6 *Enablement*

Enablement is defined as the process of leveraging technology to achieve a defined outcome. Other studies have explored various perspectives of enablement, such as inhibitors (Teo et al. (, 2006). technology competence (Zhu & Kraemer, 2005) , improved operational efficiency (Kuan et al., 2001), and technology support. “Enabling conditions must be created for innovation to triumph” (Awa, Nwibere & Inyang, 2010). Therefore, the below descriptive analysis was articulated.

(D_2): The more I4.0 technology enables a quick response to COVID-19 induced threats and opportunities, the greater the adoption of Industry 4.0 technology. An examination of the relationship between Industry 4.0 technology enablement and Industry 4.0 technology adoption was assessed.

III.4.7 *Characteristics: Organizational Contexts*

Organizational traits have historically been evaluated by vertical and horizontal characteristics (Glover & Goslar, 1993) and firm size (Rogers, 1995) (Thong, 1999).

III.4.8 *Industry*

The industry is defined as the business sector in which an organization operates. The industry is a classification of business activities associated with grouping organizations in the same industry. This study leveraged the Standard Industrial Classification (SIC) codes to recode industry groups into 12 analyzable groups.

(D_3): An examination of large and small organizations across industries and their respective adoption of Industry 4.0 technologies was evaluated.

III.4.9 *Organizational Size*

Organizational size is typically defined as categorizing employees into groups of small, medium, and large. This study constricts the corporate examination to small and large businesses alone. The generalization of small businesses is defined as less than 500 employees, while large firms have 500 or more employees.

Many studies have evaluated the role of organizational size on technology adoption (Rogers, 1995) (Duan, 2010), (Zahi, 2010), revealing that larger firms have higher technology adoption rates. The reasons for the findings range from access to more resources (Aboelmaged, 2014) to adaptability (Duan et al., 2012). Based on this evidence, this research study suggests the following descriptive analysis:

(D_4): An examination of large and small organizations across industries and their respective adoption of Industry 4.0 technologies was evaluated.

III.4.10 *Market Stressors: Environmental Contexts*

The external environment of the industry presents numerous factors that may impact the technology adoption of an organization. Government pressures and industry pressures

III.4.11 *COVID-19*

Unlike prior catastrophic market stressors, the global pandemic caused by COVID-19 halted business operations around the world. Regulatory restrictions impeded business operations across numerous industries, and social distancing transformed customer interaction.

While market volatility (Eveland and Tornatzky, 1990) has appeared in the extant literature, COVID-19 is an emerging research topic and contemporary business issue. As such, it is appropriate, given the current literature on market stressors, that COVID-19 be explored for its potential accelerant role in Industry 4.0 technology adoption.

(D_5): An examination of the perception that COVID-19 accelerated the adoption of Industry 4.0 technologies was examined.

III.4.12 *Ethical Consideration*

The researcher observed restrictions imposed by Georgia State University and relevant government or public health authorities in research activities. Due to the global pandemic (COVID-19), the survey will be administered online. Qualtrics will source participants digitally through its proprietary software and database.

The researcher was required to financially compensate Qualtrics for "Sample Services" (access to survey panel participants). For clarification purposes only, according to the Qualtrics order form, "Sample Services" may have integrated services to incentivize qualified respondents and gather respondents. Qualtrics determined any financial incentives offered to respondents and was solely responsible for the payment of such incentives. It is understood, this payment was incorporated into the Qualtrics service fee, which did not exceed $12 per small business owner and $19 per business executive.

An informed consent form was made available to each research participant, explaining the study's purpose, expectations, confidentiality, and risk factors. There were no associated physical, social, or psychological risks anticipated. Participants consented to participate in advance to receive the survey questions.

IV CHAPTER 4: FINDINGS

This study examined Industry 4.0 technology adoption across industries. This results section begins with demographics about the industries and organizations, which places context around the 520 industry adopters, representing 12 business sectors. This chapter describes the quantitative research results that address the below research questions:

RQ1: What Industry 4.0 technologies do business industries adopt?

RQ2: What factors contribute to the adoption of I4.0 technologies?

RQ3: What is the effect of COVID-19 on I4.0 technology adoption?

IV.1 Preliminary Analysis

Presented here are the results of descriptive analyses: (a) frequencies and percentages for industry qualities and respondent demographics (i.e., industry representation, organizational role, length of employment, organizational size, functional role), (b) descriptive statistics for the adoptive (independent) variables (i.e., industry, strategic objectives, technology enablement, organizational size, COVID-19 accelerator), and (c) frequencies and percentages for dependent variables (i.e., autonomous technology, cloud computing, nanotechnology, artificial intelligence, internet of things, big data, blockchain, random, 3D printing, augmented reality, cybersecurity).

The 520 respondents represented 12 industries, as listed below in Table 4.1. The largest industry representation was from information technology (38%), followed by financial services (11%) and manufacturing (8%). Agriculture, transportation, and healthcare had smaller representations, on average of 3%, respectively. All industries had double-digit frequencies.

Table IV.1: Industry Representation

Variable		*N*	%
Industry			
1.	Manufacturing	40	7.7
2.	Agriculture	14	2.7
3.	Entertainment, Leisure & Arts	34	6.5
4.	Financial Services	57	11.0
5.	Construction	42	8.1
6.	Public Services	30	5.8
7.	Healthcare	17	3.3
8.	Information Technology	195	37.5
9.	Business Services	24	4.6
10.	Professional Services	31	6.0
11.	Retail/Wholesale	21	4.0
12.	Transportation	15	2.9
	Total	520	1000

Note: due to rounding, the total percentage may not equal

The 520 respondents of this study were business owners and executives who had a role in leading Industry 4.0 technology for their respective organizations. The demographic data for those who participated in the study appear in Table 4.2. The majority were owners (*n* = 263, 50.6%). The largest percentage had been employed with the organization for 6-10 years (*n* = 210, 40.4%) and had more than 1000 employees (*n* = 138, 26.5%). They reported managing (*n* = 342, 65.8%), developing (*n* = 182, 35%), approving/authorizing (*n* = 269, 51,7%) and reviewing (*n* = 161, 31%) their organization's I4.0 technology strategy, adoption, and use.

Table IV.2: Respondent Demographic Data (N = 520)

Variable	*N*	%
Organizational role		
Owner	263	50.6
C-Suite / Executive	126	24.2
SVP / VP	29	5.6
Director	102	19.6
Total	520	100.0
Length of Employment		
2-5 years	177	34.0
6-10 years	210	40.4

> 10 years	133	25.6
Total	520	100.0
Manage Industry 4.0 technology	342	65.8
Develop Industry 4.0 technology.	182	35.0
Approve/authorize Industry 4.0 technology	269	51.7
Review Industry 4.0 technology	161	31.0
Organizational Size		
1-4	67	12.9
5-9	26	5.0
10-19	26	5.0
20-49	25	4.8
50-99	37	7.1
100-249	41	7.9
250-499	50	9.6
500-999	110	21.2
1000 or more	138	26.5
Total	520	100.0

Firms under two years were excluded as the screening requirement established respondents have a minimum of two years' experience with the current employer. Organizations were reasonably distributed across organizational size and maturity. Slightly more small businesses were between two and five years; 20% of the total survey population fell into this category. Interestingly, more small firms were over ten years of age, while larger organizations were between 6 years and ten years. Five descriptive variables were examined, as indicated in the table below.

Table IV.3: Independent Variables' Frequencies and Percentages

Variable	*N*	%
Organizational Factors/Adoption		
Manufacturing	40	7.7
Agriculture	14	2.7
Entertainment & Leisure	34	6.5
Financial Services	57	11.0
Construction	42	8.1
Public Services	30	5.8
Healthcare	17	3.3

Information Technology	195	37.5
Business Services	24	4.6
Professional Services	31	6.0
Retail / Wholesale	21	4.0
Transportation	15	2.9
Strategic Objectives:		
Transform business model	169	32.5
Expand into new markets	253	48.7
Optimize customer experiences	296	56.9
Innovate new products / services	284	54.6
Accelerate processes	264	50.8
Increase revenue	330	63.5
Lower cost	205	39.4
Technology Enablement (Quick Response to COVID-19)		
Strongly disagree	7	1.3
Disagree	25	4.8
Neither agree nor disagree	63	12.1
Agree	226	43.5
Strongly agree	199	38.3
Total	520	100.0
Organizational Size		
Small	272	52.3
Large	248	47.7
Total	520	100.0
COVID-19 accelerator (of adoption)		
Strongly disagree	7	1.3
Disagree	19	3.7
Neither agree nor disagree	61	11.7
Agree	235	45.2
Strongly agree	198	38.1
Total	520	100.0

While this research sought to identify the relationship between select technological, organizational, and environmental factors (descriptive/independent variables) and industry 4.0 technology adoption (dependent variables), it did not assess the relationship for the predictability. As such statistical analysis is fundamentally not required but understood as a research a priori. Therefore a logistic binary regression analysis was utilized to explain the relationship between the five descriptive variables and the adoption of ten technologies.

The following results present the statistical analyses used to assess the research questions.

IV.1.1 *Assumptions*

Binary logistic regression was used to test the research questions. Logistic regression overcomes many of the restrictive assumptions of linear regression. For example, linearity, normality, and equal variances are not assumed, nor is the error term variance usually distributed. One of the main assumptions of logistic regression is the appropriate structure of the outcome variable. Binary logistic regression requires the dependent variable to be binary. In this data set, the dependent variables were categorical; hence this assumption was met. Logistic regression requires an adequate sample size. A general guideline is that a minimum of 10 cases with the least frequent outcome for each independent variable is needed in the model. In addition, the independent variables were measured at the nominal, interval, or ratio level, observations were independent, and the categories of the dichotomous dependent variable and any nominal independent variables were mutually exclusive.

IV.1.2 *Data Screening*

The data were screened for missing values. As seen in Table 4.3 and Table 4.4, there were missing data for the ten dependent variables. Random and inconsistent adoption rates are the missing values that the analysis constrained.

The information technology industry represented a large portion of the survey population; thus, it was removed from analysis to balance class distribution with sample reduction (Cochran, 2007) (Laurikkala, 2001). IBM, Inc. SPSS was used to perform the analysis. The reference group was set to non-adopters (represented by the value=0) since the population of interest was company-wide adopters (represented by the value=1)(Sperandei, 2014). To allow for ample statistical power, non-adopters were selected for the smaller sample size (Sperandei, 2014).

Table IV.4: Frequency of Missing Data for the Dependent Variables

	n	Missing	
		Count	Percent
AUTOMOUS / AUTOMATION	423	97	18.7
CLOUD COMPUTING	389	131	25.2
NANO TECHNOLOGY	380	140	26.9
ARTIFICIAL INTELLIGENCE	369	151	29.0
INTERNET OF THINGS	368	152	29.2
BIG DATA	368	152	29.2
BLOCKCHAIN	367	153	29.4
3D PRINTING	360	160	30.8
AUGMENTED REALITY	346	174	33.5
CYBERSECURITY	419	101	19.4

IV.2 Research Question One

The first research question asked, *What Industry 4.0 technologies do business sectors adopt?* A crosstabulation analysis was conducted to examine which enterprises adopt Industry 4.0 technologies. The crosstabulation informs all adopter groups (company-wide, inconsistent, none) and provides percentages of overall technology adoption by industry.

The "random or inconsistent adoption" rate was held constant to examine the dichotomy of technology adoption (no adoption versus company-wide adoption). Adoption rates are listed in the below table. Nanotechnology, blockchain, and augmented reality technologies were the three technologies that had more non-adopters than company-wide adopters. The other technologies were reported to have higher percentages of company-wide adopters than non-adopters. Cloud computing had the most significant portion (87%) of overall company-wide adopters, while augmented reality had the lowest rate (42%).

Table IV.5: Dependent Variables' Frequency & Percentage

Variable	*N*	%
Autonomous / Automated Technology		
No Adoption	97	22.9
Company-wide Adoption	326	77.1
Total	423	100.0
Cloud Computing		
No Adoption	51	13.1
Company-wide Adoption	338	86.9
Total	389	100.0
Nanotechnology		
No Adoption	215	56.6
Company-wide Adoption	165	43.4
Total	380	100.0
Artificial Intelligence		
No Adoption	142	38.5
Company-wide Adoption	227	61.5
Total	369	100.0
Internet of Things		
No Adoption	74	20.1
Company-wide Adoption	294	79.9
Total	368	100.0
Big Data		
No Adoption	104	28.3
Company-wide Adoption	264	71.7
Total	368	100.0
Blockchain		
No Adoption	210	57.2
Company-wide Adoption	157	42.8
Total	367	100.0
Random__3D		
No Adoption	174	48.3
Company-wide Adoption	186	51.7
Total	360	100.0
Augmented Reality		
No Adoption	202	58.4
Company-wide Adoption	144	41.6
Total	346	100.0
Cybersecurity		
No Adoption	65	15.5
Company-wide Adoption	354	84.5
Total	419	100.0

Cloud Computing (73%) was the highest adopted technology for manufacturing, followed by cybersecurity (71%) and autonomous technology (55%). Agriculture organizations adopted cybersecurity 50% over all the technologies. In the entertainment and leisure industry, cloud computing (53%) and the internet of things (53%) were the highest adopted technologies based on survey results. Financial services adopted cybersecurity at 81%. Nearly three-quarters (71%) of the construction industry and 78% of information technology adopted autonomous technology. Public services (63%) and healthcare (83%) reported cloud computing as the most adopted technology. Business services (75%), professional services (74%), and retail/wholesale (71%) also reported cloud computing as the most adopted technology. The transportation industry leveraged autonomous/automation technology at 80%.

Table IV.6: Cross-Industry Technology Adoption (Company-Wide Percentages)

Technology Industry	Auto	Cloud	Nano	AI	IoT	Big Data	Block Chain	3D Print	AR	Cyber Security
Manufacturing	55	73	28	50	43	48	35	28	28	60
Agriculture	57	43	29	29	57	29	43	21	36	71
Entertainment	32	53	18	15	53	41	21	29	21	47
Financial Services	63	70	37	51	55	56	37	30	30	81
Construction	71	48	29	43	55	50	24	48	26	57
Public Services	60	63	33	33	53	37	40	40	40	60
Healthcare	41	83	35	35	47	65	30	41	06	82
Information Technology	78	67	41	56	46	60	32	42	32	73
Business Services	42	75	21	25	42	46	33	17	21	71
Professional Services	36	74	16	36	52	23	07	23	16	58
Retail/ Wholesale	43	71	05	19	48	33	29	29	14	67
Transportation	80	53	33	33	80	73	27	47	33	67

Several binary logistic regression analyses were conducted to investigate the statistical significance of industry adoption of Industry 4.0 technologies. The results in the below tables identify which variables contributed to the adoption models for autonomous/automation technology, cloud computing, nanotechnology, artificial intelligence, the internet of things, big data, blockchain, 3D printing, augmented reality, and cybersecurity. The regression models reported significant variables ($p<.10$), highlighted in each of the ten adoption models. Many of the variables were significant at $p<.05$, and a few were powerful at $p<.01$, while fewer were significant at $p<.10$.

IV.3 Research Question Two

The second research question asked, *what factors contribute to the adoption of I4.0 technologies?* Both descriptive and binary logistic regression analyses were conducted to understand adoption behaviors and the statistical significance of the examined factors on adoption. The below section presents adoption models for each of the Industry 4.0 technologies, followed by descriptives and summaries of strategic objectives, technology enablement, and organizational size.

IV.3.1 *Adoption Models*

The following models identified statistically significant variables and their respective contributions to the specified technology adoption model. A binary logistic regression analysis was conducted, inclusive of all the independent variables. The dependent variables were (a) automation adoption, (b) cloud computing, (c) nanotechnology, (d) artificial intelligence, (e) internet of things, (f) big data, (g) blockchain, (h) augmented reality (i), and (j) cybersecurity. The results showed varying contributions by strategy, technology enablement, industry, organizational size, and COVID-19 effects. Each technology adoption model was unique.

IV.3.1.1 Model 1: Autonomous/Automation Technology Adoption

Outliers were assessed using case diagnostics. There were no outliers for the specified model. In addition, cases with more or less than ±3 values on the standardized residual are considered outliers (Tabachnick & Fidell, 2007). None of the values fell outside the given range for the specified model. The standardized residuals ranged from -2.76 to 2.25.

A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of autonomous/automation technology. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The full binary logistic regression model containing all predictors was statistically significant, $\chi2(21) = 276.447$, $p < .001$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of autonomous/automation technology. Wholistically, the model explained between 48.0% (Cox and Snell $R2 = .480$) and 64.0% (Negelkerke $R2 = .640$) of the variance in company-wide adoption of Industry 4.0 technology adoption of autonomous/automation technology and correctly classified 84.9% of cases. Sensitivity, the percentage of cases that had the observed characteristic, was 94.5% (report company-wide adoption of Industry 4.0 technology adoption of autonomous/automation technology). Specificity, the percentage of cases that did not have the observed characteristic, was 52.6% (did not adopt the technology).

As shown in Table 4.16, several descriptive (independent) variables made a unique statistically significant contribution to the model of autonomous technology adoption. Seven of the eleven industries were statistically significant: manufacturing, entertainment, public services, healthcare, business services, professional services, and retail/wholesale. Only one strategic objective (expand into new markets) significantly contributed to the model, with an odds ratio of 2.35, indicating respondents who had expanded into new markets were 2.35 times more likely to report autonomous/automation technology adoption. Organizational size (small) was the last predictor to contribute to the model. Small organizations were 2.31 times more likely to adopt autonomous technology than large organizations.

Table IV.7: Logistic Regression Model for Autonomous Technology

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	-1.862	.544	11.714	.001	.155	.053	.451
Agriculture	-1.297	.806	2.588	.108	.273	.056	1.327
Entertainment	-2.659	.542	24.036	.000	.070	.024	.203
Financial Services	-.997	.576	2.997	.083	.369	.119	1.141
Constructions	-1.010	.606	2.784	.095	.364	.111	1.193
Public Services	-1.702	.606	7.888	.005	.182	.056	.598
Healthcare	-2.165	.762	8.071	.004	.115	.026	.511
Business Services	-2.211	.709	9.722	.002	.110	.027	.440
Professional Services	-2.582	.578	19.984	.000	.076	.024	.235
Retail/Wholesale	-1.812	.663	7.469	.006	.163	.045	.599
Transportation	-.027	1.137	.001	.981	.973	.105	9.033
Transform Business Model	.248	.335	.549	.459	1.281	.665	2.469
Expand New Markets	.855	.314	7.403	.007	2.351	1.270	4.354
Optimize Customer Exp.	-.018	.305	.003	.954	.982	.540	1.787
Innovate Products/Services	.213	.309	.475	.491	1.238	.675	2.269
Accelerate Processes	.344	.310	1.231	.267	1.410	.768	2.588
Increase Revenue	-.541	.319	2.881	.090	.582	.312	1.087
Lower Cost	-.260	.305	.726	.394	.771	.424	1.402
Technology Enablement	.359	.197	3.342	.068	1.432	.974	2.105
Organizational Size	.836	.355	5.552	.018	2.307	1.151	4.626
COVID-19 Accelerator	.165	.191	.741	.389	1.179	.810	1.716

Note. $\chi^2(21) = 276.447$, $p = .000$. (Cox and Snell R2 = .480) (Negelkerke R2 = .640)

IV.3.1.2 Model 2: Cloud Computing Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.04 to -2.91. A binary logistic regression was performed to assess the impact of the descriptive (independent) variables on the likelihood that respondents would report company-wide adoption of computing Industry 4.0 technology. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 acceleration as independent variables entered the model in separate blocks.

At Step 5, the full logistic regression model containing all predictors was statistically significant, $\chi 2(21) = 293.93$, $p < .001$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of cloud computing. The overall model explained between 53.0% (Cox and Snell R2 = .530) and 70.7% (Negelkerke R2 = .707) of the variance in company-wide adoption of Industry 4.0 technology adoption of cloud computing and correctly classified 87.7% of cases. Sensitivity, the percentage of cases that had the observed characteristic, was 97.9% (report company-wide adoption of Industry 4.0 technology adoption of cloud computing). Specificity, the rate of cases that did not have the observed characteristic was 19.6% (not adopting cloud computing).

As shown in Table 4.7.B, two industry (independent) variables made a unique statistically significant contribution to the model; agriculture and entertainment/leisure industries.

However, four strategic objectives (expand into new markets strategy, optimize customer experiences strategy, innovate new products/services strategy, and accelerate processes) had p values less than .100, but confidence intervals contained the value 1. Expand into new markets strategy had an odds ratio of 0.52 ($p > .05$), indicating that respondents who expanded into new markets were 0.52 times less likely to report adoption of cloud computing (controlling all the other variables in the model). Optimize customer experiences strategy had an odds ratio of 0.54 ($p > .05$), indicating that respondents who optimized customer experiences were 0.54 times less likely to report adoption of cloud computing (controlling all the other variables in the model). Innovate new products/services strategy had an odds ratio of 0.53 ($p > .05$), indicating that respondents who optimized customer experiences were 0.53 times less likely to report adoption of cloud computing (controlling all the other variables in the model).

Finally, accelerate processes strategy had an odds ratio of 0.51 (p > .05), indicating that respondents who accelerated processes were 0.51 times more likely to report adoption of cloud computing.

Table IV.8: Logistic Regression Model for Cloud Computing

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	.228	.607	.141	.707	1.256	.382	4.122
Agriculture	2.051	.787	6.788	.009	7.775	1.662	36.368
Entertainment	1.259	.537	5.503	.019	3.523	1.230	10.091
Financial Services	.257	.574	.201	.654	1.293	.420	3.981
Constructions	.838	.605	1.920	.166	2.311	.707	7.559
Public Services	-.097	.790	.015	.903	.908	.193	4.269
Healthcare	-3.368	2.876	1.371	.242	.034	.000	9.666
Business Services	.056	.802	.005	.944	1.058	.219	5.096
Professional Services	.402	.636	.400	.527	1.495	.430	5.203
Retail/Wholesale	.109	.818	.018	.894	1.115	.224	5.541
Transportation	.895	.876	1.043	.307	2.447	.439	13.631
Transform Business Model	-.542	.420	1.666	.197	.582	.255	1.325
Expand New Markets	-.646	.363	3.169	.075	.524	.258	1.067
Optimize Customer Exp.	-.615	.350	3.093	.079	.541	.272	1.073
Innovate Products/Services	-.629	.365	2.972	.085	.533	.261	1.090
Accelerate Processes	-.659	.368	3.218	.073	.517	.252	1.063
Increase Revenue	.095	.362	.069	.793	1.100	.541	2.234
Lower Cost	-.422	.375	1.266	.261	.656	.314	1.368
Technology Enablement	.094	.222	.178	.673	1.098	.711	1.697
Organizational Size	.169	.389	.188	.664	1.184	.552	2.537
COVID-19 Accelerator	.297	.222	1.781	.182	1.346	.870	2.081

Note. $\chi^2(21) = 294.93$, $p = .000$. (Cox and Snell R2 = .530) (Negelkerke R2 = .707)

IV.3.1.3 Model 3: Nanotechnology Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.25 to 2.18. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of nanotechnology. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant, $\chi2(21) = 102.93$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of nanotechnology. The model as a whole explained between 23.7% (Cox and Snell R2 = .237) and 31.6% (Negelkerke R2 = .316) of the variance in company-wide adoption of Industry 4.0 technology adoption of “Nano” and correctly classified 68.9% of cases. Sensitivity, which is the percentage of cases with the observed characteristic, was 61.8% (report company-wide adoption of Industry 4.0 technology adoption of nanotechnology. Specificity, the rate of cases that did not have the observed factor was 74.4% (not adopting nanotechnology).

As shown in Table 4.7.C, several independent variables made a unique statistically significant contribution to the model. Agriculture and Healthcare were statistically significant, but both confidence intervals contained the value 1. Strategic objectives (transform business model, accelerate processes, increase revenue) significantly contributed to the model. Technology enablement was the strongest predictor of nanotechnology adoption, with an odds ratio of 1.92. Organizations that perceive technology enabled a quick response to COVID-19 are 1.9 times more likely to adopt nanotechnology. Organizational size (small) was also statistically significant with odds of .453, respectively.

Table IV.9: Logistic Regression Model for Nano

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B) Lower	Higher
Manufacturing	-.102	.413	.061	.804	.903	.402	2.027
Agriculture	-1.224	.690	3.146	.076	.294	.076	1.137
Entertainment	-.026	.495	.003	.958	.974	.369	2.573
Financial Services	-.542	.374	2.103	.147	.582	.280	1.210
Constructions	-.102	.410	.062	.803	.903	.404	2.017
Public Services	-.552	.477	1.336	.248	.576	.226	1.468
Healthcare	-1.207	.634	3.618	.057	.299	.086	1.037
Business Services	-.078	.530	.021	.883	.925	.327	2.616
Professional Services	.303	.483	.392	.531	1.353	.525	3.491
Retail/Wholesale	.950	.716	1.761	.185	2.587	.635	10.530
Transportation	-.764	.582	1.721	.190	.466	.149	1.459
Transform Business Model	-.848	.258	10.772	.001	.428	.258	.711
Expand New Markets	-.358	.247	2.093	.148	.699	.431	1.135
Optimize Customer Exp.	-.325	.255	1.624	.203	.722	.438	1.191
Innovate Products/Services	-.243	.250	.946	.331	.784	.480	1.280
Accelerate Processes	.447	.254	3.087	.079	1.563	.950	2.574
Increase Revenue	.505	.253	3.984	.046	1.657	1.009	2.720
Lower Cost	.310	.253	1.504	.220	1.363	.831	2.237
Technology Enablement	.654	.191	11.725	.001	1.924	1.323	2.797
Organizational Size	-.791	.244	10.544	.001	.453	.281	.731
COVID-19 Accelerator	.238	.190	1.571	.210	1.269	.874	1.843

Note. $\chi^2(22) = 123.72$, $p = .000$. (Cox and Snell R2 = .237) (Negelkerke R2 = .316)

IV.3.1.4 Model 4: Artificial Intelligence (AI) Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.44 to 2.03. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of artificial intelligence. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant,

$\chi 2(21) = 127.77$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of artificial intelligence. The model explained between 29.3% (Cox and Snell R2 = .293) and 39.0% (Negelkerke R2 = .390) of the variance in company-wide adoption of Industry 4.0 technology adoption of artificial intelligence and correctly classified 78.9% of cases. Sensitivity, the percentage of cases that had the observed characteristic, was 88.5% (report company-wide adoption of Industry 4.0 technology adoption of artificial intelligence. Specificity is the percentage of cases that did not have the observed characteristic, 63.4% (did not adopt the artificial intelligence).

As shown in Table 4.x, eight industries and one strategic objective variable made a unique statistically significant contribution to the model. The healthcare was statistically significant, but the value 1 fell within the confidence interval. Additionally, one additional strategic objective (accelerate processes) was statistically significant at p=\> .100. Technology enablement and organizational size (small) were also substantial, but all three variables contained a value of 1 within the confidence interval. Transform business model had an odds ratio of 2.069 (p > .05), indicating that respondents who had this objective were 2.07 times more likely to report adoption of artificial intelligence technology.

Table IV.10: Logistic Regression Model for Artificial intelligence

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	-1.101	.443	6.186	.013	.333	.140	.792
Agriculture	-1.733	.764	5.146	.023	.177	.040	.790
Entertainment	-2.642	.564	21.947	.000	.071	.024	.215
Financial Services	-.679	.443	2.345	.126	.507	.213	1.209
Constructions	-1.012	.474	4.568	.033	.363	.144	.919
Public Services	-1.477	.524	7.945	.005	.228	.082	.638
Healthcare	-1.273	.726	3.073	.080	.280	.067	1.162
Business Services	-2.121	.610	12.101	.001	.120	.036	.396
Professional Services	-1.390	.507	7.513	.006	.249	.092	.673
Retail/Wholesale	-2.025	.700	8.354	.004	.132	.033	.521
Transportation	-1.152	.704	2.676	.102	.316	.079	1.256
Transform Business Model	.727	.299	5.917	.015	2.069	1.152	3.716
Expand New Markets	.370	.270	1.885	.170	1.448	.854	2.456
Optimize Customer Exp.	.358	.272	1.739	.187	1.431	.840	2.438
Innovate Products/Services	.170	.273	.387	.534	1.185	.694	2.021
Accelerate Processes	-.466	.276	2.852	.091	.628	.366	1.078
Increase Revenue	.028	.267	.011	.915	1.029	.609	1.737
Lower Cost	-.243	.267	.828	.363	.784	.465	1.323
Technology Enablement	.330	.168	3.844	.050	1.391	1.000	1.934
Organizational Size	.529	.280	3.565	.059	1.698	.980	2.941
COVID-19 Accelerator	-.098	.168	.343	.558	.906	.652	1.260

Note. $\chi^2(21) = 127.77$, $p = .0001$. (Cox and Snell R2 = .293) (Negelkerke R2 = .390)

IV.3.1.5 Model 5: Internet of Things (IoT) Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.81 to -2.10. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of the internet of things. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant, $\chi 2(21) = 214.05$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption Industry 4.0 technology adoption of industry of things. The model as a whole explained between 44.1% (Cox and Snell R2 = .293) and 39.0% (Negelkerke R2 = .390) of the variance in company-wide adoption of Industry 4.0 technology adoption of internet of things and correctly classified 83.2% of cases. Sensitivity, the percentage of cases that had the observed characteristic, was 96.3% (report company-wide adoption of Industry 4.0 technology adoption of "IOT"). Specificity, the percentage of cases that did not have the observed characteristic, was 31.1% (did not adopt the strategy).

As shown in Table 4.17, several independent variables made a unique statistically significant contribution to the model. Four industries contributed to the adoption model: manufacturing, financial services, public services, and business services. Agriculture, construction, and retail/wholesale industries were statistically significant, but confidence intervals contained the value of 1 and were thus excluded from the model. Transform business model and expand into new markets were strategic objectives that also contributed to the model. Expand into new markets had an odds ratio of 1.31 ($p > .05$), indicating that respondents who had business services were 1.31 times more likely to report adoption of the internet of things. Transform business model had an odds ratio of 1.07 ($p > .05$); respondents who had this strategic objective were 1.07 times more likely to report adoption of the internet of things. Technology enablement (quick COVID-19 response) had an odds ratio of 1.19, indicating that respondents who transformed business models were 1.19 times more likely to report adoption of the internet of things. Technology enablement was the last contributing model factor.

Table IV.11: Logistic Regression Model for Internet of Things

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	-1.249	.567	4.858	.028	.287	.094	.871
Agriculture	-1.049	.817	1.649	.199	.350	.071	1.737
Entertainment	-.666	.595	1.252	.263	.514	.160	1.650
Financial Services	-1.028	.516	3.963	.046	.358	.130	.984
Constructions	-1.095	.587	3.484	.062	.335	.106	1.056
Public Services	-1.185	.584	4.116	.042	.306	.097	.961
Healthcare	-.976	.855	1.303	.254	.377	.071	2.013
Business Services	-1.808	.659	7.531	.006	.164	.045	.596
Professional Services	-.815	.624	1.706	.192	.443	.130	1.504
Retail/Wholesale	-1.188	.696	2.914	.088	.305	.078	1.192
Transportation	-.298	.859	.121	.728	.742	.138	3.994
Transform Business Model	.822	.383	4.609	.032	2.275	1.074	4.820
Expand New Markets	.925	.333	7.725	.005	2.522	1.314	4.842
Optimize Customer Exp.	-.387	.318	1.483	.223	.679	.364	1.266
Innovate Products/Services	.501	.316	2.509	.113	1.650	.888	3.066
Accelerate Processes	.350	.317	1.219	.270	1.418	.763	2.638
Increase Revenue	.197	.319	.382	.537	1.218	.651	2.279
Lower Cost	-.210	.308	.467	.495	.810	.443	1.482
Technology Enablement	.542	.185	8.615	.003	1.720	1.197	2.471
Organizational Size	.125	.341	.135	.714	1.133	.581	2.210
COVID-19 Accelerator	-.202	.186	1.189	.276	.817	.568	1.175

Note. $\chi^2(21) = 214.05$, $p = .000$. (Cox and Snell R2 = .293) (Negelkerke R2 = .390)

IV.3.1.6 Model 6: Big Data Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.64 to 2.035. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of big data. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant,

$\chi2(21) = 212.71$ $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of big data. The model explained between 42.4% (Cox and Snell R2 = .424) and 56.5% (Negelkerke R2 = .565) of the variance in company-wide adoption of Industry 4.0 technology adoption of big data and correctly classified 83.2% of cases. Sensitivity, the percentage of cases with the observed characteristic, was 93.24% (report company-wide adoption of Industry 4.0 technology adoption of "big data"). Specifically, the percentage of cases that did not have the observed characteristic was 57.7% (did not adopt the big data).

As shown in Table 4.7.F, several independent variables made a unique statistically significant contribution to the model. Seven of eleven industries contributed to the big data adoption model. These industries were manufacturing, agriculture, entertainment, construction, public services, business services, and professional services. While financial services and retail/wholesale were statistically significant, the confidence intervals included the value one and were thus excluded from the model.

The model for statistical contribution included the strategic objectives, innovative new products/services, and lower cost. Organizations that sought to innovate new products were 1.82 times more likely to adopt big data, with an odds ratio of 1.82. Technology enablement for a quick response to COVID-19 also contributed to the adoption model. Organizations that reported technology enablement were 1.68 times more likely to adopt big data. Additionally, small organizations added to the model and were 3.41 times more likely to adopt big data, based on a 3.41 odds ratio.

Table IV.12: Logistic Regression Model for Big Data

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B) Lower	Higher
Manufacturing	-1.265	.550	5.286	.021	.282	.096	.830
Agriculture	-2.121	.797	7.073	.008	.120	.025	.572
Entertainment	-1.158	.533	4.728	.030	.314	.111	.892
Financial Services	-.962	.539	3.187	.074	.382	.133	1.099
Constructions	-1.316	.561	5.510	.019	.268	.089	.805
Public Services	-1.480	.623	5.635	.018	.228	.067	.773
Healthcare	-1.027	.729	1.982	.159	.358	.086	1.496
Business Services	-1.398	.637	4.814	.028	.247	.071	.861
Professional Services	-2.802	.624	20.136	.000	.061	.018	.206
Retail/Wholesale	-1.273	.699	3.311	.069	.280	.071	1.103
Transportation	-.639	.789	.656	.418	.528	.112	2.477
Transform Business Model	.268	.354	.572	.449	1.307	.653	2.615
Expand New Markets	.079	.309	.066	.797	1.082	.591	1.983
Optimize Customer Exp.	.601	.310	3.766	.052	1.824	.994	3.345
Innovate Products/Services	.281	.307	.839	.360	1.324	.726	2.416
Accelerate Processes	.416	.309	1.817	.178	1.516	.828	2.775
Increase Revenue	-.430	.321	1.793	.181	.651	.347	1.221
Lower Cost	-.526	.298	3.110	.078	.591	.329	1.060
Technology Enablement	.518	.193	7.206	.007	1.679	1.150	2.451
Organizational Size	1.228	.365	11.321	.001	3.413	1.670	6.979
COVID-19 Accelerator	-.167	.190	.771	.380	.846	.583	1.228

Note. $\chi2(22) = 210.24$, $p = .0001$. (Cox and Snell R2 = .424) (Negelkerke R2 = .565)

IV.3.1.7 Model 7: Blockchain Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals were 2.18. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of Blockchain. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant,

$\chi 2(21) = 73.25$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of Blockchain. The model explained between 18.1% (Cox and Snell R2 = .181) and 24.1% (Negelkerke R2 = .241) of the variance in company-wide adoption of Industry 4.0 technology adoption of Blockchain and correctly classified 66.5% of cases. Sensitivity, the percentage of cases with the observed characteristic, was 56.1% (report company-wide adoption of Industry 4.0 technology adoption of Blockchain). Expressly, the rate of cases that did not have the observed characteristic was 74.1% (did not adopt blockchain).

As shown in Table 4.7.G, several independent variables made a unique statistically significant contribution to the model. Entertainment, construction, and professional services industries added to the adoption model. Additionally, three strategic objectives (transform business model, expand into new markets and increase revenue) contributed to the blockchain adoption model. Organizations with the strategic objectives of transforming their business model and expand into new markets increase the odds of blockchain adoption by a factor of 2.64 and 2.10, respectively.

Table IV.13: logistic regression model for blockchain

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	-.355	.430	.679	.410	.701	.302	1.631
Agriculture	-.397	.628	.401	.527	.672	.196	2.301
Entertainment	-1.451	.506	8.234	.004	.234	.087	.631
Financial Services	-.162	.398	.165	.684	.851	.390	1.856
Constructions	-1.041	.442	5.548	.019	.353	.148	.840
Public Services	-.532	.462	1.325	.250	.587	.237	1.453
Healthcare	-.341	.712	.229	.632	.711	.176	2.871
Business Services	-.325	.531	.375	.540	.723	.255	2.044
Professional Services	-2.578	.797	10.456	.001	.076	.016	.362
Retail/Wholesale	-.645	.578	1.244	.265	.525	.169	1.630
Transportation	-.771	.676	1.302	.254	.462	.123	1.739
Transform Business Model	.970	.264	13.492	.000	2.637	1.572	4.424
Expand New Markets	.743	.245	9.185	.002	2.102	1.300	3.398
Optimize Customer Exp.	-.312	.246	1.605	.205	.732	.452	1.186
Innovate Products/Services	-.071	.247	.082	.775	.932	.574	1.513
Accelerate Processes	-.118	.246	.228	.633	.889	.549	1.440
Increase Revenue	-.561	.250	5.043	.025	.571	.350	.931
Lower Cost	-.172	.242	.506	.477	.842	.524	1.352
Technology Enablement	.247	.153	2.593	.107	1.280	.948	1.729
Organizational Size	-.122	.258	.223	.637	.885	.533	1.469
COVID-19 Accelerator	-.162	.153	1.127	.288	.850	.631	1.147

Note. $\chi^2(22) = 90.69$, $p = .000$. (Cox and Snell R2 = .181) (Negelkerke R2 = .241)

IV.3.1.8 Model 8: 3D Printing Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals were 2.038. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of 3D. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The full logistic regression model containing all predictors was statistically significant, $\chi2(21) = 432.561$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of 3D. The entire model explained between 16.9% (Cox and Snell R2 = .169) and 22.5% (Negelkerke R2 = .225) of the variance in company-wide adoption of Industry 4.0 technology adoption of 3D and correctly classified 68.1% of cases. Sensitivity, the percentage of cases with the observed characteristic, was 75.3% (report company-wide adoption of Industry 4.0 technology adoption of 3D). Specifically, the percentage of cases that did not have the observed characteristic was 60.3% (did not adopt the strategy).

As shown in Table 4.7.H, several independent variables made a unique statistically significant contribution to the model. The following industries were statistically significant and included in the 3D printing adoption model: entertainment, financial services, business services, and professional services. Two objectives were added to the model: transform the business model and expand into new markets. The odds of adoption increased by a factor of 1.811 (transform business model) and 1.828 (expand into new markets). Three other variables were statistically significant but failed to meet the confidence interval criteria. These variables were manufacturing innovation, new products/services, and lower costs. At the same time, innovative new products/services had an odds ratio of 1.59, although the confidence interval contained the value of 1.

Table IV.14: Logistic Regression Model for 3D Printing

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B) Lower	Higher
Manufacturing	-.862	.469	3.384	.066	.422	.168	1.058
Agriculture	-.273	1.007	.073	.786	.761	.106	5.479
Entertainment	-1.164	.457	6.501	.011	.312	.128	.764
Financial Services	-1.038	.385	7.287	.007	.354	.167	.752
Constructions	.438	.481	.830	.362	1.550	.604	3.977
Public Services	-.388	.496	.612	.434	.678	.256	1.794
Healthcare	-.419	.624	.450	.502	.658	.194	2.236
Business Services	-1.857	.626	8.802	.003	.156	.046	.532
Professional Services	-1.199	.528	5.149	.023	.301	.107	.849
Retail/Wholesale	-.628	.598	1.104	.293	.534	.165	1.722
Transportation	.347	.689	.253	.615	1.414	.367	5.456
Transform Business Model	.594	.268	4.916	.027	1.811	1.071	3.060
Expand New Markets	.603	.248	5.916	.015	1.828	1.124	2.973
Optimize Customer Exp.	-.033	.252	.017	.897	.968	.590	1.586
Innovate Products/Services	.470	.254	3.412	.065	1.599	.972	2.633
Accelerate Processes	-.090	.247	.132	.716	.914	.564	1.483
Increase Revenue	-.281	.252	1.246	.264	.755	.461	1.237
Lower Cost	-.418	.246	2.895	.089	.659	.407	1.066
Technology Enablement	.058	.163	.129	.720	1.060	.771	1.458
Organizational Size	.089	.270	.107	.743	1.093	.643	1.856
COVID-19 Accelerator	.007	.160	.002	.965	1.007	.735	1.379

Note. $\chi^2(22) = 85.61$, $p = .0001$. (Cox and Snell R2 = .169) (Negelkerke R2 = .225)

IV.3.1.9 Model 9: Augmented Reality (AR) Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from 2.09 to 2.08. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of AR. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant,

$\chi 2(21) = 72.103$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of Augmented Reality (AR). The model explained between 18.8% (Cox and Snell R2 = .188) and 25.1% (Negelkerke R2 = .251) of the variance in company-wide adoption of Industry 4.0 technology adoption of AR and correctly classified 65.6% of cases. Sensitivity, the percentage of cases with the observed characteristic, was 53.5% (report company-wide adoption of Industry 4.0 technology adoption of AR). Specifically, the rate of cases with the observed factor was 74.3% (not adopting the strategy).

As shown in Table 4.7.I, several independent variables made a unique statistically significant contribution to the model. Entertainment, professional services, retail/wholesale, transform business model objective, increase revenue objective, and lower cost objective comprised the augment reality adoption model. The odds of adoption increased by a factor of 2.81 for organizations that focus on transforming their business models. Three other variables (financial services, healthcare, and organizational size) were statistically significant but had values of 1 within the confidence interval.

Table IV.15: Logistic Regression Model for Augmented reality

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	-.500	.454	1.217	.270	.606	.249	1.475
Agriculture	-.170	.722	.056	.814	.844	.205	3.473
Entertainment	-1.065	.507	4.418	.036	.345	.128	.931
Financial Services	-.671	.396	2.871	.090	.511	.235	1.111
Constructions	-.750	.462	2.636	.104	.472	.191	1.168
Public Services	-.477	.473	1.019	.313	.620	.246	1.568
Healthcare	-2.221	1.146	3.754	.053	.108	.011	1.026
Business Services	-.967	.591	2.680	.102	.380	.119	1.210
Professional Services	-1.395	.577	5.833	.016	.248	.080	.769
Retail/Wholesale	-1.526	.724	4.439	.035	.217	.053	.899
Transportation	-.397	.653	.370	.543	.673	.187	2.416
Transform Business Model	1.032	.273	14.310	.000	2.807	1.644	4.792
Expand New Markets	-.064	.256	.062	.803	.938	.568	1.549
Optimize Customer Exp.	.039	.257	.023	.879	1.040	.629	1.719
Innovate Products/Services	-.166	.269	.381	.537	.847	.499	1.436
Accelerate Processes	.266	.251	1.116	.291	1.304	.797	2.135
Increase Revenue	-.636	.254	6.294	.012	.529	.322	.870
Lower Cost	-.474	.250	3.596	.058	.623	.381	1.016
Technology Enablement	.174	.173	1.018	.313	1.191	.848	1.671
Organizational Size	.439	.260	2.851	.091	1.552	.932	2.584
COVID-19 Accelerator	-.096	.167	.329	.566	.908	.654	1.261

Note. $\chi^2(22) = 103.42$, $p = .0001$. (Cox and Snell R2 = .188) (Negelkerke R2 = .251)

IV.3.1.10 Model 10: Cybersecurity Adoption

Outliers were assessed using case diagnostics. There were no cases for the specified model that exceeded the value of ±3 on the standardized residual. The standardized residuals ranged from -2.78 to -2.00. A binary logistic regression was performed to assess the impact of the independent variables on the likelihood that respondents would report company-wide adoption of Industry 4.0 technology adoption of Cybersecurity. The model contained industry, strategic objectives, technology enablement, organizational size, and COVID-19 as independent variables entered the model in separate blocks.

The entire logistic regression model containing all predictors was statistically significant,

$\chi 2(21) = 291.73$, $p < .01$, indicating that the model distinguished between respondents who did and did not report company-wide adoption of Industry 4.0 technology adoption of Cybersecurity. The model explained between 50.2% (Cox and Snell R2 = .502) and 66.9% (Negelkerke R2 = .669) of the variance in company-wide adoption of Industry 4.0 technology adoption of Cybersecurity and correctly classified 87.1% of cases. Sensitivity, the percentage of cases that had the observed characteristic, was 98.9% (report company-wide adoption of Industry 4.0 technology adoption of Cybersecurity). Specifically, the rate of cases with the observed factor was 23.1% (did not adopt the strategy).

As shown in Table 4.7.J, several independent variables made a unique statistically significant contribution to the mode: professional services, transportation, innovative new products, accelerate processes, and technology enablement. Technology enablement (Quick response to COVID-19) had an odds ratio of 1.96. Organizations that reported technology enablement were 1.96 times more likely to report adoption of Cybersecurity. Professional Services are more likely to adopt cybersecurity by a factor of 2.969. The transportation industry is 3.887 times more likely to adopt cybersecurity. Accelerate processes (strategic objective) were statistically significant. The value of 1 fell within the confidence interval.

Table IV.16: Logistic Regression Model for Cybersecurity

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Higher
Manufacturing	.586	.537	1.191	.275	1.797	.627	5.146
Agriculture	-3.925	2.869	1.872	.171	.020	.000	5.459
Entertainment	.809	.538	2.262	.133	2.246	.782	6.449
Financial Services	-.008	.535	.000	.989	.992	.348	2.831
Constructions	.495	.597	.687	.407	1.640	.509	5.286
Public Services	.572	.605	.894	.344	1.771	.542	5.793
Healthcare	-.576	1.052	.299	.584	.562	.072	4.421
Business Services	-.206	.833	.061	.804	.813	.159	4.163
Professional Services	1.088	.553	3.870	.049	2.969	1.004	8.778
Retail/Wholesale	.551	.666	.684	.408	1.735	.470	6.407
Transportation	1.358	.678	4.011	.045	3.887	1.029	14.673
Transform Business Model	-.147	.394	.139	.709	.863	.399	1.868
Expand New Markets	.268	.326	.677	.410	1.308	.690	2.476
Optimize Customer Exp.	-.505	.315	2.563	.109	.604	.325	1.120
Innovate Products/Services	-.674	.328	4.236	.040	.510	.268	.968
Accelerate Processes	.184	.344	.284	.594	1.202	.612	2.360
Increase Revenue	-.619	.330	3.519	.061	.538	.282	1.028
Lower Cost	-.493	.335	2.163	.141	.611	.316	1.178
Technology Enablement	.671	.212	10.008	.002	1.956	1.291	2.963
Organizational Size	-.470	.353	1.773	.183	.625	.313	1.248
COVID-19 Accelerator	.021	.216	.009	.923	1.021	.668	1.560

Note. $\chi^2(22) = 291.88$, $p = .0001$ (Cox & Snell R Square=.497) (Nagelkerke R Square=663)

While the above adoption models provided a composite view of factors, below is a summary of findings for the other independent variables (strategic objectives, technology enablement, and organizational size). The industry as an organizational variable was reported in the prior section under research question one, and the effects of COVID-19 will be noted in the next section under question three.

IV.3.2 *Strategic Objectives*

The results indicate varying strategies across industries and technologies. The following descriptions offer insight into what strategic objectives are used for the adoption of industry 4.0 technology. As well, the results inform which enterprises adopt which strategy. Increasing revenue is the most popular strategic objective of industry 4.0 technology adopters, across cloud computing (65%), artificial intelligence (66%), internet of things (67%), big data (64%), blockchain (62%), 3D Printing (66%), cybersecurity (71%). Two yielded higher adoption rates across all technologies and strategic objectives; 70% of autonomous technology adopters had innovative products and services as a strategic objective. Additionally, 71% of cybersecurity adopters had increase revenue as a strategic priority.

Table IV.17: Strategic Objectives by Technology (values in percentage)

Strategic Objective / Technology	Transform Business Model	Expand into new markets	Optimize customer experiences	Innovate products/ services	Accelerate processes	Increase revenue	Lower costs
Autonomous	36	54	59	70	56	63	36
Cloud Computing	36	53	62	60	56	65	43
Nano Tech	42	56	66	62	50	58	33
Artificial Intelligence	40	55	65	62	54	66	36
Internet of Things	36	55	60	34	57	67	39
Big Data	35	52	64	64	57	64	36
Blockchain	46	62	56	58	56	62	42
3D Printing	40	60	62	65	53	66	37
Augmented Reality	44	52	60	60	60	58	34
Cybersecurity	33	50	61	62	57	71	42
Average	35.5	**50.0**	**55.5**	53.6	50.0	**57.0**	33.6

Shifting to an industry view of Industry 4.0 Technology strategic objectives, the results showed which strategic objectives industries pursued. An increase in revenue (64%) was the most sought-after objective across industries, followed by optimizing customer experience (56%) and innovative products and services (49%). The following firms had increase revenue as a strategic objective: manufacturing (58%), entertainment (59%), financial services (68%), construction (67), business services (88%), professional services (68%), and retail/wholesale

(86%). Of all industry 4.0 technology adopters, transportation was least focused on transforming business models, with a percentage of 7%. The majority (60%) of industry respondents reporting lower costs as the priority. Agriculture sought to innovate products by a factor of 64%. The public sector (53%) focused on optimizing the customer experience. Healthcare set its objective to innovate products (65%) and accelerate processes (64%). Additionally, Information Technology (68%) held innovative products/services as the objective

Table IV.18: Strategic Objectives by industry (values in percentage)

Industry	Transform Model	New Markets	Optimize CX	Innovate Products	Accelerate Process	Increase Revenue	Lower Costs
Manufacturing	25.00	47.50	52.50	50.00	40.00	**57.50**	45.00
Agriculture	28.57	42.86	57.14	**64.29**	10.00	57.14	14.29
Entertainment	32.35	47.06	44.12	32.35	22.50	**58.82**	44.12
Financial Services	40.35	49.12	59.65	47.37	59.65	**68.42**	45.61
Construction	30.95	45.24	50.00	50.00	57.14	**66.67**	30.95
Public Sector	30.00	46.67	**53.33**	40.00	46.67	46.67	40.00
Healthcare	41.18	29.41	58.82	**64.71**	**64.71**	58.82	47.06
Information Technology	36.41	55.38	59.49	**67.69**	54.87	61.54	29.74
Business Services	33.33	58.33	66.67	54.17	54.17	**87.50**	62.50
Professional Services	29.03	25.81	64.52	54.84	45.16	**67.74**	51.61
Retail/Wholesale	14.29	47.62	57.14	23.81	52.38	**85.71**	61.90
Transportation	6.67	40.00	46.67	40.00	46.67	53.33	**60.00**
Average	29.01	44.58	**55.84**	**49.10**	46.16	**64.16**	44.40

IV.3.3 *Technology Enablement*

Across industries, 82% agree that Industry 4.0 technologies enabled their organization to quickly respond to COVID-19 induced threats and opportunities, of which 44% agree, and 38% strongly agree. Only one percent strongly disagreed with this statement, and these organizations were widely non-adopters of Industry 4.0 technologies.

Table IV.19: Frequency of Technology Enablement

	Variable	*N*	%
1.	Strongly disagree	7	1.3
2.	Disagree	25	4.8
3.	Neither agree nor disagree	63	12.1
4.	Agree	226	43.5
5.	Strongly Agree	199	38.3

The below chart reflects the cross-industry perceptions of Industry 4.0 technologies used to respond quickly to the threats and challenges presented by COVID-19. Higher levels of agreement are seen in construction (45%), information technology (45%), and transportation (47%). Several industries indicated (0%) no strong disagreements to this statement; they were: manufacturing, agriculture, healthcare, information technology, business services, professional services, and transportation. Retail and wholesale expressed the most substantial disagreement (9.5%), followed by entertainment, leisure, and the arts (8.8%).

Table IV.20: Cross-Industry Technology Enablement (values in percentage)

Industry 4.0 technologies enabled my organization to respond to COVID-19 induced threats and opportunities quickly.					
Level of Agreement / Industry	1 Strongly disagree	2 Disagree	3 Neither agree nor disagree	4 Agree	5 Strongly agree
Manufacturing	0.0	7.5	17.5	40.0	35.0
Agriculture	0.0	14.3	14.3	28.6	42.9
Entertainment & Leisure	8.8	5.9	26.5	47.1	11.8
Financial Services	1.8	7.0	10.5	40.4	40.4
Construction	2.4	4.8	9.5	38.1	45.2
Public Services	0.0	10.0	20.0	30.0	40.0
Healthcare	0.0	5.9	11.8	52.9	29.4
Information Technology	0.0	0.5	7.2	47.2	45.1
Business Services	0.0	16.7	16.7	33.3	33.3
Professional Services	0.0	6.5	19.4	51.6	22.6
Retail / Wholesale	9.5	4.8	14.3	42.9	28.6
Transportation	0.0	0.0	0.0	53.3	46.7

Less than 10% of entertainment, financial services, construction, and retail strongly disagreed that big data-enabled quick response to COVID-19 induced challenges and opportunities. Of the latter three, respondents (100%) unanimously reported their organization had no big data adoption. Based on survey results, 57% of company-wide adopters agree that industry 4.0 technology-enabled their organization to respond to COVID-19 induced challenges and opportunities quickly. Across all sectors, the highest percentages fell within agree or strongly agree that industry 4.0 technologies enabled a quick response to COVID-19 induced challenges and opportunities.

IV.3.4 *Organizational Size*

The industry representation across small (52%) and large (48%) was nearly equal. Agriculture was unrepresented in large organizations. Entertainment, healthcare, professional services, and retail were disproportionately representative in small organizations, averaging over 80% individually.

Table IV.21: industry by organizational size

Industry	*Organization Size*			
	Small		Large	
	n	%	*n*	%
Manufacturing	27	67.5	13	32.5
Agriculture	14	100	0	0
Entertainment & Leisure	28	82.4	6	17.6
Financial Services	25	43.9	32	56.1
Construction	22	52.4	20	47.6
Public Services	18	60.0	12	40.0
Healthcare	14	82.4	3	17.6
Information Technology	56	28.7	139	71.3
Business Services	14	58.3	10	41.7
Professional Services	26	83.9	5	16.1
Retail / Wholesale	18	85.7	3	14.3
Transportation	10	66.7	5	33.3
Total	272	52.3	248	47.7

IV.4 Research Question Three

The final research question asked, *What is the effect of COVID-19 on I4.0 technology adoption?* Descriptive and binary logistic analyses were conducted to investigate the relationship between COVID-19 and Industry 4.0 technology adoption. The dependent variables were ten unique industry 4.0 technologies. The below chart reflects the overall perceptions of COVID-19 effects on technology adoption. Over 38% of respondents strongly agree that COVID-19 accelerated the adoption of Industry 4.0 technology, while 45% approve.

Table IV.22: COVID-19 as an Accelerator (values in percentage)

Overall, COVID-19 accelerated my organization's adoption of Industry 4.0 technologies			
		N	*%*
Valid	1 Strongly disagree	7	1.3
	2 Disagree	19	3.7
	3 Neither agree nor disagree	61	11.7
	4 Agree	235	45.2
	5 Strongly agree	198	38.1

The table below depicts respondents' industry-level sentiment regarding COVID-19 as an accelerator of Industry 4.0 technology adoption. Most respondents (45%) agree that COVID-19 accelerated adoption; 33% strongly agree with this statement.

Table IV.23: COVID-19 as an Accelerator by industry (values in percentage)

Overall, COVID-19 accelerated my organization's adoption of Industry 4.0 technologies					
Level of Agreement Industry	1 Strongly disagree	2 Disagree	3 Neither agree nor disagree	4 Agree	5 Strongly agree
Manufacturing	0.0	5.0	15.0	40.0	40.0
Agriculture	0.0	7.1	14.3	57.1	21.4
Entertainment & Leisure	11.8	5.9	23.5	41.2	17.1
Financial Services	1.8	0.0	12.3	35.1	50.9
Construction	2.4	7.1	7.1	47.5	35.7
Public Services	10.5	6.7	13.3	36.7	43.4
Healthcare	0.0	0.0	5.9	64.7	29.4
Information Technology	0.5	3.1	9.2	13.1	44.1
Business Services	0.0	0.0	20.8	45.8	33.3
Professional Services	0.0	3.2	9.7	64.5	22.6
Retail / Wholesale	0.0	4.8	14.3	52.4	28.6
Transportation	0.0	6.7	6.7	60.0	26.7

COVID-19. Higher levels of agreement are seen in healthcare (65%), professional services (65%), and transportation (60%). Several industries indicated (0%) no strong disagreements to this statement; they were: manufacturing, agriculture, healthcare, information technology, business services, professional services, retail/wholesale, and transportation. Entertainment/leisure expressed the most substantial disagreement (12%), followed by public service (11%).

V CHAPTER 5: DISCUSSION

This research study explored several technological, organizational, and environmental factors related to adopting industry 4.0 technologies across different industry classifications. This research intended to broaden the knowledge of industry 4.0 technology adoption in the United States by detecting factors distinguishing non-adopters from adopters. This chapter delivers the study summary, conclusions, practical and theoretical implications, and recommendations for further research analysis.

V.1 Study Summary

Industry 4.0 technology is unavoidable. Advanced technologies transform the business landscape (Agostini et al., 2020), propelling organizations into the unchartered technological territory. The effect of this global disruptor spans beyond information technology. Industry 4.0 transforms business models, the way firms do business and interact with their customers. Left unaddressed or ignored, industry 4.0 threatens success and even business survival. Many leaders are ill-equipped to manage the impetus industry 4.0 presents and overwhelm organizations compelled to implement simultaneous technologies (Alok et al., 2020).

While industry 4.0 technology, often referred to as digital technology, can be ascribed to many factors, it is often associated with challenges related to real-time responsiveness, costs (Chauhan et al., 2020), and organizational challenges (Alok et al., 2020) that impede the adoption of these advanced technologies. High-performing organizations and company-wide adopters successfully integrate industry 4.0 technologies across broad organizational applications (Agostini et al., 2020). Emerging research has centered around the adoption of specific technologies (Alsheibani et al., 2018), barriers to adoption (Chauhan et al., 2020), the current research landscape (Nazarov et al., 2020), and small and midsize enterprise (SME) adoption, (Agostini et al., 2020). While some research explored international implications (Sivathanu, 2019) (Afolayan et al., 2015; Hemming Kagermann et al., 2016), very few have analyzed Industry 4.0 technology adoption within the context of the United States across multiple technologies and multiple industries, highlighting the value of this study.

This exploration is significant, given the need to increase digital interactions due to COVID-19, but there is a considerable void in understanding the relationship between business factors and industry 4.0 technology adoption. Many studies that highlight adoption factors fail to provide an expansive view beyond manufacturing and information technology and do not offer a distinct view into various technologies. Therefore, the body of knowledge is minuscule regarding industry adoption patterns of multiple technologies.

As a result, to provide insight into which factors contribute to adoption across industries and technologies, the current study examined technological, organizational, and environmental factors. Specifically, strategic objectives, industry, firm size, technology enablement, and COVID-19 were independent variables explored in this research. Sentiments and perceptions about the attributes as mentioned above were gathered from survey results of 520 Qualtrics panel respondents. Descriptive and binary logistic regression analyses were conducted. Information technology was the largest represented industry, accounting for over 30% of all survey respondents. Information technology was thus excluded from the binary logistic regression analysis and set as the reference group.

V.2 Interpretation of Findings

The following interpretations are based on confirmations of model performance, goodness-of-fit, and the appropriateness of data for binary logistic regression. The results section presented coefficients for each independent variable, along with statistical significance.

The interpretations that followed focused the discussion on terms of the odds ratio of the company-wide adopters (Pampel, 2000). The results will be discussed in terms of percentages, which identified the adoption impact. The equation reads as such:

$$\frac{odds\ of\ company\text{-}wide\ adoption\ (x+1)}{odd\ no\text{-}adoption\ (x)} = Exp(\beta) \qquad \text{1- } Exp(B) = odds\ of\ adoption$$

V.2.1 *Cross-Industry Adoption of Industry 4.0 Technology*

Overall, the adoption of industry 4.0 technology varied by sector. Each industry had a unique set of adoption factors, which indicated Industry 4.0 technology adoption was determined more by industry-specific considerations than strategy, enablement, size, or huge societal or market stressors, such as COVID-19. This section interprets each adoption model, which offers a novel comparative view of industries in the United States. This research intended to establish "what" technologies were adopted by various industries but did not explain "why" these factors were so. However, some context is offered from extant research and researcher expertise.

The chart below shows a graphical depiction of adoption patterns across all twelve industries and ten technologies in terms of percentage. Cloud computing, cybersecurity, and the IoT were the most broadly adopted technologies. Transportation, information technology, and financial services were higher adopters than other sectors.

V.2.2 *Manufacturing Adoption of Industry 4.0*

The manufacturing industry had statistically significant relationships that contributed to adopting autonomous/automation technology, artificial intelligence, the internet of things, big data, and 3D printing. The likely adoption of these digital technologies enables the connectivity, interoperability, and real-time communication requirements of machinery and devices (Shi et al., 2020). Manufacturing automation, artificial intelligence, big data, and the internet of things work synergistically to form an intelligence factory that operates with little human intervention and self-regulates across a vast ecosystem of machines, devices, infrastructure, and people.

Manufacturing firms were more likely to adopt autonomous technology by 84.5%, artificial intelligence by 66.7%, IoT by 71.3%, big data by 71.8%, 3D printing by 57.8% than not adopt. This means manufacturing firms overall are more focused on establishing the MTA. It appears that MTA adoption begins with cloud computing and cybersecurity, although they are insignificant factors of adoption for manufacturers. Cloud computing is an enabling technology (L. D. Xu et al., 2018) that facilitates ample data storage and computation. One may reason, there is little difference between manufacturing adopters and non-adopters; both substantially adopt cloud computing, which may explain it is not deemed a significant contributor to the adoption model. Similarly, this may be the case with cybersecurity adoption.

V.2.3 *Agriculture Adoption of Industry 4.0*

According to the survey results, agriculture firms were 22.5% less likely to adopt cloud computing but 70.6 more likely to adopt nanotechnology, artificial intelligence (82.3%), and big data by 88%. While these technologies significantly contributed to the adoption, they are not widely used across the agriculture industry based on percentages. Cybersecurity, IoT, and automation are more widely adopted. However, there is little differentiation of use between adopters and non-adopters. The distinction is explained by chance rather than by the adoption class.

According to Chavas et al. (2020), the agriculture industry embraces technology to lower costs and increase production. Technology adoption in agriculture is wrought with challenges. A vast taxonomy of agriculture technology creates a complex landscape for analysis. Innovative solutions are minutely specific, ranging from information communication technologies to weed control (de Oca Munguia et al., 2020). Advanced technology induces lower prices and higher production. The benefits are countered by an inverse relationship between revenue and lower prices (Chavas et al., 2020; Michler et al., 2019), where consumers reap the financial benefits at farmers' cost (Michler et al., 2019). Risk aversion (Sanch-Maritan et al., 2019) and acquisition costs may deter adoption rates.

V.2.4 *Entertainment & Leisure Adoption of Industry 4.0*

Entertainment and leisure firms were more likely to adopt autonomous technology, cloud computing, AI, big data, blockchain, 3D printing, and AR technologies than non-adopters. Specifically, the entertainment and leisure industry had 93% higher odds of adopting autonomous technology, 87% higher odds of using cloud computing, and 92.9% higher artificial intelligence adoption odds. The odds increase 68.6% for the adoption of big data, 76.6% odds for blockchain adoption, 68.8 higher odds of adoption for 3D printing, and 65.5% higher augmented reality adoption odds.

Entertainment firms broadly implement cloud computing, contributing greater adoption power than any other Industry 4.0 technology. It was plausible that the storage capacity required by the sector's voluminous data fosters cloud computing. Based on the survey results, entertainment organizations essentially utilize cybersecurity and the internet of things, although IoT is not indicative or a predictor of technology adopters. Artificial intelligence is used as a tool in media to engage customers (Cheng et al., 2020); in gaming (Yannakakis et al., 2007), which may explain its implementation impact on the entertainment industry. Statistically, there is little difference between IoT use between adoption groups (company-wide and non-adoption). Augmented reality, 3D printing, and blockchain had low adoption levels across the entertainment industry but could be used as predictors of adoption.

V.2.5 *Financial Services Adoption of Industry 4.0*

In the financial services, the odds increase adoption for the following industry 4.0 technologies: internet of things (64.2%), big data (61.8%), and augmented reality (48.9%); these technologies are predictive factors in financial services. Adopters were more likely to use these technologies than non-adopters. However, the likeliness of use departs from broad adoption, as seen in Image 5.2.d, below. While adopters may be more likely to implement IoT, big data, and augmented reality, their adoption may best be explained by early innovation diffusion due to low industry usage overall.

More financial service firms used cybersecurity and cloud computing regardless, which were insignificant predictors of adoption. This implies that cybersecurity and cloud computing were broadly ratified as industry standards and were not indicators of an adoption class (company-wide adoption versus non-adoption). Augmented reality is not generally embraced in financial services, but adopters' odds of use were higher. Artificial intelligence is used in financial services for many reasons, including chatbot and digital advisor services (Belanche et al., 2019). The extensive use of AI across the financial services industry may explain high acceptance rates but the lower predictive power of adopters versus non-adopters.

V.2.6 *Construction Adoption of Industry 4.0*

The construction industry saw similar increased adoption odds with higher likeliness for artificial intelligence (63.7%), the internet of things (66.5%), big data (73.2%), and blockchain (64.7%). Across construction firms, these four technologies were more likely to be adopted to improve productivity and lower costs (Low Sui et al., 2019).

However, 3D printing and autonomous technology were primarily implemented across construction firms that it can be considered an industry standard since it is unimportant in discerning between adopter groups. Hence, it can be assumed 3D printing, cybersecurity, and autonomous technology are generally embraced across the industry and have become staple technologies, albeit their selections were indistinguishable between adopter groups (i.e., company-wide adopters, non-adopters).

V.2.7 *Public Services Adoption of Industry 4.0*

In the public services industry, firms were more likely to adopt artificial intelligence and big data by 77.2%, augmented reality by 81.8%, and the internet of things by 69.4% than not. While public services were likely to adopt augmented reality, overall, the industry adoption rate is still low. This alludes to potential industry barriers or early stages of innovation diffusion.

No significant predictors of adoption were cloud computing, autonomous technology, and cybersecurity. Hence, it can be assumed these technologies are generally embraced across the industry and have become staple technologies. The adoption levels are indistinguishable between adopter groups (i.e., company-wide adopters, non-adopters).

Healthcare firms had increased odds of adopting autonomous technology (88.5%), nanotechnology (70.1%), artificial intelligence (72%), and augmented reality (89.2%). According to survey results, augmented reality and autonomous technology adoption was lower but significant predictive power. This implies these technologies are emerging across the industry by early adopters.

Cloud computing, big data, and cybersecurity were commonly accepted by not significant predictors of adoption. Hence, it can be assumed these technologies are generally adopted across the industry and have become foundational technologies. The adoption levels are indistinguishable between adopter groups (i.e., company-wide adopters, non-adopters). The motivation of real-time data availability and decision-making (Alrahbi et al., 2021) may substantiate this inference.

Table V.1: Cross-Industry View of I4.0 Technology Adoption (in terms of statistical significance)

Industry
1. Manufacturing
Autonomous/Automation
Artificial intelligence
Internet of things
Big Data
3D Printing
2. Agriculture
Cloud Computing
Nano Technology
Artificial Intelligence
Big Data
3. Entertainment & Leisure
Autonomous/Automation
Cloud Computing
Artificial Intelligence
Big Data
Blockchain
3D Printing
Augmented Reality
4. Financial Services
Internet of Things
Big Data
3D Printing
Augmented Reality
5. Construction
Artificial Intelligence
Internet of Things
Big Data
Blockchain
6. Public Services
Autonomous/Automation
Artificial Intelligence
Internet of Things
Big Data
7. Healthcare
Autonomous/Automation
Nanotechnology

Artificial Intelligence
Augmented Reality
8. Business Services
Autonomous/Automation
Artificial Intelligence
Internet of Things
Big Data
3D Printing
9. Professional Services
Autonomous/Automation
Artificial Intelligence
Big Data
3D Printing
Augmented Reality
Cybersecurity
10. Retail/Wholesale
Autonomous/Automation
Artificial Intelligence
Internet of Things
Big Data
Augmented Reality
11. Transportation
Cybersecurity

V.2.8 *Business Services Adoption of Industry 4.0*

Favorable odds of increased adoption were also identified in the business services industry. Autonomous technology demonstrated 89% higher odds of adoption. Additionally, the artificial intelligence adoption odds (88%) were higher than in other sectors. The adoption of the internet of things had higher odds of adoption (69.4%). Big data adoption in the business services sector experienced higher adoption odds (77.2%). 3D printing adoption also experienced higher odds of adoption (68.8%).

Cloud computing and cybersecurity were frequently employed but were not significant predictors of adoption. It can be assumed these technologies are generally adopted across the industry and have become foundational technologies. The adoption levels are indistinguishable between adopter groups (i.e., company-wide adopters, non-adopters). For example, there is a growing trend for artificial intelligence deployment in auditing. Industry experts believe auditing benefits between machine learning, artificial intelligence, and automation (Siddique, 2018). Still, studies show higher adoption when the use is of internal efficiency versus customer-based (Buchheit et al., 2020).

V.2.9 *Professional Services Adoption of Industry 4.0*

Professional service firms that adopted autonomous technology had 92.4% higher adoption odds than non-adopters of the technology. Also, 75.1% increased odds of adoption were shown for artificial intelligence, 93.9% odds ratio of big data adoption, 64.6% increase odds of adoption for 3D printing, 75.2% higher adoption odds for augmented reality, but 3% lower odds of adoption of cybersecurity.

Cloud computing and the internet of things were often utilized by professional service firms but were not significant predictors of adoption. It can be assumed these technologies are commonly used across the entire industry, regardless of adopter groups (i.e., company-wide adopters, non-adopters). The results of this study revealed adoption was influenced more by the industry sector than strategic objective; however, another study (Nwankwo et al., 2021) concluded technology adoption is determined by business intent. This may explain the lower adoption percentages across many technologies, but this study provided cross-industry insights.

V.2.10 *Retail/Wholesale Adoption of Industry 4.0*

In retail and wholesale firms, the odds of adopting autonomous technology were higher (83.7%). Augmented reality was also had a higher odds ratio of 78.3%., 93.9% higher odds of big data adoption, and 69.5% higher for the internet of things. Thus, autonomous technology, augmented reality, big data, and the internet of things are significantly adopted by the retail/wholesale industry. Autonomous technology, big data, and augmented reality, while predictors of adoption, are less widely adopted across the retail sector. The internet of things is by large the most significant and broadly adopted technology in retail.

Cloud computing and cybersecurity were often utilized by retail/wholesale firms but were not significant predictors of adoption. It can be assumed these technologies are generally adopted across the industry, regardless of adoption strength. Artificial intelligence, according to the survey results, had low frequency. However, artificial intelligence is deemed a significant contributor to the modernization of the retail industry (Shankar et al., 2021).

Technology adoption in the retail industry is risk-averse due to low industry profit margins (Shankar et al., 2021). The technology selection often replaces a legacy system, which increases the barriers to adoption. The choice of technology may be highly scrutinized based on scalability, impact, cost, and diffusion speed (Shankar et al., 2021). This may explain low adoption rates across many industry technologies and high adoption percentages in cybersecurity, cloud computing, and IoT. In many regards, these technologies serve as the platform upon which more industry-specific technologies may operate.

V.2.11 *Transportation Adoption of Industry 4.0*

Transportation saw the least adoption significance of the other industry 4.0 technologies. The adoption odds were 11.3% lower for cybersecurity for transportation firms. According to survey results, transportation firms are less likely to adopt cybersecurity, while adopters expressed high adoption frequencies for cybersecurity.

Overall, the transportation industry demonstrated more robust autonomous technology, IoT, big data, and cybersecurity than other industries. Interestingly, none of these technologies rendered significant as a predictor of adoption. This may be attributed to the broad adoption of these tools across the industry regardless of adoption class. Consistent with other study findings, automation is arguably the most critical technology in the industry (Kaplan et al., 2019), threatening to transform the sector.

V.2.12 *Summary*

Across industries, adopters were more likely to use specific Industry 4.0 technologies, and these vary by the business sector. While adopters were more likely to use a particular technology, overall, there may not be broad adoption of that technology or early diffusion. In some cases, the most widely applied technologies were not significant in differentiating the odds of adoption. The inferences suggested that some technologies were so widely used across an industry that their use was not indicative of company-wide adoption due to a possible industry technological standard.

Overall, the results showed industry as a viable adoption factor of industry 4.0 technologies. While the specific technology adoption varies vastly by business sector, artificial intelligence, big data, autonomous/automation technology, and IoT were the most adopted technologies across industries. The adoption odds were higher across most technologies with few exceptions, indicating industries are more likely to adopt industry 4.0 technologies than not.

V.2.13 *Additional Adoption Factors*

With clearer insight into which industries adopt which technologies, the second research examined what factors contributed to adopting autonomous/automation technology, big data, artificial intelligence, blockchain, the internet of things, nanotechnology, cybersecurity, augmented reality, 3D printing, and cloud computing. The following discussion leverages the ten technology adoption models above and descriptive data to address the research question.

V.2.14 *Strategic Technology Objectives*

The study showed strategic objectives and organizational size had less impact on autonomous/automation technology adoption overall when compared to the industry sector. For cloud computing adoption, a firm's strategic objectives had a more significant influence than industry classification. Industry and organizational size were most impactful for nanotechnology, with a greater likelihood of adoption by larger firms. The strategic objectives were less relevant in terms of nanotechnology adoption.

The adoption of artificial intelligence (AI) saw mixed results. While the industry sector had a more significant role in the adoption odds, organizational size and technology enablement factors were less likely to influence the adoption of AI. According to survey results, the strategic objectives also yielded mixed results; whereas accelerating processes as an adoption factor increased the overall adoption odds, transforming the business model decreased the odds.

Industry selection influences the adoption of the internet of things more than strategic objectives and technology enablement.

Regarding the adoption of big data, product innovation, technology enablement, and organization size decreased adoption. The business sector (industry) increased odds of adoption; agriculture appeared to have the greatest sensitivity. The industry sector more influenced blockchain adoption than strategic objectives, specifically business model transformation and market expansion. However, increase revenue did show to have a more significant influence on the adoption of blockchain technology.

Similarly, lowered costs influenced 3D printing adoption, along with industry factors, then other strategic objectives. Again, as strategic objectives, increased revenue and reduced expenses were more influential in adopting augmented reality than model transformation or organizational size. The industry was a powerful influencer in the adoption of augmented reality. Lastly, cybersecurity was less influenced by industry and technology enablement, greatly influenced by product innovation and process acceleration.

This study provided actionable insights for management across industries. The fourth industrial revolution brings both opportunities and challenges. The competitive strategy will vary by industry, and consideration of the strategic objective and the desired outcome must be considered. Adopting Industry 4.0 Technology provides the groundwork for competitive advantage (Y. Li et al., 2020). Firms innovate products and services to increase revenue and optimize customer experiences. It is recommended all industries advance the adoption of these technologies. Contemporary organizations operate in complexly dynamic environments that require informed decisions and heightened responsiveness. Thus, the efficiency, speed, and accuracy by which strategic actions are made are of great importance.

It can be inferred; cybersecurity was strategically an essential industry 4.0 technology for those seeking to increase revenue. While the data here does not shed light on why the study showed that 64% of cybersecurity adopters were able to facilitate remote work during COVID-19 because of Industry 4.0 technologies. The inference can be made that remote work was enabled by cybersecurity adoption. Remote work allows firms to continue operations and sales instead of stopping business activities. When companies are faced with physical interruptions to in-person operations, the ability to quickly shift to a digital platform is critical during extreme circumstances such as COVID-19.

The below table identifies the strategic objectives of Industry 4.0 Technology company-wide adopters across industries. The following table identifies the statistically significant strategic objectives (independent variable) for each industry 4.0 technology (dependent variable). The results below are compiled from the binary logistic regression models reported in Chapter 4; see Table 4.7.a to Table 4.7.j.

Table V.2: Significant Strategic Objectives by technology (statistically significant values)

Variable	B	S.E.	Wald	Sig.	Exp(B)	95% CI for EXP(B)	
						Lower	Upper
Autonomous/Automation							
Expand into new markets	.855	.314	7.403	.007	2.351	1.270	4.354
Cloud Computing							
Expand into new markets	-.646	.363	3.169	.075	.524	.258	1.067
Optimize CX	-.615	.350	3.093	.079	.541	.272	1.073
Innovate products / services	-.629	.365	2.972	.085	.533	.261	1.090
Accelerate processes	-.659	.368	3.218	.073	.517	.252	1.063
Nanotechnology							
Transform business model	-.848	.258	10.772	.001	.428	.258	.711
Accelerate processes	.447	.254	3.087	.079	1.563	.950	2.574
Increase revenue	.505	.253	3.984	.046	1.657	1.009	2.720
Artificial Intelligence							
Transform business Model	.727	.299	5.917	.015	2.069	1.152	3.716
Accelerate processes	-.466	.276	2.852	.091	.628	.366	1.078
Internet of Things							
Transform business Model	.822	.383	4.609	.032	2.275	1.074	4.820
Expand into new markets	.925	.333	7.725	.005	2.522	1.314	4.842
Big Data							
Innovate products / services	.601	.310	3.766	.052	1.824	.994	3.345
Lower cost	-.526	.298	3.110	.078*	.591	.329	1.060
Blockchain							
Transform business Model	.970	.264	13.492	.000	2.637	1.572	4.424
Expand into new markets	.743	.245	9.185	.002	2.102	1.300	3.398
Increase revenue	-.561	.250	5.043	.025	.571	.350	.931
3D Printing							
Transform business Model	.594	.268	4.916	.027	1.811	1.071	3.060
Expand into new markets	.603	.248	5.916	.015	1.828	1.124	2.973

Innovate products / services	.470	.254	3.412	.065*	1.599	.972	2.633
Lower cost	-.418	.246	2.895	.089*	.659	.407	1.066
Augmented Reality							
Transform business Model	1.032	.273	14.310	.000	2.807	1.644	4.792
Increase revenue	-.636	.254	6.294	.012	.529	.322	.870
Lower cost	-.474	.250	3.596	.058*	.623	.381	1.016
Transform business Model	1.032	.273	14.310	.000	2.807	1.644	4.792
Cybersecurity							
Innovate products/services	-.674	.328	4.236	.040	.510	.268	.968
Accelerate processes	-.619	.330	3.519	.061*	.538	.282	1.028

** Indicates the confidence interval contains the value one*

In summation, the organizational traits of an organization, specific industry sector, had more influence on the select adoption of most industry 4.0 technologies. While this can be generalized, some nuances vary by industry, which was explained above. Overall, the most significant consideration for industry adoption of industry 4.0 technology pertained more to the business sector than any other variable. On average, cloud computing (71%) and cybersecurity (75%) had the highest percentages of strategic objectives across all industries. The internet of things averaged 63%. It can be inferred; cloud computing and cybersecurity are strategically the most critical Industry 4.0 technologies across all sectors.

V.2.15 *Technology-Enabled Responsiveness*

Perceptions of technology enablement align with overall adoption levels within an industry and across technology platforms. The lower the adoption rate, the lower the perception was of the technology's enablement of fast response to COVID-19. However, for company-wide adopters, there were higher percentages of enablement across industries. For those fully acceptant of an Industry 4.0 Technology, the effectiveness of that tool and how the tool was deployed to address COVID-19 was substantial. Inference can thus be made that Industry 4.0 technologies can be used as a tool to overcome market stress. For highly volatile industries, those facing regulatory changes, or entering a risky merger or acquisition, there is an opportunity to adopt Industry 4.0 technology to aid in reducing, avoiding, or resisting these environmental stressors. In conclusion, cloud computing, nanotechnology, artificial intelligence, the internet of things, and big data enabled quick responses to COVID-19 opportunities and threats.

Identified in the below chart are the statistically significant technology enablers (independent variable) across industry 4.0 technologies: in terms of p values ($p=<.05$). Technology as an enabler to a fast response to COVID-19 induced threats and opportunities was not statistically significant for autonomous technology, cloud computing, blockchain, 3D printing, augmented reality, and cybersecurity. Technology enablement contributed to the overall industry 4.0 technology adoption model for nanotechnology, artificial intelligence, the internet of things, and big data as a statistically significant variable. The results below are compiled from the binary logistic regression models reported in Chapter 4; see Table 4.7.a to Table 4.7.j.

Table V.3: significant technology enablement (only statistically significant values reported)

"Industry 4.0 technologies enabled my organization to quickly respond to COVID-19 induced threats and opportunities."

Variable	*B*	*S.E.*	Wald	Sig.	Exp(*B*)	95% *CI* for EXP(*B*)	
						Lower	Upper
Tech Enablement (cybersecurity)	.671	.212	10.008	.002	1.956	1.291	2.963
Tech Enablement (nanotechnology)	.654	.191	11.725	.001	1.924	1.323	2.797
Tech Enablement (AI)	.330	.168	3.844	.050	1.391	1.000	1.934
Tech Enablement (IoT)	.542	.185	8.615	.003	1.720	1.197	2.471
Tech Enablement (Big Data)	.518	.193	7.206	.007	1.679	1.150	2.451

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V.2.16 *Matters of Size*

Organizations were reasonably distributed across organizational size and maturity. Slightly more small firms were between the ages of two and five years; 20% of the total survey population fell into this category. Interestingly, more small firms were over ten years of age, while larger organizations were between 6 and ten years, as reflected in the below image.

Figure V.1: Organization Maturity and Organizational Size (percentage)

Expectedly, there were more small organizations with lower annual revenue and larger firms with higher yearly revenue. Annual revenues over $20M were more likely to be large firms. Organizations of both sizes reported low frequencies between $15M and $19.9M in annual revenue. An exciting dip occurred across organizational size for this revenue level.

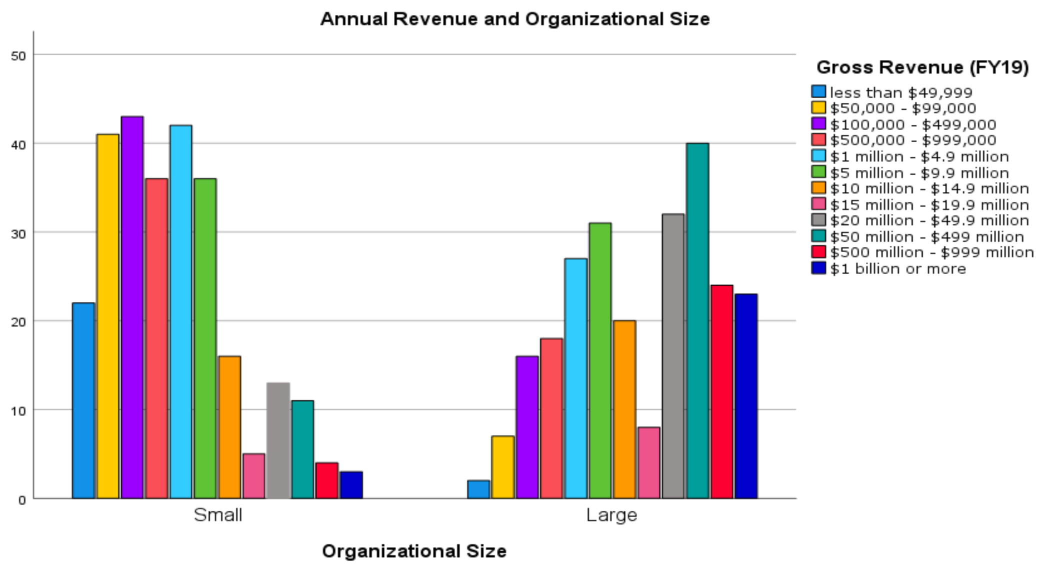

Figure V.2: Organizational Size and Annual Revenue (Frequency)

The following table shows the statistical significance of organizational size as a contributing industry 4.0 technology adoption factor in terms of p values (p<.10). Organizational size (small) contributed to the adoption models for the following technologies: autonomous/automation, nanotechnology, artificial intelligence, big data, and augmented reality. The organizational size was not statistically significant for cloud computing, the internet of things blockchain, 3D printing, and cybersecurity. The results below are compiled from the binary logistic regression models reported in Chapter 4; see Table 4.7.a to Table 4.7.j.

Table V.4: Significance of Organizational Size (Only Statistically Significant Values Reported)

Organizational Size (small)							
Variable	*B*	*S.E.*	Wald	Sig.	Exp(*B*)	95% *CI* for EXP(*B*)	
						Lower	Upper
Org. Size (Autonomous)	.836	.355	5.552	.018	2.307	1.151	4.626
Org. Size (Nanotechnology)	-.791	.244	10.544	.001	.453	.281	.731
Org. Size (Artificial Intelligence)	.529	.280	3.565	.059	1.698	.980	2.941
Org. Size: (Big Data)	1.228	.365	11.321	.001	3.413	1.670	6.979
Org. Size: (Augmented Reality)	.439	.260	2.851	.091*	1.552	.932	2.584

V.2.17 *The COVID-19 Accelerant*

When it came to COVID-19 as an accelerant, the results were shockingly mixed across industries. Manufacturing (40%), financial services (51%), public services (43%) led the strongly agreed responses. A few industries had (0%) no strongly disagreed responses; those were transportation, wholesale, professional services, business services, public services, agriculture, and manufacturing. Entertainment (12%) strongly disagreed responses were higher than financial services (2%) and information technology (.5%). Across industries, larger percentages fell within the agreed category, showing favorable sentiment that COVID-19 accelerated the adoption of industry 4.0.

Statistically, COVID-19 was not statistically relevant for the adoption of any of the ten I4.0 technologies. While business owners and leaders' sentiment differed, agreeing that COVID-19 was an accelerant for adoption, the adoption models provided otherwise, this may be partly due to the perception that while COVID-19 was the impetus, other longstanding and underlying motivations may have surfaced to respondents' recollection. Industry 4.0 technology implementation is complex and often arduous due to the convergence of complex system integration across multiple functions and platforms. COVID-19 raised a sense of urgency, which precipitated many organizations concentrating on sweeping changes instead of incremental steps. The shift in priority created a backlog of other initiatives and infused further chaos into an already chaotic technology environment. According to this survey's results, COVID-19 was not an accelerator for Industry 4.0 technologies despite the marketing banter.

V.3 Implications

V.3.1 *Theoretical Implications*

This study provided an analysis of an emerging yet infant field of industry 4.0 technology adoption. The analysis described adoption factors across 12 industries and explained which factors contributed to adopting ten industry 4.0 technologies. The research revealed industry 4.0 technology adoption patterns across industries, which to knowledge is the first of its kind. The study also explored the role of COVID-19 on adoption, which can serve as a proxy for market stressors, catastrophic events that disrupt business, and financial stressors.

V.3.2 *Practical Implications*

The World Economic Forum (2016) identified potential week and strong opportunities for various industries to adopt Industry 4.0 technology. The image was presented in the introduction section of this paper. Several industries and job functions were identified as either had weak or strong I4.0 technology adoption potential. The below chart compares the potential adoption (weak and strong), as predicted by the World Economic Forum (2026), and compared it to the results of this study.

Table V.5: World Economic Forum Comparison

World Economic Forum Strong opportunity	This Study Company-wide Adoption	World Economic Forum Weak opportunity	This Study No-Adoption
Manufacturing	Manufacturing (55%)	Physicians/Dentists	Healthcare (29%)
Real Estate	Financial / Real Estate (63%)	Education	Education (23%)
Farmers	Agriculture (57%)	Mechanics, Plumbers	Professional Services (48%)
Sports	Entertainment/Arts (32%)	Arts & Entertainment	Entertainment & Arts (50%)
Cashiers	Retail (43%)	Lawyer/Accountant	Professional Services (48%)
Couriers & Messengers	Business Services (42%)	Clergy	Public Services (23%)

The World Economic Forum (2016) assessment indicated manufacturing, real estate, farmers, sports, cashiers, and couriers/messengers had a solid opportunity to adopt Industry 4.0 technology. Compared to the company-wide adopters from this study, all support this claim, exempt sports entertainment (32%). From a percentage view, there were sizeable differences between company-wide adopters and non-adopters in these industries. A minor variance is noted with cashiers from the retail/wholesale sector, as adopters make up 43% of this demographic, while 38% remain non-adopters.

The weak projections from the World Economic Forum (2016) had mixed results in our study. Physicians in healthcare accounted for only 29% of non-adopters, indicating greater adoption in this industry than the World Economic Forum anticipated. Similarly, education had only a 23% non-adoption rate, as the majority (60%) of the field are company-wide adopters. Clergy in the public services arena also showed higher adoption rates. Again, only 23% of this market sector were non-adopters. The non-adopters in our study aligned more closely with the weak opportunity in the World Economic Forum (2016) report. Mechanics (professional/technical services), entertainment and art, lawyers, and accountants (professional services) had higher overall non-adoption rates.

In conclusion, the overall adoption of industry 4.0 technology appears to be progressing. Industries with more dispersed adoption rates across all levels indicated some movement towards greater adoption. Other industries have high/low adoption inflections, where the polar adoption ends have vast industry percentages. This shows the possible presence of earlier adopters, who account for a surge in the adoption movement. Fewer industry organizations with inconsistent or random adoption indicated a phenomenon of all-or-nothing scenarios. This seems less likely across an industry, given the diversity of the firm population in this study. It is likely due to industry leaders who adopt technology as competitive leaders to remain at the forefront. An inference can be made; there was a more positive movement towards adopting Industry 4.0 technology than initially evaluated. COVID-19 has accelerated the adoption of Industry 4.0 technology, based on the results of this study.

V.4 Limitations

Survey respondents were recruited via a Qualtrics, LLC. Panel and were compensated for their participation. Qualtrics, LLC, solely determined the compensation criteria and fee. Survey participation was voluntary, and as such, this research relied upon the accuracy and honesty of Qualtrics, LLC. Panel survey respondent. The below screening criteria were leveraged by Qualtrics, LLC. in recruiting efforts, which excluded all partial survey results and omitted respondents who did not meet the participation criteria. It was impossible to control all elements of the recruitment process; thus, this researcher was unable to observe how many respondents represented the same organization or were sourced from unique firms. Therefore, this limitation may impact internal validity.

V.4.1 *Delimitations*

The online survey was not timed, and as such, respondents controlled the amount of time spent to complete the questionnaire. However, all incomplete surveys were automatically terminated after 72 hours. Survey questions built upon one another around related topics. The period between completion of survey questions may have impacted the recall ability of the respondent. This research was unable to observe wherein the survey process these gaps occurred and how they may have affected the quality of the answers. Thus, this delimitation may impact external validity.

V.5 Further Analysis

While this study focused on the descriptive conditions within an Industry 4.0 technology adoption environment, quantitative statistical analysis was not deployed. The N=520 across all industries warrants further evaluation of statistical significance. The evaluation of variables and their role in adoption can be further assessed through statistical means. This researcher understands further analysis a priori; thus, a preliminary data analysis matrix has been included in the Appendix.

APPENDIX

Table 6.1 Recode Organizational Size

Organizational Size	Number of Employees		Frequency	Percent
1.00 Small *272 Frequency 52.3%*	1.	**1-4**	**67**	**12.9**
	2.	**5-9**	**26**	**5.0**
	3.	**10-19**	**26**	**5.0**
	4.	**20-49**	**25**	**4.8**
	5.	**50-99**	**37**	**7.1**
	6.	**100-249**	**41**	**7.9**
	7.	**250-499**	**50**	**9.6**
2.00 Large *248 Frequency 47.7%*	8.	**500-999**	***110***	***21.2***
	9.	**1000+**	***138***	***26.5***
Total			*520*	*100.0*

Table 6.2 Recode Department "Other" Text

Question	"Other" Text	Recoded to	Justification
Q.23.10	CEO or Chief Executive Officer	Q.23.6 Management/leadership	The CEO is the highest leader in an organization
Q.23.10	Insurance	Q.23.2 Finance/economics	Insurance manages financial risk
Q.23.10	Director	Q.23.6. Management/leadership	A director is typically in management or holds a leadership role
Q.23.10	Construction	Q.23.7 Operations	Construction is an operational task
Q.23.10	Owner	Q.23.6 Management/leadership	The owner is typically the highest leader

Q.23.10	Legal	Q.23.1 Administration	The legal team performs administrative tasks across the entire organization
Q.23.10	Project Director	Q.23.7 Operations	A project is an operational task
Q.23.10	Hairstylist	Q.23.7 Operations	This best aligns with the operational function of cosmetology
Q.23.10	Executive Vice President	Q.23.6 Management/leadership	An EVP is a high-level leader
Q.23.10	Healthcare Management	Q.23.6 Management/leadership	Healthcare is an industry; management is the function
Q.23.10	Government	Q.23.6 Management/leadership	Governance as a dept. function is management
Q.23.10	Fashion	Q.23.7 Operations	Fashion is an operational task
Q.23.10	Wholesale	Q.23.9 Sales & Marketing	Wholesale describes a type of sales function
Q.23.10	Information Technology	Q23.4 Information management, technology, equipment	Information technology is contained within this dept. description
Q.23.10	Arts and entertainment	Q.23.7 Operations	Arts and entertainment as a departmental function aligns best with operations

Table 6.3 Recode Industry Classifications

Recoded Industry based on SIC Codes	Industry (NAIC based)	Frequency	Percent
1.00 Manufacturing	Aerospace &b Defense (1) Food & Beverage (7) Manufacturing & Production (13)	**40**	**7.7**
2.00 Agriculture	Agriculture, Forestry, Fishing Hunting & Mining (2)	**14**	**2.7**
3.00 Entertainment & Leisure	Arts, Media & Design, Sports & Entertainment (3) Travel & Leisure (18)	**34**	**6.5**
4.00 Financial Services	Banking, Finance & Insurance (4) Real Estate (16)	**57**	**11.0**
5.00 Construction	Construction (5)	**42**	**8.1**
6.00 Public Services	Education (6), Non-Profit / NGO (14) Government – Federal (8) Government – State (9)	**30**	**5.8**

7.00 Healthcare	Healthcare & Pharmaceuticals (10)	**17**	**3.3**
8.00 Information Technology	Information Technology, Services & Management (11)	**195**	**37.5**
9.00 Business Services	Management Consulting, Business Services, Administrative Services (12)	**24**	**4.6**
10.00 Professional Services	Professional Services, Scientific Services & Technical Services (15)	**31**	**6.0**
11.00 Retail / Wholesale	Retail & Wholesale Trade (17)	**21**	**4.0**
12.00 Transportation	Transportation &b Warehousing (19) Utilities, Sanitation & Telecommunications (20)	**15**	**2.9**
Total	(20 Industry Categories)	**520**	**100.0**

Table 6.4 Detailed Model Analyses

3d Printing

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.002**	**1**	**.965**
	Block	**.002**	**1**	**.965**
	Model	**66.505**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**432.561[a]**	**.169**	**.225**

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**5.256**	**8**	**.730**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: 3d Printing 1.00 No Adoption	Predicted: 3d Printing 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	3d Printing	1.00 No Adoption	**105**	**69**	**60.3**
		3.00 Company-wide Adoption	**46**	**140**	**75.3**
	Overall Percentage				**68.1**

a. The cut value is .500

Artificial Intelligence

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.345**	**1**	**.557**
	Block	**.345**	**1**	**.557**
	Model	**127.776**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**383.767[a]**	**.293**	**.390**

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**17.225**	**8**	**.028**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Artificial Intelligence 1.00 No Adoption	Predicted: Artificial Intelligence 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	Artificial Intelligence	1.00 No Adoption	**90**	**52**	**63.4**
		3.00 Company-wide Adoption	**26**	**201**	**88.5**
	Overall Percentage				**78.9**

a. The cut value is .500

Augmented Reality

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.332**	**1**	**.565**
	Block	**.332**	**1**	**.565**
	Model	**72.103**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**407.555**[a]	**.188**	**.251**

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**8.951**	**8**	**.346**

(Percent Concordant) Classification Table[a]

			Predicted		
			Augmented Reality		
	Observed		1.00 No Adoption	3.00 Company-wide Adoption	Percentage Correct
Step 1	Augmented Reality	1.00 No Adoption	**150**	**52**	**74.3**
		3.00 Company-wide Adoption	**67**	**77**	**53.5**
	Overall Percentage				**65.6**

a. The cut value is .500

Autonomous

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.741**	**1**	**.389**
	Block	**.741**	**1**	**.389**
	Model	**276.447**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**309.956**[a]	**.480**	**.640**

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.777**	**1**	**.378**
	Block	**.777**	**1**	**.378**
	Model	**202.716**	**21**	**.000**

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**12.195**	**8**	**.143**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Autonomous: 1.00 No Adoption	Predicted: Autonomous: 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	**Autotonomous**	**1.00 No Adoption**	**51**	**46**	**52.6**
		3.00 Company-wide Adoption	**18**	**308**	**94.5**
	Overall Percentage				**84.9**

a. The cut value is .500

Big Data

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**307.441[a]**	**.424**	**.565**

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**8.958**	**8**	**.346**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Big Data: 1.00 No Adoption	Predicted: Big Data: 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	Big Data	1.00 No Adoption	**60**	**44**	**57.7**
		3.00 Company-wide Adoption	**18**	**246**	**93.2**
	Overall Percentage				**83.2**

a. The cut value is .500

Blockchain

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**1.137**	**1**	**.286**
	Block	**1.137**	**1**	**.286**
	Model	**73.247**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**435.523[a]**	**.181**	**.241**

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**4.524**	**8**	**.807**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Blockchain 1.00 No Adoption	Predicted: Blockchain 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	Blockchain	1.00 No Adoption	**156**	**54**	**74.3**
		3.00 Company-wide Adoption	**69**	**88**	**56.1**
	Overall Percentage				**66.5**

a. The cut value is .500

Cloud Computing

Model Summary

Step	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	**245.340[a]**	**.530**	**.707**

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	**Chi-square**	**df**	**Sig.**
1	**5.800**	**8**	**.670**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Cloud Computing 1.00 No Adoption	Predicted: Cloud Computing 3.00 Company-wide Adoption	Percentage Correct
Step 1	Cloud Computing	1.00 No Adoption	**10**	**41**	19.6
		3.00 Company-wide Adoption	**7**	**331**	97.9
	Overall Percentage				87.7

a. The cut value is .500

Cyber Security

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**.641**	**1**	**.423**
	Block	**.641**	**1**	**.423**
	Model	**288.270**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	**292.588[a]**	**.497**	**.663**

a. Estimation terminated at iteration number 20 because maximum iterations have been reached. The final solution cannot be found.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	**10.602**	**8**	**.225**

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Cybersecurity 1.00 No Adoption	Predicted: Cybersecurity 3.00 Company-wide Adoption	Percentage Correct
Step 1	Cybersecurity	1.00 No Adoption	**15**	**50**	**23.1**
		3.00 Company-wide Adoption	**4**	**350**	**98.9**
	Overall Percentage				**87.1**

a. The cut value is .500

Internet of Things

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	**1.207**	**1**	**.272**
	Block	**1.207**	**1**	**.272**
	Model	**214.052**	**21**	**.000**

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	296.105[a]	.441	.588

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9.851	8	.276

(Percent Concordant) Classification Table[a]

			Predicted		
			Internet of Things		
	Observed		1.00 No Adoption	3.00 Company-wide Adoption	Percentage Correct
Step 1	Internet of Things	1.00 No Adoption	23	51	31.1
		3.00 Company-wide Adoption	11	283	96.3
	Overall Percentage				83.2

a. The cut value is .500

Nano Technology

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1.575	1	.210
	Block	1.575	1	.210
	Model	102.927	21	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	423.865[a]	.237	.316

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.076	8	.528

(Percent Concordant) Classification Table[a]

	Observed		Predicted: Nano Technology: 1.00 No Adoption	Predicted: Nano Technology: 3.00 Company-wide Adoption	Predicted: Percentage Correct
Step 1	Nano Technology	1.00 No Adoption	**160**	**55**	74.4
		3.00 Company-wide Adoption	**63**	**102**	61.8
	Overall Percentage				68.9

a. The cut value is .500

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VITA

Dr. Dawn Gregory is an accomplished executive with 25+ years of experience across diverse industries, including healthcare, finance, government, non-profit, and management consulting. Dawn has held numerous leadership roles spanning innovation, strategic planning, operations, and customer experience during her career.

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