UNIVERSITY OF GHANA

COLLEGE OF HUMANITIES

THE ADOPTION OF INDUSTRY 4.0 TECHNOLOGIES AMONG GHANAIAN MANUFACTURING FIRMS: A TECHNOLOGY READINESS AND ACCEPTANCE MODEL PERSPECTIVE

BY

MONICA BAFFOWAA

DEPARTMENT OF OPERATIONS AND MANAGEMENT INFORMATION SYSTEM

JANUARY 2023

UNIVERSITY OF GHANA

COLLEGE OF HUMANITIES

BY

MONICA BAFFOWAA

(10875307)

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES IN PARTIAL FULFILMENT OF THE AWARD OF DEGREE OF MASTER OF PHILOSOPHY IN MANAGEMENT INFORMATION SYSTEMS

DEPARTMENT OF OPERATIONS AND MANAGEMENT INFORMATION SYSTEMS

JANUARY 2023

DECLARATION

I do by declare that this thesis is the result of my own research undertaken under supervision and has not been presented by anyone for any academic award in this or any institution. All references used in this research are fully acknowledged.

I bear any responsibility for any shortcomings.

25/01/2022

…………………………………………….. …………………………..

DATE

MONICA BAFFOWAA
(10875307)

25/01/2023

……………………………………………… ……………………………...

DR. JOSHUA OFORI-AMANFO
(SUPERVISOR)

DATE

25/01/2023

……………………………………………… ……………………………...

DR. ACHEMPONG OWUSU
(CO-SUPERVISOR)

DATE

ABSTRACT

Industry 4.0 refers to a set of multi-dimensional concepts for corporate operations based on cyber-physical systems (CPS) and the Internet of Things (IoT), such as computerization, digitalization, and Artificial Intelligence.

Studies on Industry 4.0 appear to be Europe-centric at the moment. Previous studies indicated that there is a lack of responsiveness in many developing and underdeveloped countries in embracing Industry 4.0 in their manufacturing industries. The purpose of the study was therefore to examine the awareness of Industry 4.0 technologies among manufacturing firms in Ghana and to ascertain their readiness for accepting and embracing such technologies.

To achieve this purpose, a convenience sampling technique was used to select the manufacturing firms. Purposive sampling was also employed to select the respondents from the selected manufacturing firms. The Partial Least Square Structural Equation Modelling was used as the quantitative data analysis technique (PLS-SEM). The PLS-SEM is a statistical analysis method used to analyze multivariate structural relationships. The Technology Readiness and Acceptance Model (TRAM) proposed by Lin et al. (2007) was employed to provide the theoretical lens for the study. Awareness and support resources were introduced into the proposed model. The findings of the study revealed that manufacturing firms in Ghana are aware of Industry 4.0 technologies. The finding showed that Internet of Things was the most dominant technology that the manufacturing firms in Ghana are aware of. It was also revealed that, awareness influences firms' intention to adopt a new technology.

The study contributed to the knowledge already known about the readiness in accepting a new technology. The study added that awareness of a technology will influence the readiness to adopt

a new technology. This finding of the study revealed that support resources do not moderate the relationship between perceived usefulness and intention to adopt industry 4.0 technologies.

DEDICATION

I would like to dedicate this work to the Almighty God who has given me the wisdom and strength to enable me to undertake this study.

I also dedicate this work to my mother Mary Fosua, my late dad Charles Yaw Anane, my junior brother Emmanuel Ayeh, and other family & friends who believed in my ability to achieve this goal.

ACKNOWLEDGEMENT

My special appreciation and profound gratitude goes to my supervisors Dr. Joshua Ofori-Amanfo and Dr. Acheampong Owusu for their diverse contributions, encouragement, and supervision throughout this work. I would not have made it this far without you. May the good Lord continue to bless you with more wisdom.

My heartfelt gratitude also goes to my beloved family especially my mother and brother for their continued support and encouragement in both hard and good times during the period of my studies. My special thanks to Mr. Davis Attuahene, Mr. Denis Osei, Mr. Benjamin Nsiah, Mr. John Makija, Mr. Julian Provencal, Miss. Janet Takyiwaa, Mad. Rebecca Adomako and Miss. Ellen Abanga for their outstanding mentorship and encouragement. May the good Lord continue to bless all of you.

TABLE OF CONTENT

LIST OF ABBREVIATIONS

IT	Information Technology
PLC	Programmable Logic Controller
ERP	Enterprise Resource Planning
SCMS	Supply Chain Management Systems
TPS	Transaction Process System
IMS	Information Management System
ICT	Information Communication Technology
IOT	Internet of Things
CPS	Cyber Physical System
CC	Cloud Computing
BDA	Big Data Analytics
TAM	Technology Acceptance Model
TR	Technology Readiness
TRI	Technology Readiness Index
TRAM	Technology Readiness and Acceptance Model
PEOU	Perceived Ease of Use

PU Perceived Usefulness

GLSS Ghana Living Standard Survey

PLS Partial Least Square

SEM Structural Equation Modelling

SPSS Statistical Package for Social Sciences

ANOVA Analysis of Variance

MANOVA Multivariate Analysis of Variance

CB-SEM Covariance Based Structural Equation Modelling

AVE Average Variance Extracted

HTMT Heterotrait-monotrait Correlation Ratio

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Research Background

Emerging digital technologies have changed the way societies communicate and connect (Garay-Rondero et al., 2020; Nasiri et al., 2020). Some of these emerging digital technologies have been introduced into the logistics, supply chain, education, manufacturing, and transportation industries (Acioli et al., 2021). The future of every industry is significantly shaped and dependent on innovations and technology (Olsen & Tomlin, 2020). Manufacturing is one such industry where advances in technology are constantly changing the nature of operations (Fatorachian & Kazemi, 2021a). In particular, the fourth industrial revolution (Industry 4.0) emerging in manufacturing operations is making most manufacturing firms undergo a rapid shift in their innovativeness and time to market (Zekhnini et al., 2021). Globally, technology-based products and services are being introduced at an increasing rate (Rojas-Méndez et al., 2017). Chawla & Goyal (2022) revealed in their study that, following and contributing to this trend, many international companies and other organizations have adopted new technologies for their internal and external operations and market service strategies.

Other scholars Ekonomist & Trebinje (2020) and Onileowo et al. (2021) have indicated that given the increase in globalization, innovation should be viewed not only as a requirement for competitive advantage and profitability in the industry but also as a key consideration in the long-term sustainability and survival. The effect of these innovations has been most visible in industries where major changes in business processes and changes in the way services are designed, developed, and delivered have occurred (Ferreira et al., 2021; Kumar et al., 2018). Consumers are becoming more demanding, have more information to make their own decisions about which products to purchase, and expect their needs to be met in a timely manner (Ferreira et al., 2021; Viswanathan et al., 2021). The current diverse and evolving business environment has compelled manufacturers in various nations to integrate their customers and suppliers to improve their operations and enhance the firm's performance in both domestic and global markets (Abdallah et al., 2021).

There have been various industrial revolutions. The first industrial revolution, named Industry 1.0 (Mechanical power) dawned in England in 1780 and stretch out to other European countries during the 19th century (Vinitha et al., 2020). Industry 1.0 was driven by the use of steam and water to power machines. During this revolution, iron, textile, agriculture, gas lighting, chemical, transportation and other industries were developed. The aforementioned developments and innovations from Industry 1.0 gave way for urbanization to take its course (Baygin et al., 2016). Specifically, the transportation sector was significantly improved. The use of steam engines to power steamships made the transportation of goods easier, fast and relatively cheaper (Coenen et al., 2012). The success of Industry 1.0 led to an increase in population in the cities (Allen, 2003). A large number of workers were readily available to be employed in emerging industries (Pfeiffer, 2016).

Towards approaching the end of19th century, the second phase of Industrialization (Industry 2.0) emerged (Chauhan & Singh, 2020). The dependence on electricity was the mainstream of the second industrial revolution and the main attention was on mass consumption (Baygin et al., 2016). The steam engines were substituted by machines powered by electricity (Nurdiana & Pandin, 2021). Studies (Baygin et al., 2016; Vitha et al., 2020) pointed out that, the technologies adopted in the second revolution were telephones and electric power. Workplace communication was developed further in this era through the use of telegraphs and telephone calls. Transport also advanced by travelling via both air and sea. Maritime technology, automobile, bicycles, modern business management and telecommunication were all developed during the second industrial revolution (Kumar Mohajan, 2020).

In the 1970s, the third industrial revolution (Industry 3.0) was launched. This revolution was focused on automation by employing information technology and electrical engineering (Taalbi, 2019). There was fast-paced advancement in computer technology. During this era, the manufacturing sector advanced in the field of engineering. Industrial robots were used to automate most of the production processes. These robots were used for assembling, labelling, welding and testing. The third revolution was influenced by automation (Vinitha et al., 2020).

The most current industrial revolution is industry 4.0 (new world transformation) (Ben-Daya et al., 2019; Tang & Veelenturf, 2019) which is characterized by the internet and the network of systems and operations. Industry 4.0 is based on the new world transformation. The new world transformation is the integration of advanced information communications and information systems technologies with industrial technologies (Ben-Daya et al., 2019).

According to Sung (2018), in the year 2011, the terminology "Industry 4.0" came from a project started by the German government's high-tech plan to boost computerization in the manufacturing sector. The drivers of industry 4.0 in the manufacturing sector are the emergence of analytics and business-intelligence capabilities; new forms of human-machine interaction such as touch interfaces and augmented-reality systems; and improvements in transferring digital instructions to the digitized manufacturing sector.

Industry 4.0 refers to a set of multi-dimensional concepts for corporate operations based on cyber-physical systems (CPS) and the Internet of Things (IoT), such as computerization, digitalization, and Artificial Intelligence (K. C. Lin et al., 2017). Industry 4.0 symbolizes the novel frontier for the world's economy which has the potential to influence many industries and impact the way their goods could be manufactured, sold and serviced (Ralston & Blackhurst, 2020). The concept of Industry 4.0 is an integrated business ecosystem where the operational processes, products and machines network with one another (Frank et al., 2019).

The fundamental principle of the fourth industrial revolution is independently connecting the operational processes, machines and systems, generating smart networks within the whole supply chain that add value for consumers (Raj et al., 2020). The latest revolution advocates for a smart system that adapts and advances on its own, incorporating and utilizing human engagement (e.g., consumer orders or inputs), but do not necessitate human management and monitoring (Ralston & Blackhurst, 2020).

Industry 4.0 is now very significant to the growth of the industrial sector (Baryshnikova et al., 2021). It has the potential to increase productivity and production performance (Ralston & Blackhurst, 2020). Many businesses have adapted and implemented the new industrial revolution's ideas and technology to boost production and performance (Ghadge et al., 2020a). A study by Tortorella et al. (2019) has shown that there are many economic benefits associated with this revolution such as improvement in operations and productivity. These include a 30% reduction in lead time and a 21% reduction in product fault rates (Tang & Veelenturf, 2019).

Industry 4.0 technologies are rapidly growing and spreading their roots, but it is still in their initial stages, and there is a need for much more studies on this industrial revolution (Falwadiya & Dhingra, 2022). According to Zhong et al. (2017), due to the limited understanding of Industry 4.0

technologies currently, it is vital to illuminate the literature on Industry 4.0 adoption. This study is aimed at uncovering how manufacturing firms in developing economies such as Ghana are embracing the technological advances in manufacturing which are driven by globalization, to stay competitive. The study is designed to ascertain Ghana's manufacturing industry awareness and readiness to adopt Industry 4.0 technologies.

1.2 Research Problem

Industry 4.0 is believed to have a positive impact on the performance of an organization; its adoption by firms is noted to help firms to solve challenges associated with operational complexities (Tian et al., 2021; Tirkolaee et al., 2021). The adoption of this industrial revolution in the developed world has assisted many industries, especially the manufacturing sector to improve their production processes (Erboz et al., 2021).

Despite the numerous studies on the adoption, barriers and implementation challenges of Industry 4.0 in the developed world, the concept has not gained sufficient literature attention in developing economies. For instance, a study by Anitah et al (2019) focused on Industry 4.0 technologies and the operational performance of Unilever Kenya and L'Oréal East Africa. Another study by Mukwawaya et al(2018) also focused on assessing the readiness of South Africa for Industry 4.0 analysis of government policy, skills and education. Taking a clue from these studies, the current research examines the readiness and awareness of the manufacturing sector in embracing Industry 4.0 technologies in manufacturing sector in Ghana.

Information Technology (IT) has always been and will continue to be the key enabler for the flow of information within an organization. It is vital in assisting the organizational operations in dealing with the challenges of the ever-changing environment and a wide range of hazards at all levels (Jahani et al., 2021; Tian et al., 2021). Because of its potential to integrate multiple operations internally and, externally with suppliers and customers, IT has had a significant impact on the character and structure of a firm's operational strategies to boost performance (Ben-Daya et al., 2019). This has been accomplished via increasing communication, data acquisition, and transmission, allowing for more effective decision-making and improvements in business operation systems (Tian et al., 2021). Unfortunately, the extent of IT usage in developing countries is very minimal and certainly may be so with the adoption of Industry 4.0 (Kinkel et al., 2022; Shareef et al., 2009). It is against this backdrop that this study is needed to understand manufacturing firms' awareness and readiness for the adoption of these emerging technologies.

According to Zekhnini et al. (2021) majority of studies are done and published by countries that have much knowledge and awareness of the significance of digital transformation. Hence, studies on Industry 4.0 appear to be Europe-centric at the moment. Research by Fatorachian & Kazemi, (2021) and Zekhnini et al. (2021) indicated that there is a lack of responsiveness in many developing and underdeveloped countries in embracing Industry 4.0 in their manufacturing industries. Thus, the current study falls in place to fill in the gap by exploring the concept of Industry 4.0 within the context of a developing economy.

1.3 Research Purpose

The purpose of the study is to examine the awareness of Industry 4.0 technologies among manufacturing firms in Ghana and to ascertain their readiness for accepting and embracing such technologies.

1.4 Research Objectives

The study is designed to achieve the following objectives:

1. Determine the awareness of dominant Industry 4.0 technologies among manufacturing firms in Ghana.
2. Determine Industry 4.0 technologies' readiness and acceptance among manufacturing firms in Ghana.
3. Examine the effect of Industry 4.0 technologies awareness, readiness and acceptance factors on the intention to adopt these technologies among manufacturing firms in Ghana.

1.5 Research Questions

1. What are the dominant Industry 4.0 technologies that manufacturing firms in Ghana are aware of?
2. What is the extent of readiness and acceptance of Industry 4.0 technologies among manufacturing firms in Ghana?
3. What is the effect of Industry 4.0 technologies awareness, readiness and acceptance factors on the intention to adopt these technologies among manufacturing firms in Ghana?

1.6 Scope of the Study

The study covered the manufacturing industries in Ghana. Especially, the study focused on manufacturing firms located in the Greater Accra region of Ghana. The research assesses the manufacturing firm's awareness, readiness and acceptance of Industry 4.0 technologies in their operations. The respondents of the study include the IT (Information technology) managers, operations and supply chain managers, and procurement managers of the sampled manufacturing firms.

1.7 Significance of the Study

This study is significant in three ways with respect to research, practice and policy.

For research, the findings from the study will serve as the basis for further research to be conducted to deepen understanding of the concept of Industry 4.0 adoption in emerging and developing economies.

Industrialization is continuously evolving due to the rapid pace of change in many markets and economic, financial, social, and technological elements. For practice, the study will provide insights into how prepared and ready the manufacturing industry in Ghana is, for Industry 4.0 technologies. These insights would be useful in determining industry needs relative to the adoption of Industry 4.0 technologies.

In the context of policy, the findings from the study will provide policymakers with insights on the need to communicate the concepts and technologies of industry 4.0 within local manufacturing firms. Insights from the study may equally be useful for policymakers to formulate policies to regulate the adoption of Industry 4.0 in the operations of the manufacturing firms.

1.8 Chapter Outline

The study is presented in six chapters.

The first chapter is titled introduction. The chapter covers the research background, research problem, research purpose. Other chapter headings include, research objectives, and research questions, the significance of the study, the scope of the study, and the chapter outline.

The second chapter is the literature review which focuses on the review of the literature on the various phases of the industrial revolution in the manufacturing sector, the definition of concepts of Industry 4.0, the emerging digital technologies, the possible implementation, its challenges as well as the benefits of adoption of Industry 4.0 are also discussed.

The third chapter presents the theoretical framework and the development of the research hypothesis. The chapter discusses the theory adopted for the study and provides justification as to why the theory is used as the analytical lens, following which the research hypotheses are developed.

Chapter four introduces the methodology adopted for the study, which further explains the research paradigm, research methods, the population of the study, sample size determination and the sampling technique employed, description of the data collection instrument and the procedure for data collection, the methods of analysing the data and ethical considerations for the study.

The fifth chapter highlights the Data analysis and discussion of the findings of the study.

The final chapter, chapter six presents the summary, conclusions and contributions of the study. The chapter further presents the limitations of the study and future research directions. The references and appendices follow after the last chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents the general idea of Industry 4.0 by discussing how the manufacturing sector has evolved over the years. The chapter also reviews relevant literature on Industrial evolution, digital technologies, importance, implementation challenges, barriers, and benefits of Industry 4.0.

2.2 The Evolution of the Industrial Sector

Industrialization plays a vital role in developing a nation's economy (Cardinale & Scazzieri, 2021; da Rosa Righi et al., 2019; Szirmai, 2012). Several paradigms have influenced the evolution of production systems (Jiang et al., 2022). The industrial revolution is defined as "the Industrial utilization of different technologies" (da Rosa Righi et al., 2019 p.3). A study by Meindl et al (2021) indicated that there has been a constant evolution in the industrial sector. Jiang et al. (2022) argued that manufacturing systems have experienced continuous and perpetually change since the first industrial revolution (Industry 1.0). This is due to the change in market demand characterized by environmental pressures and the globalized market from mass production, small batch and multi-variety production, to mass customization to personalized customization (Li et al., 2020).

2.2.1 Industry 1.0

Baygin et al (2016) indicated in their study that, in the era of 1780 in England, the first industrial revolution (Industry 1.0) emerged and spread across other European countries during the 19th century. The first evolution is also known as the mechanical era (Frederico et al., 2020; Clark et al., 2005). Vinitha et al. (2020) and Zhou et al. (2016) discovered that the sectors that developed during the first phase of industrialization included the iron industry, agriculture, chemical, glassmaking, machine tools, mining, transportation, and textiles manufacturing. Industry 1.0 changed the focus of human activities from agriculture to industrial society, the supplies in this revolution were smaller because the industrial products had only one dimension demand environment known as the simple market (da Rosa Righi et al., 2019; Oztemel & Gursev, 2020; Yin et al., 2018). Other study by da Rosa Righi et al. (2019) revealed that the main changes of the first industrial revolution were the dominance of the machine-based manufacturing over manual production and the factory mass production over small-scale workshop production. The study further indicated that, based on the revolution, Industry 1.0 facilitated growth in the economy.

Studies (da Rosa Righi et al., 2019; Schwab, 2016) have showed that, similar to the transition from the agricultural to the industrialized periods, it was obvious that alternative transportation methods would be required; especially against animal power-provided logistics. There was an increase in demand for more raw materials for production in the cities, based on that, railroad construction became a priority for transportation (Nederveen et al., 2003; Vinitha et al., 2020). These developments were powered by steam and water for mass production (Baygin et al., 2016; Bruland & Mowery, 2006; Wrigley, 1962).

Steam became a driving force to increasing productivity at the time (Horváth & Szabó, 2019). Steam locomotives and steamships used the functions of the steam engine (Baygin et al., 2016). In the transportation industry according to Crafts (2021) and Clark et al. (2005), steam locomotives and steamships used steam engines. This allowed goods to be transported in the shortest time possible and at a lower cost (Butner, 2010). According to Kurt (2019), an increase in population caused the steam power to be limited in facilitating production to meet demand.

Figure 2.1 Steam Locomotive

Source: (da Rosa Righi et al., 2019)

Table 2.1 Illustration of First Evolution

Revolution	Period	Technologies	Drawbacks	Achievements
Industry 1.0	18th Century	Steam Power	Time Consuming,	Agriculture developments,
		Water Power	Pollution	Employment, Transportation

Source: Drafted by Researcher

2.2.2 Industry 2.0

Yang & Gu (2021) indicated that the achievements of the first industrial revolution industry 1.0 led to an increase in population in cities. A lot of workers were available to be employed in the gradually growing economy (Clark et al., 2005). This gave room for the emergence of the second industrial revolution in the 1830s where several technological innovations influenced the development of the second industrial revolution (Zhou et al., 2016). A study by Adeyeri (2018) argue that the second industrial revolution, also known as the technological revolution, began in Germany and was aimed at steel production, rail system development, petroleum, and chemical production.

Literature from Yin et al. (2018) indicated that electricity, electronic and mechanical devices, and automobiles were among the major technological advances, however, Industry 2.0 products are still widely used today. Another study by Koren & Shpitalni (2010) also stated that electricity and combustion engines power the machines in the second industrial revolution. According to Baygin et al. (2016), industry 2.0 was powered by the introduction of electricity and was centered on mass production lines (Schwab, 2016), which aided Henry Ford in his car production in the 19th century (Kurt, 2019).

At the time of the second industrial revolution (Industry 2.0), literature stated that demand had two dimensions: volume and variety (Yin et al., 2018). According to Aguiar et al. (2020), Taylor's theory was practiced and extended by two innovators, Henry Ford and Taiichi Ohno. Yin et al. (2018) further added that Ford used mass production assembly lines to address a supply shortage in product volumes by developing the Toyota production system. Ohno also addressed various customer interests in product variety. “Toyota Production System is the management that organizes manufacturing and logistics for the automobile manufacturer, including interaction with suppliers and customers"(Wada, 2020 p.236).

da Rosa Righi et al. (2019) postulated that steam-powered engines were gradually being replaced by electric generators, which powered refrigerators and washing machines. Another engine-related change in the 1890s was the introduction of internal combustion engines, which aided in the development of the first automobiles and airplanes (da Rosa Righi et al., 2019; Nurdiana & Pandin, 2021). Another study conducted by Vinitha et al. (2020) also revealed that the second industrial revolution adopted communication technologies such as telegraphs, telegrams and telephone calls. This was because communications at the workplaces were advanced and production had increased in addition to electrification (Phillips, 2000).

Vinitha et al. (2020) further stated that the technological developments in the second revolution led to today's globalization. The telecommunication and transport sector developed to sea and air which made it possible to transport goods to other continents (Nederveen et al., 2003). Vickers & Ziebarth (2019) argue that after the introduction of electricity into various industries, the methods performing job tasks changed intensely from manual form of production changed to machine-based.

Figure 2.2 The Assembly Line for Mass Production

Source: (da Rosa Righi et al., 2019)

Table 1.2 Illustration of Second Revolution

Revolution	Period	Technologies	Drawbacks	Achievements
Industry 2.0	19th Century	Telephone	High Cost of electrical power	Improvement in communication
		Telegram		Ease in transportation
		Telegraph		Increase in employment

		Electric Power Electronic		Increase in production

Source: Drafted by Researcher

2.2.3 Industry 3.0

The third phase of industrialization started in the mid of the twentieth century (Frederico et al. 2021; and Xu et al. 2018). A study by da Rosa Righi et al. (2019) revealed that Industry 3.0 witnessed a flurry of technological advances in a relatively short period of time, beginning with advancements in semiconductors and leading mainframe computers in the mid-1960s and personal computers in the mid-1970s. This evolution was about electronic technology and automation in the manufacturing sector (Baygin et al., 2016; History et al., 2005; Mukwawaya et al., 2018). Research by Vinitha et al. (2020) stated that industry 3.0 gave entrants to the use of automation and computers. The automation increased the efficiency and reliability of manufacturing systems (Oztemel & Gursev, 2020).

According to da Rosa Righi et al. (2019), the Programmable Logic Controller (PLC) was the catalyst for this automation progress in the 1960s. The study further revealed that the more different electronic devices (hardware) that are adjusted to manufacturing processes and systems, the more programs (software) are required to enable these devices. Further studies indicated that advances in electronic devices have given rise to the software market and all of its derivatives for various industries, such as ERP (enterprise resource planning), SCMS (supply chain management systems), TPS (transaction processing systems), and IMS (information management systems) (inventory management systems) (Akkermans et al., 2011; da Rosa Righi et al., 2019; Jede & Teuteberg, 2015; Larasati, 2017). However, these were achieved through Information technology (IT) and electrical engineering (Benešová & Tupa, 2017).

Manusia & Timur (2019) further stated that in the third industrial revolution, robots were the new technology at the time. The robots were programmed for assembling, labelling, testing, welding and painting (Baygin et al., 2016; Chodha et al., 2022; Vinitha et al., 2020). Yin et al. (2018) showed that Industry 3.0 is distinguished by technological innovations such as the shift from analogue to digital, which had a significant impact, particularly on the electronics industry. The study further revealed that most electronic product architectures shifted from integral to modular, resulting in dramatic reductions in average product life cycles. According to Yin et al. (2018), during Industry 3.0, product demand increased in three dimensions: volume, variety, and delivery time.

Table 2.3 Illustration of Industry 3.0

Revolution	**Period**	**Technologies**	**Drawbacks**	**Achievements**
Industry 3.0	20th Century	Robotics	Automated systems could not work under certain conditions	Productivity increased
		Automation		Automated industries were made
		Programming		Robots helped increase production

Source: Drafted by Researcher

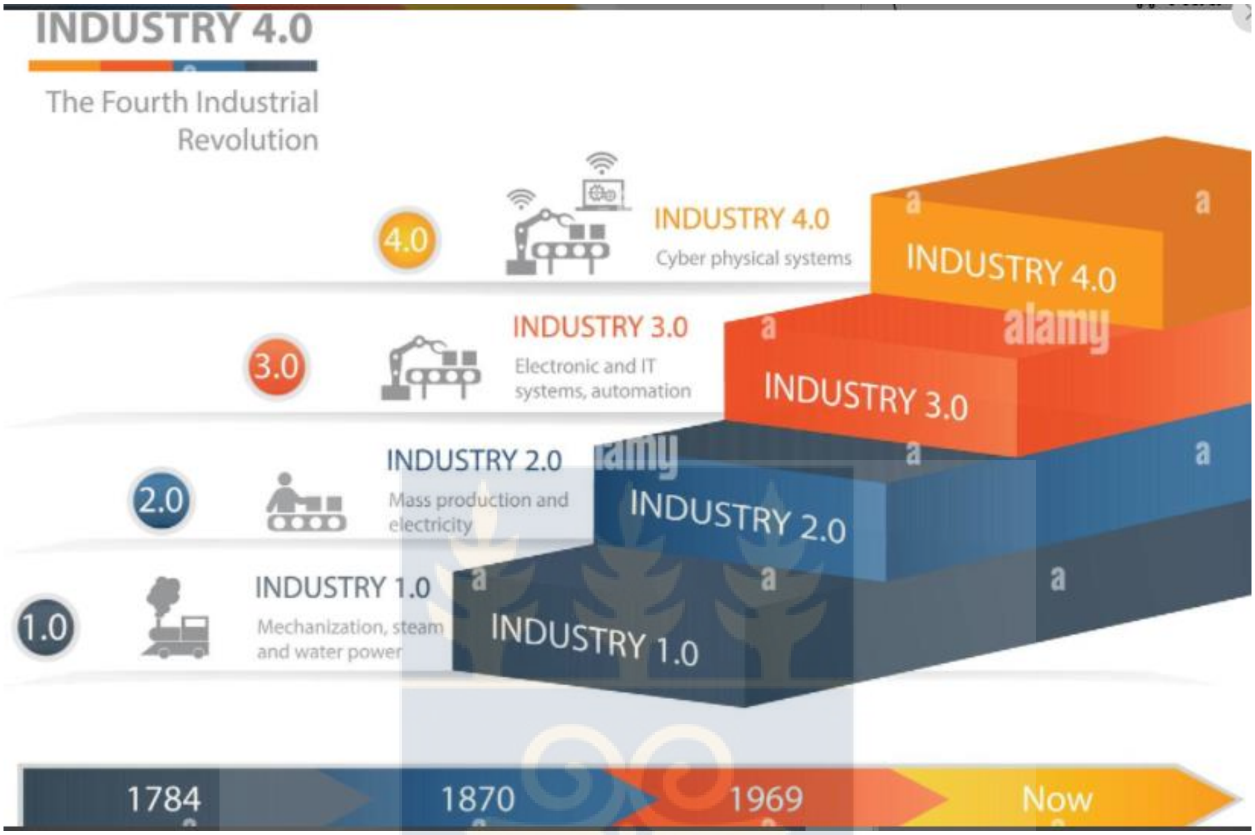

Figure 2.3 Illustration of the four phases of the Industrial revolution

Source: (*Industrial Revolution Stages From Steam Power To Cyber Physical Systems, Automation And Internet Of Things Royalty Free SVG, Cliparts, Vectors, And Stock Illustration. Image 68697111.*, 2022.)

2.2.4 Industry 4.0

The fourth evolution of industrialization Industry 4.0 emerged in the 21st century (Vinitha et al., 2020). Industry 4.0, which is also referred to as the Fourth Industrial Revolution (or 4IR), was introduced in Germany in 2011 during the Hannover Fair (Frederico et al., 2020; Ghobakhloo, 2018). Dalenogare et al. (2018) stated in their studies that, Industry 4.0 is a novel industrial phase of industrialization. It is the integration between Information and Communication Technology (ICT) and the operating systems in manufacturing which is connected by the Internet of Things

(IoT) and Cyber-Physical System(CPS) (Bi et al., 2021; Fatorachian & Kazemi, 2021b; Oztemel & Gursev, 2020; Pivoto et al., 2021).

According to Yang & Gu (2021), this stage of evolution when first announced, consisted of the following nine pillars: Internet of Things, Cyber-Physical System, Big Data, Robotics, 3D printing, Cloud Computing, Cyber Security, Simulation and Augmented Reality. Industry 4.0 is centred on data. It is based on how data can be gathered and analyzed to develop precise decisions in a firm's operations (Nagy et al., 2021). However, with the rapid advancement in technology, other technologies such as Blockchain, Business Intelligence and Artificial Intelligence have also emerged (Banerjee et al., 2018; Choi et al., 2018; Gohil & Thakker, 2021; Hofmann & Rutschmann, 2018; Min, 2010; Tsochev & Sharabov, 2021; Xu & Duan, 2019).

Liao et al. (2017) stated in their study that, Industry 4.0 represents an industry defined by connected machines, smart products and systems, and interconnected solutions. This new industrial stage has an impact on competitive regulations, industry structure, and customer needs (Bartodziej, 2017). Wang et al. (2015) revealed that Industry 4.0 is redefining the principles of competition since business models are being reframed as a result of the adoption of IoT concepts and factory digitization (Holl & Mariotti, 2021; Masood & Sonntag, 2020).

Industry 4.0 arose in developed countries where previous industrial stages were already established in terms of automation and ICT usage. These two notions of the third industrial revolution converged in Industry 4.0 (Benešová & Tupa, 2017; Hermann et al., 2016; Mukwawaya et al., 2018). The principles of Industry 4.0 are intended to enable organizations to have flexible manufacturing processes and to analyze vast volumes of data in real-time, hence boosting strategic and operational decision-making (Schwab, 2016).

Currently, Industry 4.0 is being researched and incorporated into the development agendas of several countries, including the United States, France, Singapore, Japan, the United Kingdom, and China (Liao et al., 2017). The reason for this increased in attention is that Industry 4.0 can redefine how value is created and delivered, as well as how businesses compete (Frederico et al., 2020; Zhou et al., 2016). As a result of Industry 4.0 adoption, its implementation has awakened high attentiveness (Ghadge et al., 2020b).

Table 2.3 Illustration of Industry 4.0

Revolution	Period	Technologies	Draw Backs	Achievements
Industry 4.0	21st Century	Internet of Things,	Cyber Security threats	Automation at its peak
		Blockchain, Artificial Intelligence,	Not fully expertise in operation	Data resilience
		Big Data,		
		Cloud Computing		

Source: Drafted by Researcher

2.2.5 Composition of Industry 4.0

Industry 4.0, led by intelligent manufacturing is regarded as the fourth industry to emerge from the industrial revolution (Cheng et al., 2016; ElMaraghy, 2019; Zhong et al., 2017; Zhou et al., 2016). The concept of Industry 4.0 is anchored on the integration of information and communication technologies (ICT) and industrial technology. It is primarily dependent on the development of a Cyber-Physical System (CPS) to create a digital and intelligent factory, to enable manufacturing to become more digital, information-led, customized, and green (Lin et al., 2019; Pivoto et al., 2021; Wang et al., 2015; Zhou et al., 2016).

Industry 4.0 is purposed to create a highly flexible production model of personalized and digital products and services, with real-time interactions between humans, products, and devices throughout the manufacturing process (Ghobakhloo, 2018; Shi et al., 2020; Terziyan et al., 2018; Zhou et al., 2016). For instance, extant literature according to Nascimento et al. (2019) and Thames & Schaefer (2017), indicated that any factory that receives consumer orders and promptly manufactures and delivers the required product will require Industry 4.0 technologies to facilitate the processes involved in production (Belhadi et al., 2021; Dahmani et al., 2021).

Hence, Industry 4.0 is the driving factor in changing accustomed industrial production methods and influencing future manufacturing (Hermann et al., 2016; Nurdiana & Pandin, 2021). Studies conducted by Rüßmann (2015) and Thames & Schaefer (2017) identified that the adoption of digital technology will enable industrial production systems to become more intelligent in the future. Zhou et al. (2016) further added that there will be more professed thinking-type factories and knowledge-based factories, which will improve factory efficiency and competitiveness.

2.3 Main Principles of Industry 4.0

A study by Carvalho et al. (2018) outlined seven main principles of Industry 4.0.

2.3.1 Interoperability

Interoperability refers to the exchange of equipment and machine that performs the same function, even if they are manufactured by different companies (Carvalho et al., 2018). This gives rise to multiple networks in a trusted environment for equipment to intercommunicate, enabling the awareness required for the development of Industry 4.0 intelligent functions (Qin et al., 2016). Interoperability requires networks of machines and equipment, making manufacturing processes more important for current and future operations (da Rosa Righi et al., 2019).

2.3.2 Decentralization

In Industry 4.0, decentralization is the decision-making ability of local businesses, operations personnel, and machines in manufacturing processes (Carvalho et al., 2018). Decentralization allows for the localization of manufacturing processes in their original locations by dedicating a system control mechanism instead of using central computers or delegating making decisions hierarchically, empowering and capacitating local operators to respond to changes (Carvalho et al., 2018; da Rosa Righi et al., 2019). The increasing demand for individual products makes centrally controlling systems increasingly difficult (Qin et al., 2016; Roblek et al., 2016). Decentralization of networks is one of the key facilitators of the fourth industrial revolution (Carvalho et al., 2018; da Rosa Righi et al., 2019; Qin et al., 2016).

2.3.3 Virtualization

Virtualization focuses on creating a virtual twin of the physical world of objects through constant monitoring and sensor-based machine (da Rosa Righi et al., 2019). Through the use of monitoring and machine-to-machine communication, a virtual twin can be abstracted and the sensor data is linked to virtual plant models and simulation models (Carvalho et al., 2018). In this way, a virtual copy of the physical world is created, furthermore, all necessary information, such as the next work steps or safety precautions, is provided (Qin et al., 2016). Cyber-Physical Systems bridge the gap between sharing of information and sense-making by promoting decentralized communication. A study by Carvalho et al. (2018) indicated that there are two key features of Industry 4.0. The first feature is sensors' activeness that allow the quickest possible acquisition of information about a new level of granularity. The second is real-time data-driven simulation that allows prediction of the effect of local optimization, allowing better decision-making and the use of decentralized control circuits (Carvalho et al., 2018; da Rosa Righi et al., 2019; Qin et al., 2016).

2.3.4 Real-Time Capability

Industry 4.0 focuses on real-time data collection and analysis, then progresses to taking immediate action in response to identified problems or communication demands (da Rosa Righi et al., 2019). Smart grid systems are excellent examples of real-time energy management capabilities for any system (Carvalho et al., 2018). To achieve organizational tasks, data must be collected and analyzed in real-time, but Industry 4.0 takes this concept a step further thus it includes plants that can respond to failure of one machine by forwarding products to another Roblek et al. (2016). Real-time as a principle of Industry 4.0 facilitates continuous link between the end consumer, via social networks, that allows for a faster response to changes in demand (Carvalho et al., 2018; da Rosa Righi et al., 2019). The use of real-time information and robotic systems is set to disrupt traditional manufacturing modes and organizational structures (Carvalho et al., 2018).

2.3.5 Modularity

The new form of industrial manufacturing brings a significant benefit to the entire production life-cycle by allowing any module of the production process to be replaced by another due to its flexible structure addressing production need changes (da Rosa Righi et al., 2019). This principle includes modular systems that can respond flexibly to changing requirements by replacing or expanding individual modules, making adding or removing production modules much easier (Carvalho et al., 2018). These modular systems can be easily adjusted in the incident of seasonal fluctuations or changes in product production needs, such as when incorporating new technologies (Carvalho et al., 2018; Schlick et al., 2017). Furthermore, many manufacturing processes, such as product

design, production planning, production and production engineering, and services, will be simulated as modular and then tightly connected end-to-end and interchangeably in industry technologies (Carvalho et al., 2018; Qin et al., 2016).

2.3.6 Service Orientation

According to this principle, business, human, and CPS services are available through the internet of services and can be used by other participants, facilitating the creation of product-service systems (Carvalho et al., 2018). Service orientation and transformation enable organizations to be more agile and flexible, responding to market changes much more quickly than in the past (Schlick et al., 2017). Service orientation makes manufacturing processes more agile in response to supply demands, hence, different production stakeholders could help with agility by providing data to the system (da Rosa Righi et al., 2019). Large unstructured data solutions enable organizations to collect and process unprecedented amounts of data (Pivoto et al., 2021).

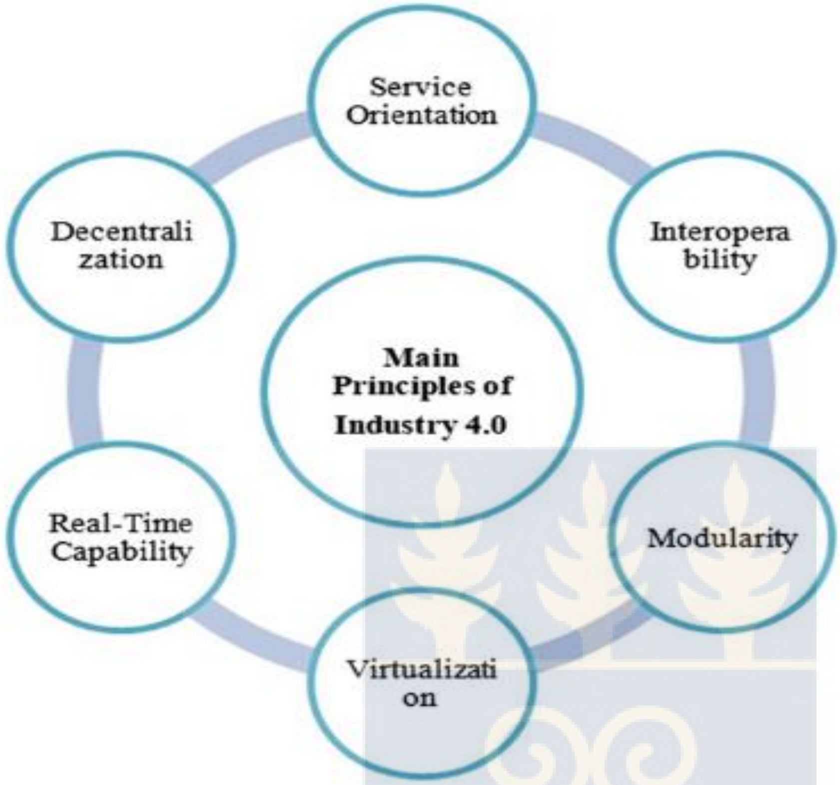

Figure 2.4 The main principles of Industry 4.0

Source: (da Rosa Righi et al., 2019)

2.4 Industry 4.0 digital Technologies

This section discusses some technologies that are used in the Fourth Industrial Revolution (4IR). According to Dalenogare et al. (2018a), digital technologies are changing the way firms operate. Digital technologies enable significant business improvements such as improving streamlining operation, customer experience, and developing new business models (Chawla & Goyal, 2022). Ghadge et al. (2020b) indicated Big Data Analytics (BDA), Autonomous robots, Industrial Internet of Things, cloud technology, Simulation, Additives Manufacturing, Augmented Reality, Business Intelligence, Cybersecurity as the core Industry 4.0 technologies. Blockchain technology aids in the connection of all firms in a production network, as well as the efficiency and traceability of the entire supply chain process (Cole et al., 2019)

2.4.1 Internet of Things

The term “Internet of Things” is literally the combination of “Internet” and “Things” (Ben-Daya et al., 2019; Vinitha et al., 2020). Internet is the linkage of networks like human to things, human to human, things to things and things to human (Vinitha et al., 2020). Ben-Daya et al. (2019) indicated in their study that, the Internet of Things is the network of physical things which are digitally linked to monitors, and sensors and intermingle within a firm and its operations facilitating tracking, visibility, agility and sharing of information (Wang et al., 2021) to enable coordination, control and the planning time of manufacturing (Oztemel & Gursev, 2020). The IoT enable the networking of products that makes it possible to connect the whole processes in manufacturing (Kerin & Pham, 2019). Bhushan & Agrawal (2020) pointed out in their study that the Internet of Things (IoT) is one of the most recent Information Technology (IT) innovations and revolution that is causing a paradigm shift in various fields which includes manufacturing.

Garay-Rondero et al. (2020) postulated that technological advancement has led to a constant and ever-changing business environment. Due to this, customers are becoming increasingly demanding in terms of product customization, pricing and quality of service (de Vass et al., 2021). A study by Bi et al. (2021) indicated that in other to survive in the constantly changing business environment, firms need to develop high levels of resilience, risk mitigation capabilities, and structural flexibility to quickly respond to the rapid business evolution.

The IoT enhance communications in manufacturing by allowing human-to-thing communication and autonomous coordination among ‘things’ while being held at a facility as well as transfers between multiple supply chain entities (Ben-Daya et al., 2019; Rejeb et al., 2019). In addition, Bhushan & Agrawal (2020) also identified that IoT provides various benefits to the production processes including cost savings, product tracking and inventory accuracy.

Internet of Things enablement increases organizational agility and proactivity by giving prompt detection of machine issues and predictive maintenance (Rejeb et al., 2019; Waller & Fawcett, 2013). In addition to the various enablement of the Internet of Things identified in the literature, IoT helps boost competitiveness by effectively tracking material flow, resulting in improvements in the effectiveness and efficiency of key processes and timelines (Shrouf et al., 2014).

2.4.2 Blockchain

Blockchain contributes to a wide range of manufacturing processes, procedures, and projects, thus allowing different stakeholders to interact on a networked business model (Banerjee et al., 2018). Research conducted by Cole et al. (2019) revealed that trust among stakeholders, transparency and efficiency at each level of the supply chain are all factors that slows the processes of manufacturing. Blockchain is a system of documenting information in a particular way that makes it difficult to hack and change the system (Rejeb et al., 2019). Wang et al. (2018) emphasize that consensus protocol is used in the distribution process of a Blockchain system, allowing mutually untrustworthy, uncoordinated parties to agree on transactions and blocks on a Blockchain server.

Viriyasitavat et al. (2019) adds that Blockchain enables stakeholders who are involved in the business ecosystem to share, validate and participate in the flow of data and information. Blockchain server allows them to synchronize and track shipments, logistics data and automate payments. A related study by Esmaeilian et al. (2020) also suggest that Blockchain technology allows business organizations to keep track of human exchanges, monetary exchanges, and all kinds of physical assets. A distributed ledger connected to millions of computers can be used to store, transport, transact and manage all forms of assets (Banerjee et al., 2018; Ivanov et al., 2019; Xu et al., 2018).

Although most organizations utilize enterprise resource planning (ERP) systems for management and planning, ERP can only be used internally (AlMuhayfith & Shaiti, 2020). However, Kim & Laskowski (2018) argued that Blockchain can help to connect all the processes of production networks in an organization on a single server, with all responsible members and stakeholders. Studies by Gohil & Thakker (2021) and Kim & Laskowski (2018) mentioned that the main goal of Blockchain technology in the production process is to trace all product transactions and the whole product life cycle (Hopkins, 2021; Sheel & Nath, 2019). However, tracking of processes and things from raw materials stage, and supplies to customers, including data, manufacturing, and location information, improves transparency and operational control (Nascimento et al., 2019; Saberi et al., 2019; Van Der Vorst et al., 2005). For instance, in production, Blockchain allows members to validate requested data before uploading it to the Blockchain server, ensuring that data is not tamper with Viriyasitavat et al (2019). This aids all participants in gaining trust in the systems (Gohil & Thakker, 2021).

It provides consumers and other organizations in the supply chain with real-time input (Banerjee et al., 2018; Cole et al., 2019; Wang et al., 2018). Apte & Petrovsky (2016) also added that Blockchain has the potential to transform the digital world by enabling distributed consensus, which allows any online transaction involving digital assets, past or present, to be confirmed at any time in the future (Wang et al., 2018).

2.4.3 Big Data Analytics

A study by Xu and Duan (2019) referred to Big data as the technique for processing massive amounts of data, such as data search, capture, storage, transport, curation, analysis, visualization, security, and privacy. With each passing year, the growth of information and communication technologies (ICT) in the manufacturing sector accelerates, and the potential and opportunities for manufacturing businesses are limitless (Sahoo, 2021). This transition can be seen not only in the need to introduce a product category or new product but also in the growing need to identify and design new advanced techniques and production methods to improve production processes (Kache & Seuring, 2017; Maheshwari et al., 2021; Zhong et al., 2017). Studies by Akanmu et al. (2021) and Javaid et al. (2021) indicated that modern manufacturing facilities are a data-intensive business environment that enables information generation, exchange, and processing via ubiquitous networks to deliver manufacturing intelligence. Jabbour et al. (2020); Fatorachian & Kazemi (2021a) revealed from their studies that, the application of BDA has emerged as a competitive advantage facilitator in the field of production and inventory management. Literature (Maheshwari et al. 2021; Pivoto et al. 2021; and Tao et al. 2019) reveal that Big Data Analytics is increasingly being viewed as a means for industries to streamline production management.

Nguyen et al. (2018) note that in their studies that, BDA in manufacturing has attracted the interest of practitioners and researchers due to its excellent function in the production process. The primary goal of the BDA is cost reduction through the use of BDA technologies such as Hadoop and cloud-based analytics (Attaran, 2007; Govindan et al., 2018; Zekhnini et al., 2021). According to Ardito et al. (2019), BDA investigates enormous amounts of data to find hidden patterns, correlations, and other concepts. BDA enables organizations to make faster and better decisions

(Ardito et al., 2019; Chodha et al., 2022; Ivanov et al., 2019). Furthermore, BDA enables industries to employ data and quantitative methodologies to improve decision-making across all production activities (Addo-Tenkorang & Helo, 2016; Dubey et al., 2019; Nguyen et al., 2018).

Adoption of BDA in the manufacturing processes helps to promote flexibility, transparency, and integration of global logistics operations and supply chains to efficiently control demand variations and manage costs (ElMaraghy, 2019; Frank et al., 2019; Zhou et al., 2016). Frank et al. (2019) further indicated that the significance of BDA is for organizations and decision-makers to determine the quality and analysis of the data rather than its quantity. In addition, Maheshwari et al. (2021) revealed that BDA helps provide sufficient data that can be utilized to assist businesses in troubleshooting errors, forecasting future system difficulties and generating information about customers at the point of sale to help elevate their experience, and assisting businesses in developing strategies for time and cost reduction efforts.

2.4.4 Cloud Computing

Cloud computing is a computing paradigm in which tasks are allocated to a collection of network connections, services and software (Büyüközkan & Göçer, 2018; Cegielski et al., 2012; Jede & Teuteberg, 2015; Tiwari, 2013). Cloud computing (CC)provides a competitive advantage primarily through the use of speed and agility as well as its promotion of innovation and scalability (Jede & Teuteberg, 2015; Pivoto et al., 2021; Vinitha et al., 2020; Xu & Duan, 2019). Cloud computing reduces the financial barrier of experimenting new ideas while shortening the time to market (Sharma et al., 2021; Taghipour & Mahboobi, 2020). Research by Gupta et al. (2021) indicated that, in today's global setting, cloud computing enhance delivery on-demand computing services with excellent dependability, scalability, and availability.

In addition, a study by Kumari & Kaur (2021) revealed that Cloud computing allows more flexible outsourcing of software for manufacturing procedures collaboration and infrastructure demands. Cloud Computing is a suitable technology for supporting and administering a constantly changing and dynamic network and production processes (Abimbola, 2021; Kumari & Kaur, 2021; Leukel et al., 2011). The concept of cloud computing is that everyone in the production process can have access to data and information the same way that they use water, electricity, gas, and telephones (Ali Akbar, 2019; Rashid & Chaturvedi, 2019). Data and information are easily available via the cloud, and information can be shared to the greatest extent possible, facilitating group project collaboration in the production (Addo-Tenkorang & Helo, 2016; Jede & Teuteberg, 2015; Mourtzis, 2022).

According to Sharma et al. (2021), the key feature of cloud computing is the availability of dependable services via data centers and servers. The cloud is frequently portrayed as a single point of contact for all of a consumer's computing requirements (Agrawal & Narain, 2018; Anitah et al., 2019; Zhou et al., 2016). Cloud computing is having a big impact on the production process, and the application market and its adoption are projected to increase in the coming years (Attaran, 2020; Shamout et al., 2022).

Hopkins (2021) pointed out that, Cloud technology has been used in the industrial sector and has resulted in development of numerous cloud manufacturing systems. Cloud manufacturing denotes an integrated cyber-physical system capable of providing on-demand manufacturing services, both digitally and physically, while making the most use of manufacturing resources (Cegielski et al., 2012; Kumari & Kaur, 2021; Oztemel & Gursev, 2020; Pivoto et al., 2021).

CC provides a pool of shared resources such as manufacturing software, manufacturing facilities, and manufacturing competencies (Charro et al., 2018; Zhong et al., 2017). Siderska & Jadaan,

(2018) added that Cloud manufacturing goes beyond simply placing manufacturing software programs in the cyber cloud. Aside from data storage and virtual machines, the physical resources connected to the manufacturing processes, CC provide adaptable, secure, and on-demand manufacturing services for the Internet of Things, such as work cells, robots and machine tools (Abimbola, 2021; Taghipour & Mahboobi, 2020; Zhong et al., 2017) .

2.5 Implementation of Industry 4.0

Due to various growth in technological advancements, the classic production functions have transformed into larger and more sophisticated strategic approaches in recent times (Frank et al., 2019; Kaliani Sundram et al., 2016; Nascimento et al., 2019; Ralston & Blackhurst, 2020). These technological advancements are part of Industry 4.0, the Fourth Industrial Revolution (Herceg et al., 2020; Müller et al., 2018; Norouzi, 2021). I4. 0 has been employed in several manufacturing processes, and it depicts a connection between smart and physical assets, such as smart products and machines that function autonomously with self-coordinating systems (de Vass et al., 2021; Meindl et al., 2021; Sheel & Nath, 2019).

Several studies Dalenogare et al. (2018b), Hermann et al. (2016), Liao et al. (2017), Norouzi (2021) and Nurdiana & Pandin (2021) have shown that the number of organizations engaging in the transition to Industry 4.0 is constantly increasing. According to a recent survey, the number of German companies that did not consider implementing Industry 4.0 declined from 34% to 9% between 2014 and 2018 (Basl, 2017; Ghobakhloo, 2018). During the same period, the number of companies that began to adopt to Industry 4.0 projects climbed from 14% to 43% (Dalenogare et al., 2018a; Frank et al., 2019).

Similarly, Basl (2017) discovered that 40% of responding Czech enterprises had already begun to interact with Industry 4.0 for more than a year, whilst 20% had only recently begun the shift at the time of the survey. However, these figures solely reflect the conditions in Germany and the Czech Republic, both of which are World Economic Forum Industry 4.0 leaders (2018) (Basl, 2017; Dalenogare et al., 2018b). As a result, it is not surprising that research that addressed a broader international audience yielded different results. For example, Hoyer et al. (2020) discovered that the number of organizations that have begun to implement Industry 4.0 is yet to reach the 25% mark.

A study by Basl (2017) included 1,155 participants from 26 countries, discovered that 31% of the participating companies had already begun to use Industry 4.0-related technology. However, the figures reported only represent companies that have begun individual Industry 4.0 projects (Hoyer et al., 2020). Despite the enthusiastic expectations made in recent years, the number of companies that have fully embraced Industry 4.0 remains low (Lin et al., 2018). For example, studies estimated in 2014 that the digitalization of the entire manufacturing processes and operations would exceed 80% in the next five years (Basl, 2017; Dalenogare et al., 2018a; Hoyer et al., 2020). On the contrary, the findings from Hofmann & Rüsch (2017), Oztemel & Gursev (2020) and Xu et al. (2018) indicated that the number of German companies taking a broader approach to Industry 4.0 is still low at 9% four years after the initial found that only 40% of American, German, and Japanese enterprises working on Industry 4.0 made substantial progress in further implementing it within a year (Pfeiffer, 2017; Piccarozzi et al., 2018; Zhong et al., 2017). These figures demonstrate the overall difficulties of merging separate Industry 4.0 initiatives into a unified approach that extends beyond the boundaries of particular machines, departments, and factories and is consistent with the notion of Industry 4.0 (Ghobakhloo, 2018; Oztemel & Gursev, 2020; Zhong et al., 2017).

Castellacci and Natera (2013) argue that the policies developed by industrialized countries to embrace Industry 4.0 digital revolution differ from policies adopted by developing countries. Frank et al. (2019) note that developed countries mainly enact national polices to embrace development strategies in emerging strategies. On the contrary, in the case of developing economies, Industry 4.0 technologies adoption is on organizational efforts rather than national and coordinated strategies (Castellacci & Natera, 2013; Frank et al., 2019; Nagy et al., 2018).

Dalenogare et al. (2018b) stated in their study that because the economies of emerging countries have historically been more focused on the extraction and commercialization of commodities, enterprises in these countries are frequently behind their counterparts in developed countries in terms of technology adoption. Frank et al. (2016) added that, other factors such as culture, ICT infrastructure, education level, and economic and political instability can all influence developing economies in adopting and implementing Industry 4.0 and, as a result, the low level of investing in sophisticated technology.

2.5.1 Drivers of Industry 4.0 Implementation

Despite the rapid rise of Industry 4.0, studies on identifying potential drivers and challenges to Industry 4.0 deployment are a minimal (Lu, 2017). According to the existing research Albach et al. (2015), digital technology integration can provide various benefits to the industry. Study by Wang & Cheng (2020) revealed that communication between machines and products enables reconfigurable and flexible lines for the creation of customized items, even in small batches, for business operations. Furthermore, with the cyber physical system (CPS) for information processing, businesses have better assistance for decision-making processes and faster response to various types of occurrences, such as manufacturing line breakdowns (Colli et al., 2019; Schumacher et al., 2019). As a result, these systems can boost company productivity by improving resource utilization efficiency, for example, by combining production with smart grids for energy savings (Dalenogare et al., 2018b). Industry 4.0 also provides prospects and benefits for future growth (Thames & Schaefer, 2017). Hermann et al. (2016) and Tao et al. (2019) added that the technological integration concept allows collaborative networks of firms to pool resources, divide risks, and quickly react to market changes, embracing new opportunities.

A study by Oztemel & Gursev (2020) indicated that implementing Industry 4.0 in production process offers real-time planning and control, allowing organizations to be flexible and nimble in responding to rapidly changing situations; for instance, minimizing planning cycles and frozen periods by responding to changes in demand, supply, and prices more quickly (Ghadge et al., 2020b). Ghobakhloo (2018) added that business analytics methods can forecast future events and trends such as customer behavior, delivery time, and industrial output. Real-time delivery routing and tracking further improves logistics operations' flexibility, efficiency, and agility (Addo-Tenkorang & Helo, 2016; Ghadge et al., 2020b; Ivanov et al., 2019).

Industry 4.0 technologies give real-time, consistent, and reliable data to help businesses make better decisions (Horváth & Szabó, 2019; Nagy et al., n.d.; Oztemel & Gursev, 2020; Tao et al., 2019). As a result, next-generation performance management systems will enable improved end-to-end visibility across the value chain (Miragliotta et al., 2018; Shrouf et al., 2014). The data ranges from key top-level performance metrics like customer service and order fulfillment level to detailed process data like vehicle location in the logistics network (Ghadge et al., 2020a; Helo & Shamsuzzoha, 2020).

According to Pereira and Romero (2017), the automation of physical tasks, planning, control, and information exchange processes improve manufacturing efficiency. A large number of businesses use automated technologies, particularly in their logistics operations (Dogru & Keskin, 2020; Nantee & Sureeyatanapas, 2021). Material handling robots and cranes, automated pallet handling systems, shipment tracking, unmanned autonomous vehicles, and fully automated warehouses are examples of these Industry 4.0 enablement (Ghadge et al., 2020a; Vaidya et al., 2018; Xu et al., 2018). Plasch et al. (2021) also added that companies adopt cross-company transport optimization to improve track utilization and boost transport flexibility by cooperating and sharing facilities. Hence Industry 4.0 implementation enables the entire production network configuration and constantly improve to offer an optimal fit for business requirements (Fatorachian & Kazemi, 2021a; S. S. Kamble et al., 2018). Micro-segmentation, mass customization, and advanced scheduling practices enable businesses to provide multi-choice packages for customers, efficiently solve last mile problems for high-value customers, deliver customers' orders at a faster rate by utilizing innovative, digitized delivery and distribution techniques such as drone delivery, and exceed customer expectations (Ghobakhloo, 2018; Hofmann & Rüsch, 2017).

2.5.2 Challenges of Industry 4.0 Implementation

The challenges for emerging countries in adopting Industry 4.0 technology differ from those faced by developed countries (Dalenogare et al., 2018b; Griffith & Tengnah, 2011). Because the idea of Industry 4.0 is still in its early stages, there is considerable uncertainty and a lack of understanding about the its true impact and contribution (Dalenogare et al., 2018b; Frank et al., 2016). Dalenogare et al. (2018b) argue that few studies on Industry 4.0 technologies have been done in the emerging economies on the assessment and the readiness and adoption in the industrial sector.

For most developed nations, governments supply the necessary infrastructure for the digital world (such as the internet and communication systems) (Shareef et al., 2009) . There is a lack of plan for transforming the industrial infrastructure in the developing world, owing to a lack of understanding about its benefits and repercussions of Industry 4.0 (Almada-Lobo, 2015; Ghadge et al., 2020b; Hermann et al., 2016; Hofmann & Rüsch, 2017; Kamble et al., 2018).

Theorin et al. (2017) stated in their studies that, financial constraints are a fundamental issue in implementing Industry 4.0 in terms of the creation of advanced contemporary infrastructure and sustainable process improvements. A study by Ghadge et al. (2020b) revealed that the key priority that influences the volume of investment is the focal organization's technical competency. However, the economic perspective is still in its infancy; the lack of clarity on cost-benefit analysis and monetary rewards for digital investments is a critical issue for implementing Industry 4.0 in the context of developing countries (Masood & Sonntag, 2020; Müller et al., 2018).

Müller et al. (2018) revealed that large amounts of data exchanged across the value chain pose a cybersecurity risk; thus, security and privacy concerns must be addressed in the implementation of Industry 4.0 when adopted. Any digital transformation or adoption of inadequate infrastructure and internet connectivity are significant impediments to the Industry 4.0 implementation (Hofmann & Rüsch, 2017; Kamble et al., 2018; Saste & Files, 2017).

Ghadge et al. (2020) states that with the globalization of company networks and markets, operational and management systems are becoming increasingly complicated. Companies are hesitant to implement Industry 4.0 technologies due to a lack of competencies for managing global data as well as the most recent technological breakthroughs (Masood & Sonntag, 2020; Olsen & Tomlin, 2020). Industries are uncertain and not acquainted with the term Industry 4.0, and they are unaware of the benefits of digital transformation, hence they will be reluctant in accepting it (Ras et al., 2017; Theorin et al., 2017).

Industry 4.0 transformational changes are rapid and necessitate proper skill development and training, which is difficult to execute without strong management backing (Gökalp et al., 2017). Other obstacles confronting firms attempting to integrate Industry 4.0 technologies include insufficient research and development procedures, a lack of infrastructure, low-quality data, a lack of digital culture, and a lack of trust among partners (Ghadge et al., 2020b; Ghobakhloo, 2018; X. Wang & Cheng, 2020)

2.6 Ghanaian Manufacturing Firms

Otchere et al. (2022), the manufacturing firms in Ghana are constantly challenged to introduce new products, cost-cutting processes, and procedures to ensure long-term viability . The study further added that market base for the manufacturing firms in Ghana are relatively saturated, customers seek superior products at lower prices in order to maintain their loyalty to a specific brand. As a result, in order to remain competitive in this saturated market, these firms must improve their innovation performance. The industrial sector in Ghana, experienced average annual growth of more than 10% from 2017 to 2019, and was a key contributor to economic growth (Ghana Investment Promotion Centre (GIPC), 2022). The most significant manufacturing firms in Ghana are those that process wood, produce pharmaceuticals, manufacture chemicals and cement, smelt aluminum, refine oil, and make textiles and apparel (Achaw & Danso-Boateng, 2021). Ghana Investment Promotion Centre (GIPC) (2022) express that industrialization drive is led by the private sector, which will arm and empower local communities to utilize their natural resources to produce goods that are in high demand both locally and internationally.

2.7 Chapter Summary

This chapter examined relevant literature regarding the evolution of the industrial sector, the composition of Industry 4.0, its implementation and associate importance in adoption, some theories that have been used in previous studies and some related gaps in the adoption of I.4.0 technologies. The next chapter looks at the theoretical framework underpinning the study.

CHAPTER THREE

THEORETICAL FRAMEWORK AND DEVELOPMENT OF HYPOTHESES

3.1 Introduction

This chapter presents the theoretical framework underpinning the study, justification for the choice of theory and formulation of the research hypotheses.

3.2 Technology Acceptance Model

A common model for examining attitudes and elements that influence the acceptance of new technology is the Technology Acceptance Model (TAM), which was first developed by Davis (1989) (Chen & Lin, 2018). TAM focuses on elements that influence people's usage intentions when they are exposed to new technology (Douglas & Sutton, 2018). A person's intention to use new technology and attitude towards it has a role in determining whether or not they use it (S. Kumar et al., 2018). The Technology Adoption Model (TAM) is a theory of information systems that explains how users come to embrace and employ new technologies (Harryanto et al., 2018). According to Agag & El-Masry (2016), this model presupposes that the two key factors influencing a person's adoption of a particular technology are his perception of the technology's usefulness and ease of use.

Davis (1989) postulated that attitudes toward adopting a particular technology and subsequent plans to utilize and implement that technology are influenced by perceived usefulness and perceived ease of use. Perceived usefulness is defined “as the extent to which a person believes that using a particular system will enhance performance, and perceived ease of use refers to the extent to which a person believes that using a particular system will be free of effort” (Chien-Hsin Lin & Hsin-Yu Shih, 2007 p. 643).

According to the Technology Acceptance Model, three constructs, i.e., perceived ease of use (PEOU), perceived usefulness (PU), and intentions to utilize an innovation explain what influences or drives a user to adopt new technology (Rafdinal & Senalasari, 2021). Davis (1989) has shown that behavioral intention is another factor that influences how people utilize and accept new technology.

TAM has been empirically tested in previous scholarly works to explain a variety of technological adoption-related (Castillo S & Bigne, 2021; Ferreira et al., 2021; Kamble et al., 2021; Masood & Sonntag, 2020; Pai & Alathur, 2019). Erdoğmu & Esen (2011) also revealed that TAM has been empirically tested and validated through applications, replications, and in other scholarly works such as Flavián et al. (2022), Kaushik & Rahman (2017) and Razali et al. (2021). The TAM provides results that enable the prediction and explanation of users in accepting innovation (Rafdinal & Senalasari, 2021) and is used to explore the adoption of new technology (Flavián et al., 2022).

3.2.1 Technology Readiness Index

Parasuraman (2000) established the Technology Readiness Index (TRI) paradigm, which has its roots in the technological paradox work (Mick & Fournier, 1998). Technology readiness "refers to the people's propensity to embrace and use new technology for accomplishing goals in home life and at work" (Parasuraman, 2000 p. 3 08). The Technology Readiness (TR) model is employed as a theoretical foundation for technology adoption because it is connected to one's propensity to use new technology as well as overall sentiment regarding the new technology, and it is also pertinent to the marketing environment (Castillo S & Bigne, 2021; Chien-Hsin Lin, Hsin-Yu Shih, 2007; Rafdinal & Senalasari, 2021). Omar et al. (2021) assert that the chances of technology adoption is increased by technology readiness.

Parasuraman & Colby (2001) indicated that explorers, pioneers, skeptics, paranoids, and laggards are the five categories used to classify individual technology usage behavior. When new technology is launched, explorers are hopeful about utilizing it and becoming early adopters. Pioneers are the next group to experiment with new technology, and they will need some help and level of assurance. Technology sceptics need to be persuaded of the advantages of using new technology before they will adopt it. Because they lack confidence and are worried about the hazards and adoption hurdles associated with new technology, Paranoids are slow to adopt it. Technology laggards, an extreme group, are those who refuse to adopt new technology unless required to (Omar et al., 2021; Parasuraman & Colby, 2001).

The TR is appropriate to increase the understanding of Industry 4.0 technology adoption since it looks at the key factors influencing the adoption of new technology usage (Rafdinal & Senalasari, 2021). The TR is used to evaluate a person's or people's technological readiness (Park et al., 2021). TR comprise four constructs which include all four of the individual components of technology readiness: optimism, innovativeness, discomfort, and insecurity (Kim & Chiu, 2019; Parasuraman, 2000). TR has many facets, each of which is distinguished by people's dominant personality traits about technology use. According to Parasuraman (2000), TR is split into two categories: positive and negative technology readiness.

The positive technology readiness includes, in particular, the following variables that encourage acceptance of new technology: Innovation is the propensity to be a technical trailblazer and thought leader. Optimism is a favorable attitude towards technology and the conviction that it gives individuals more control, flexibility, and efficiency in their life. The negative technology includes two things that prevent people from accepting modern technology: Discomfort – feelings of not having control over technology and feeling overwhelmed by it; Insecurity – feelings of mistrust of technology arising from doubts about its reliability and worries about potential negative effects (Omar et al., 2021; Parasuraman, 2000; Raman & Aashish, 2021; Rojas-Méndez et al., 2017).

3.3 Technology Readiness and Acceptance Model (TRAM)

McFarland & Hamilton (2006) argue that although the TAM has been thoroughly evaluated as a model for predicting consumers' adoption of new technologies, however it has been recommended that in order to improve its explanatory and prediction of technology acceptance behavior, the TAM should be expanded and augmented with additional elements (Kim & Chiu, 2019; McFarland & Hamilton, 2006).

An integrated TRAM, which combines TR with the TAM, was developed to expand the TAM model and explain how TR influences users' adoption of new technologies (Lin et al,. 2007). The TRAM asserts that consumers' prior technological exposure and general technological understanding have an impact on how they perceive new technology and how they react to it (Lin et al., 2007; Kim & Chiu, 2019). In the TRAM, TR represents the person's viewpoint on technology in general, while the TAM connects this viewpoint to views regarding a particular technology (Kim & Chiu, 2019).

Lin et al. (2007) postulated the TRAM examines how trends in technology readiness and adoption relate to one another by linking the TRI to the system-specific characteristics of the TAM. The outcome demonstrates that TRAM enhances the prior two models' (i.e., the TAM and TRI) applicability and their explanatory potency. As a result, this model can be said to be predictive of technological adoption.

TRAM has been used in prior research to examine how quickly technology is being adopted (Acheampong et al., 2017; Martens et al., 2017). Parasuraman (2000) argued that a firm's view of whether technology is valuable for adoption depends on its prior experiences. The firm's ability to embrace any technology will be influenced by its technological preparedness, making it a vital antecedent in models of technology adoption (Rafdinal & Senalasari, 2021; Sinha et al., 2019). This demonstrates the connection between a firm's technological readiness and their adoption of new technology.

Previous research has demonstrated how technology readiness affects how easily usable and valuable new technology is seen in the context of adoption (Acheampong et al., 2017; Huang et al., 2015; Park et al., 2021). Literature suggests that an entity's perceived usability and convenience of use of a technology are impacted by its technological readiness. The consequences of TRAM has not yet been adequately investigated (Rafdinal & Senalasari, 2021). As a result, this study aims to analyze how the TRAM dimensions and technological awareness affect Industry 4.0 adoption among manufacturing firms.

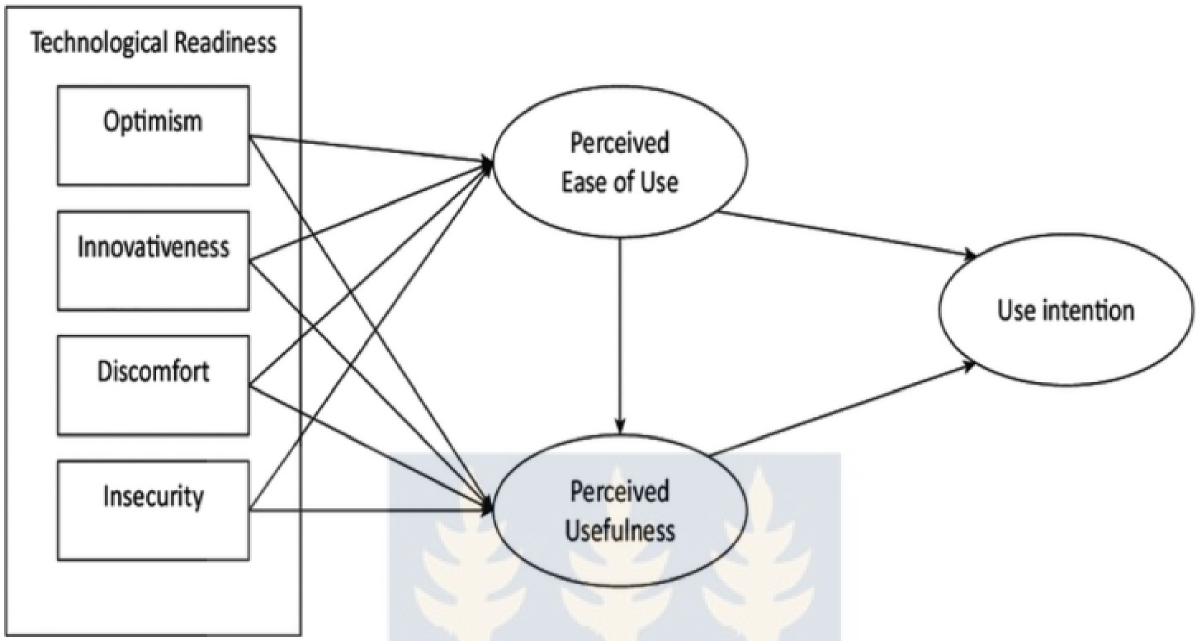

Figure 3.1 TRAM Model

Source: Lin et al. (2007)

3.4 Discussion of the Concepts in the Model

3.4.1 Optimism

Optimism "refers to a positive attitude towards technology with the belief that technology will improve daily living quality and provide convenience, flexibility or efficiency"(Parasuraman, 2000 p.311). Technology optimism refers to a favorable view of technology and the conviction that it provides more power, flexibility, and efficiency (Ferreira et al., 2021). Consequently, optimists are more likely than the broader population to accept new technology, and they also get to experience its advantages first (Huang et al., 2015).

Optimists are more willing to accept new technologies and agree the way things are (Acheampong et al., 2017). Prior studies have linked the adoption of new technologies to optimism (Kim & Chiu, 2019; Raman & Aashish, 2021). Hence, optimism has an impact on technology readiness which will facilitate manufacturing firms to adopt Industry 4.0 technologies in their manufacturing processes with the view that, the new technology will improve manufacturing performance to enhance customer satisfaction (Park et al., 2021).

3.4.2 Innovativeness

Innovativeness “refers to the tendency to be a pioneer in the adoption of technology and a leader in technological thinking”(Kumar et al., 2018 p.149). Agarwal & Prasad (1999) explained innovativeness as the willingness of people's openness to adopt and utilize new technologies. Innovative people are always eager to use the latest cutting-edge technology (Larsen, 2011). When using new technology products, they are able to pick them up quickly and do not require manuals or expert advice and they are also eager to assist their pals when they run into difficulties with new technology (Huang et al., 2015).

Users who are considered "innovative" adopt new concepts earlier than other users (Rogers, 2003). Thus, if firms perceive Industry 4.0 technologies as new and innovative, it could influence their readiness to adopt. High-capability innovators are more likely to be aware about new technologies and act as information seekers about the technologies occurring in their field (Pai & Alathur, 2019). Therefore, firms that are innovative may be quicker and faster in exploring the capabilities of Industry 4.0 technologies and the associated benefits of adopting such technologies in their manufacturing process.

3.4.3 Discomfort

Discomfort is defined by Parasuraman (2000 p.311) “as the perceived lack of control over technology and a feeling of being overwhelmed by it”. Huang et al. (2015) stated that discomfort is the overwhelming perception of technological knowledge and use being difficult. A user's readiness to use the system could be affected if they believe it to be discouraging to use or a source of physical or mental discomfort (Omotayo & Adekunle, 2021). However, a lack of relevant firms' technological experience is also a factor in customers' unease to adopt a new technology (Huang et al., 2015).

Raman & Aashish (2021) observed that people who are hesitant to adopt innovative technologies often become cautious of novel technologies. It can be stipulated that, manufacturing firms which are apprehensive of new technologies will be reluctant in embracing Industry 4.0 technologies in their manufacturing processes. Such firms may be well-informed about the benefits of adopting Industry 4.0 technologies but would be hesitant in the adoption of these technologies because of their apprehension.

3.4.4 Insecurity

The term "insecurity" describes a lack of confidence and skepticism regarding the accuracy and dependability of new technology (Parasuraman, 2000). Huang et al. (2015) argues that, although technology increases the standard of living and productivity at work, it is possible for software bugs, outdated technology, or information technology programs to result in significant losses and damages. Arguably, Industry 4.0 technologies are relatively new particularly relative to African manufacturers. It is therefore possible to have manufacturing firms lacking confidence and others being skeptical about these technologies. As a result, manufacturing firms that associate a higher level of insecurity and perceive the possibility of threats with adopting Industry 4.0 technologies in their operations will be reluctant in accepting it.

3.4.5 Perceived Ease of Use

Perceived ease of use (PEOU) "refers to the extent to which a person believes that using a particular technology system will be free of efforts" (Lin et al. 2007 p. 643). According to Park et al. (2021) perceived ease of use affect how technology users feel about using a new technology. Industry 4.0 combines intelligent production processes and embedded production system technologies to create a new technological era that will profoundly alter business models, production value networks, and industry value chains (Zhong et al., 2017). The argument can therefore be made that, where manufacturers perceive Industry 4.0 technologies to be easy to use, given the usefulness of a technology, firms will be willing to adopt Industry 4.0 technologies to enhance their manufacturing operations.

3.4.6 Perceived Usefulness

Perceived usefulness (PU) is "defined as the extent to which a person believes that using a particular system will enhance his or her performance" (Lin et al., 2007). PU measures an individual's level of optimism that a particular system will enable them to complete a particular task (Rafdinal & Senalasari, 2021). According to Erdoğmu & Esen (2011), perceive usefulness is the subjective likelihood that a certain application system will improve a user's capacity to perform their job in an organizational setting. More precisely, if manufacturing firms believe that adopting Industry 4.0 technologies will improve their operations performance dimensions (cost, quality, flexibility, speed and dependability), there will be a high readiness of such firms in embracing the Industry 4.0 technologies.

3.4.7 Use Intention

Intention to use is the desire and effort to engage in a behavior (Erdoğmu & Esen, 2011). Use intention is the extent to which a person has made conscious decisions to engage in or refrain from engaging in a particular future behavior (Maity et al., 2019). Al-Rahmi et al. (2019) postulated that use intention influences how an Information System (IS) is really used, which determines how well a technology is adopted. Use intention is very much dependent on the perceived usefulness of the technology together with the perceived ease of use of that technology. Consequently, manufacturing firms who perceive Industry 4.0 technologies to be useful and easy to use will demonstrate a higher level technology acceptance and readiness in its adoption.

3.5 Justification of TRAM

Stănescu & Romașcanu (2022) emphasize that, with the rapid improvement and advancement in technology in information system research, it makes it challenging to choose between accepting and rejecting new models to explain the adoption of new technology. TRAM stands out among the models and theories that have been produced in this regard to describe how technology is used effectively in terms of adopting and utilizing new technologies (Chen & Lin, 2018).

The Technology Readiness and Acceptance Model is thought to be the best suitable for the study because it to helps explain how effectively new technology would be adopted and used and it forecast how users would behave when embracing new technology and their readiness in adopting (Huang et al., 2015; Omar et al., 2021; Rojas-Méndez et al., 2017). The TRAM has been used to examine user approval of a variety of technological services, such as online stock trading platforms (Lin et al., 2007), self-service (S. Kumar et al., 2018; P. Raman & Aashish, 2021), augmented reality application (Castillo S & Bigne, 2021) and application of software (Omotayo & Adekunle, 2021). The multiple TRAM implementations in the mentioned above scholarly works demonstrate how important the variables of TRAM play in influencing behavioral intention to adopt new technology.

TRAM is one of the prominent models used to assess the readiness and acceptance of technology (Chen & Lin, 2018). Prior studies have established the TRAM as a robust model with appropriate variables in predicting user readiness and acceptance of novel technologies (Kumar et al., 2018; Omotayo & Adekunle, 2021; Park et al., 2021). Thus, the use of TRAM leads to a better prediction of the readiness and acceptance of new information resource. Therefore, in the context of the adoption of Industry 4.0 technologies, this study has provided a complete assessment of previous TRAM related investigations. For instance, (Lin et al., 2007) revealed that technology readiness and acceptance, is one of the prominent models for information technology readiness and acceptance research and the prevailing theoretical approach regarding user's adoption of Industry 4.0 technologies.

Therefore, to ascertain the extent of readiness for the adoption of Industry 4.0 technologies in manufacturing firms, it is appropriate to adopt a model that incorporates optimism, innovativeness, discomfort, insecurity, perceived ease of use, perceived usefulness and user intention to adopt the technology. This study therefore adapts the TRAM to achieve it outlined objectives.

3.6 Research Model and Hypothesis Development

TRAM examines how technology readiness trends relates to acceptance of technology by connecting the TRI to the system-specific dimensions of the TAM. The outcome demonstrates that TRAM improves the applicability and explanatory strength of the proceeding two models in marketing contexts (Lin et al., 2007). TRAM has been used in prior research to examine how quickly technology is being adopted (Acheampong et al., 2017; Martens et al., 2017). As a result, this model can be said to be predictive of technological adoption.

The current research therefore employs the TRAM as the theoretical lens to explore the phenomenon under study. The theoretical framework (Figure 3.2) is underpinned by the TRAM. In the framework, TRAM measures users' positive (i.e. optimism and innovativeness) and negative (i.e. discomfort and insecurity) towards technological readiness (Parasuraman, 2000). The TRAM dimensions examine users' perception of embracing Industry 4.0 technologies such as enthusiasm (optimism and innovativeness), perception of control and reliability (discomfort and insecurity); these often influences users' decisions that leads to adopting new technology in firms manufacturing processes. In addition to complement the framework, the study proposed awareness of Industry 4.0 technologies among the manufacturing firms.

Awareness is an essential variable (Sinha et al., 2019), the factors that influence how quickly users adopts new technologies depend on their level of awareness or how much they are aware those technologies. Hence, optimism, innovativeness, discomfort, insecurity and awareness are considered as the technology readiness factors influencing manufacturing firms' perceived ease of use and perceived usefulness of Industry 4.0. The perceived ease of use and perceived usefulness to adopt Industry 4.0 technologies which is moderated by support resources such as Information Technology (IT) infrastructure, IT capabilities and financial resources also influences the intention to adopt Industry 4.0 technologies.

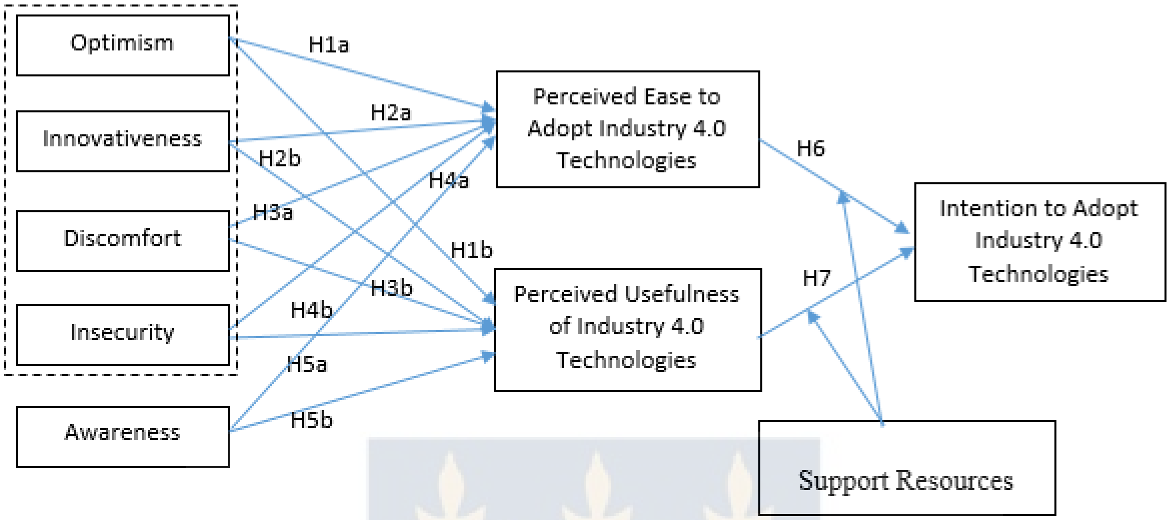

Figure 3.1 Theoretical Framework of the study

Source: Researcher

3.6.1 Optimism, perceived ease to adopt and Perceived usefulness

Optimism is the expectation of a user towards a new system is optimism (Omotayo & Adekunle, 2021). Parasuraman postulated that, optimism relates to "a positive view towards technology and trust that it will offer people more efficiency, flexibility and control"(Parasuraman, 2000 p. 311). He discovered that optimism influenced technological readiness. Hence, if firms have a positive assessment of Industry 4.0 technologies such as perceiving the technologies to offer them control, efficiency and flexibility in their operations, they would be most likely adopting it. Users who are optimistic and confident about a technology are less likely to focus on its drawbacks and are more likely to accept it (Raman & Aashish, 2021). These users believe that a novel technology will offer several benefits, including improved ownership, increased adaptability, and a successful means of satisfying their needs (Parasuraman, 2000). Other scholarly works (Hasan & Bao, 2022; Kim &

Chiu, 2019; Raman & Aashish, 2021) have shown a correlation between optimism perceived ease to adopt and perceived usefulness. On the basis of this, the initial hypothesis is put forth.

H1a: Optimism about Industry 4. 0 technologies positively influence manufacturing firms' perceived ease to adopt the technologies.

H1b: Optimism about Industry 4.0 technologies positively influences manufacturing firms' perceived usefulness of the technologies.

3.6.2 Innovativeness, Perceived ease to adopt and Perceived usefulness to adopt

Innovativeness is referred to "as a propensity of being a technology pioneer and influencer" (Parasuraman 2000 p.311). According to Omotayo & Adekunle (2021), innovativeness is the perception of a user about a system. Chen & Lin (2018) posited that innovation is a key factor in cognitive absorption, which affects how easily and effectively information technology (IT) is considered and used. Although the potential worth of new technology is uncertain and its benefits are not immediately apparent (Codini et al., 2022), people who are more innovative have less complex belief systems about it and positive perceptions of the technology's utility (Pai & Alathur, 2019). Singh & Aggarwal (2022) describe how the term "innovativeness" is frequently used to evaluate the "newness" of an innovation, and how innovative products are typically marked with a high level of newness. In light of this, firms that embrace technological innovation are more likely to believe that adopting Industry 4.0 technologies will make them easier to use and will emphasize their advantages. Rogers (2003) states that users who are deemed "innovative" quickly adopt new concepts earlier than other users. Thus, it is therefore hypothesized that:

H2a: Innovativeness of manufacturing firms positively influences their perceived ease to adopt Industry 4.0 technologies.

H2b: Innovativeness of manufacturing firms positively influences their perceived usefulness to adopt Industry 4.0 technologies.

3.6.3 Discomfort, perceived ease to adopt, perceived usefulness to adopt

Discomfort is defined as "a perceived lack of control over technology and a feeling of being overwhelmed by it"(Parasuraman & Colby, 2001 p. 44). People who are uneasy with new technology frequently feel anxious about using it, such people frequently regard some new technologies as being inappropriate for laypeople and feel controlled by new technology (Parasuraman, 2000). Concerns about implementing new technology have a detrimental impact on how easy it is to be adopted and how beneficial it is when adopted (Chen & Lin, 2018). Higher levels of discomfort among firms lead to a perception that technology is more complicated and difficult to utilize (Musyaffi et al., 2021), hence, discomfort regarding the adoption of Industry 4.0 technologies has a negative impact on perceived ease to adopt and perceived usefulness to adopt these technologies. It is therefore hypothesized that:

H3a: The discomfort of manufacturing firms about Industry 4.0 technologies negatively influences their perceived ease to adopt the technologies.

H3b: The discomfort of manufacturing firms about Industry 4.0 technologies negatively influences their perceived usefulness of adopting the technologies.

3.6.4 Insecurity, Perceived ease to adopt and Perceived usefulness to adopt

Insecurity is defined as "a distrust of technology and skepticism about its ability to work properly" (Parasuraman & Colby, 2001 p. 44). Parasuraman & Colby (2001) further added that people who feel more insecure may be aware of certain potential risks associated with using modern technologies. As a result, these people frequently lack confidence in the security of new technologies (Chen & Lin, 2018). Ali et al. (2021) indicated that the perceived usefulness to adopt and perceived ease to adopt a technology are adversely affected by perceived hazards. According to Musyaffi et al. (2021), because of worries about security and privacy, some people mistrust new technology and refuse to adopt it. Therefore, people are reluctant to take the risk to adopt new technology unless they think they may gain significant benefits from doing so (Chen & Lin, 2018). Thus, it is hypothesized that:

H4a: Manufacturing firms' feeling of insecurity about Industry 4.0 technologies negatively influences their perceived ease to adopt these technologies.

H4b: Manufacturing firms' feeling of Insecurity about Industry 4.0 technologies negatively influences their perceived usefulness to adopt these technologies.

3.6.5 Awareness, Perceived ease to adopt and Perceived usefulness to adopt

According to information management principles, in adoption of ICT, the primary factors for adoption are raising awareness among stakeholders, i.e., end users, about the implementation of innovation in terms of factors and issues, basic paradigms of the new system, a comprehensive view of advantages and disadvantages, and overall system security (Shareef et al., 2009). The factors that influence the adoption of new technologies in manufacturing is based on the knowledge a firm has on the technology (Kinkel et al., 2022). Okot-Uma & Caffrey (2000) defined awareness as "providing information about the political process, about services and about choices available, the time horizons for the decisions-making process and about the exponents of the decision-making process". From the Industry 4.0 perspective, new technologies are affecting traditional manufacturing processes and hastening the transition to digitalized manufacturing (Barreto et al., 2017; Frederico et al., 2020; Zhong et al., 2017).

To adopt the new technologies for manufacturing process to improve performance, firms must develop basic capabilities, taking into account digitalization and their integration with workers, customers, and suppliers throughout their operations (Queiroz et al., 2019). However Queiroz et al. (2019) maintains that, in this day and age of digitalization, neither decision-makers nor organizations are fully aware of their capabilities or how a set of resources and capabilities can be developed and managed to support global competition. Firms must be aware of the characteristics of the technology as well as its functional benefits in order to adopt new technology in manufacturing (Ardito et al., 2019). Awareness, ability, intention, and preparation all contribute to the overall readiness for industry 4.0 adoption and implementation (Shareef et al., 2009). In this regard, it’s hypothesized that:

H5a: Manufacturing firms’ awareness of Industry 4.0 technologies positively influences their perceived ease to adopt these technologies.

H5b: Manufacturing firms’ awareness of Industry 4.0 technologies positively influences their perceived usefulness to adopt such technologies.

3.6.6 Perceived ease to use and Intention to adopt

Perceived ease of use “is the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989 p. 320). Perceived Ease of Use (PEOU) is assumed, would positively influence firms’ intention to adopt Industry 4.0 technologies, if the technology is easier to use. Considering the rapidly emerging and continuing technological revolution where changes are taking place in all business environments and industries (Zekhnini et al., 2021), with global competition intensifying, firms are scouting for technologies which can enhance their efficiencies and their responsiveness. Manufacturing firms uses innovative information and manufacturing technology to create flexible, intelligent, and adaptable manufacturing processes to serve a dynamic and international market (Zhong et al., 2017). Such technologies must be perceived to be easy to use rather than complicating their operations. Studies have discovered relations between PEOU and the intension to adopt a new technology (Pai & Alathur, 2019; R. Raman et al., 2021). Acheampong et al. (2017) identified that PEOU has a key effects on adopting and use of new technology. Hence, this study seeks to know how PEOU influences intention to adopt.

H6: Manufacturing firms' perceived ease of use of Industry 4.0 technologies positively influences their intention to adopt such technologies.

3.6.7 Perceived usefulness and Intention to adopt

According to Lin et al. (2007), technology readiness and people's intentions to employ a certain technology are entirely mediated by perceived ease to adopt (PEOU) and perceived usefulness (PU). Perceived usefulness is the of the idea that adopting a technology would enhance a user's ability to execute a particular task (Park et al., 2021). Technologies enable information flow and processes in manufacturing firms to be available where and when they are needed across their phases of operations industries (Zhong et al., 2017). Wang (2018) indicated that in this recent time of technological advancement, manufacturing firms require certain underpinning technologies in order to enable their operational devices to respond to different requirements and situations based on learning capabilities and past experiences. These technologies enable manufacturing with direct communication systems, thereby allowing the making of adaptive decisions and helping challenges to be solved in real-time (Tangahu et al., 2021). This implies that, people intend to adopt or use a technology to the extent that it will improve their ability to enhance their performance (Omotayo & Adekunle, 2021). Scholarly works in the field of information systems research have provided evidence of PU on adoption (Erdoğmu & Esen, 2011; Mensah, 2020; Rojas-Méndez et al., 2017). Based on this, a hypothesis is developed that:

H7: Manufacturing firms' perceived usefulness of Industry 4.0 technologies positively influences their intention to adopt such technologies.

3.6.8 Moderating role of Support Resources

Support resources are referred to as personnel, capabilities, equipment and materials to enable continuity in a firm's operations. Support resources are also essential for routine operational and maintenance processes (Yu & Wang, 2012). For the purposes of the present study, support resources may include IT infrastructure, IT capabilities and financial resources. A firm's intention to adopt Industry 4.0 technologies would be dependent on its existing support resources such as IT infrastructure, IT capability and financial resource. Support resources are therefore anticipated to moderate effect of perceived ease to use and perceived usefulness on a firm's intention to adopt a new technology (Faqih & Jaradat, 2015). Prior studies indicate that firms' willingness to adopt Industry 4.0 technologies are heavily influenced by the perceived usefulness, perceived ease, and external elements such as support resources (Liu et al., 2014; Mensah, 2020). Perceived usefulness and perceived ease of use have large and favorable impact on the intention to adopt Industry 4.0 technologies. Mensah (2020) discovered that, the primary factor influencing firms' intention to adopt Industry 4.0 technologies are the perceived usefulness and perceived ease of use. Support resources will have a moderating effect on the relationship between perceived ease of use and the firm's intention to adopt Industry 4.0 technologies as well as on the relationship between perceived usefulness and the firm's intention to adopt Industry 4.0 technologies (Srivastava et al., 2022). Further, support resources have been found to be relevant moderators of the relationship between firms' perceived ease to adopt, perceived usefulness to adopt and intention to adopt Industry 4.0 technologies (Kim & Garrison, 2009; Zailani et al.,2015).

H8a: Support resources moderate the relationship between perceived ease to adopt Industry 4.0 technologies and the intention to adopt Industry 4.0 technologies.

H8b: Support resources moderate the relationship between perceived usefulness of Industry 4.0 technologies and the intention to adopt Industry 4.0 technologies.

3.7 Chapter Summary

This chapter discussed the theoretical foundations of the study which formed the basis for the development of the proposed theoretical framework and the development of the hypotheses. Fourteen hypotheses were developed for the study. The study is theoretically anchored on the foundations of the Technology Readiness and Acceptance Model (TRAM). The research variables have been borrowed from the TRAM to ascertain the factors influencing manufacturing firms' adoption of Industry 4.0 technologies. By considering an individual's prior experiences and general knowledge of utilizing technology, TRAM makes it easier to comprehend how they see adopting a new technology (Raman et al., 2021). TRAM helps in evaluating a user's viewpoint on any generic technology using the following constructs optimism, innovativeness, discomfort and insecurity.

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 Introduction

The third chapter presented the theories underpinning the study where the constructs of the Technology Readiness and Acceptance Model (TRAM) were explained. Furthermore, because the study used a quantitative approach, there was the development of hypotheses to predict research outcomes. This chapter discusses the research methodology employed comprising methodological issues such as the research paradigm, research design, research population, sampling technique employed, sample size determination, design of the data collection instrument, the mode of the data collection process, techniques for analyzing data collected and ethical considerations.

4.2 Research Paradigm

Researchers have a perspective that informs and directs their study and how they understand, interact and interpret events in their environment. This is referred to as a paradigm (Bostley, 2019). Anand et al. (2020) argued that a paradigm establishes distinct limits for the components of a certain area or specifies which theories are pertinent. Buriro et al. (2021) indicated in their study that a paradigm of research is the way of thinking philosophically. As a result, researchers need to choose a suitable paradigm in their field of research.

A paradigm outlines which theories are relevant or establish clear boundaries for what constitutes a given field (Anand et al., 2020). Anand et al. (2020) further added that these boundaries allow researchers to harmonize the selection of research questions, methods, and, ultimately, the direction of investigation in their respective fields. Gannon et al. (2022) emphasized that different research paradigms yield different types of understanding while emphasizing that philosophical diversity does not contradict an external reality.

Paradigms can be categorized by how their proponents respond to three basic questions (Lincoln & Guba, 2011). A paradigm is categorized into ontological, epistemological and methodological philosophies. Ontological philosophy is concerned with the nature of social reality and the nature of things that exist, such as existing conditions and relationships. Epistemological philosophy seeks to answer the fundamental question of what separates adequate knowledge from inadequate knowledge whilst methodological philosophy involves the ability to be objective in the real world (Gannon et al., 2022a; Guba & Lincoln, 1990; Thomas, 1970). Gannon et al. (2022a) argued that different research paradigms produce different types of understanding and diversity in philosophical perspectives.

The difference in understanding and diversity does not imply superiority, but rather the best way to achieve the research goals (Gannon et al., 2022b). In addition, Briggs & Coleman (2019) also proposed that the three paradigm-related philosophies (ontology, epistemology, and methodology) assist the researcher in establishing assumptions and events the researcher is studying or researching on. These philosophies tell how to explore, investigate, and comprehend the research problem and the methods used to address the research questions (Ednut & Khatoon, 2021).

4.3 Choice of Paradigm

Various classifications distinguish paradigms hence, there are various paradigms (Krauss, 2015; Žukauskas et al., 2018). Critical realism, interpretivism, pragmatism and positivism paradigms are the most well-known and widely used paradigms that reflect major theoretical directions in information systems (Cecez-Kecmanovic, 2013; Douglas & Sutton, 2018). The positivist paradigm is adopted in this study to help achieve the study's goal. According to Gannon et al. (2022b), the core of positivism is sovereign ‘truth’. This is used to shape subsequent attempts to explain phenomena by the development and testing of hypotheses. Park et al. (2020) highlighted that one of the primary goals of positivist inquiry is to generate causal relationships or explanatory associations that eventually predict and control the phenomena under consideration.

The perspective of positivist research contends that reality is independent and external with it many parts open to being measured objectively (Krauss, 2015). Krauss (2015) further added that positivists believe in experimentation and are of the view that observation and measurement are significant to scientific inquiry. The positivist paradigm establishes that the individual’s values, biases, and beliefs cannot alter the results of any robust study due to its objective view of ‘reality’ (Gannon et al., 2022a; Lincoln & Guba, 2011). As a result, Savin-Baden & Major (2013) indicated that positivist research contends that knowledge is discovered rather than created, with measurements and measurable facts, propositions, and hypotheses at the base of knowledge discovery.

The positivist paradigm enables researchers in determining consistencies and other types of association between constructs through the manipulation of reality (Park et al., 2020). Kasim & Antwi (2015) indicated in their study that positivism allows researchers to investigate things experimentally and then explain them logically. Park et al. (2020) further argued that positivism employs the hypothetico -deductive method to verify theoretical hypotheses, which are frequently stated quantitatively. Hypothetico-deductive “refers to the scientific model based on forming a testable hypothesis and developing an empirical study to confirm” (Park et al., 2020 p. 691). Lan (2018) argued that positivism shows functional relationships and can be derived between explanatory factors and causal factors, that is, independent variables and dependent variables.

Positivism helps avoid frustration by connecting the research through a structured plan that shows how all of the major parts of the research work together consistent with respondent s' knowledge (Douglas & Sutton, 2018; Lan, 2018). Ofori-Amanfo et al. (2022) indicated that positivism is uniquely concerned with gathering facts through direct experiences or observations, quantifying them empirically through quantitative methods (surveys and experimentations), and applying statistical analysis to the data. Similarly, the positivism paradigm is used to gain a thorough understanding of the experiment and observations (Krauss, 2015). Hence, positivism enables the study to obtain scientific information objectively. The positivist paradigm is considered to be appropriate for this study due to the nature of the causal relationships being explored in the study.

4.4 Research Methods and Design

Research design is the pattern for gathering, organizing, and analyzing data to produce appropriate research findings (Creswell, 2014). Bostley (2019) describes research design as a plan, structure, and strategy of investigation used to obtain answers to research questions while maintaining optimal control of variables. Creswell & Creswell (2003) describes research design as the phases used in gathering, organizing, and analyzing data for research to achieve the desired results and the research finding. A researcher's ideas are reflected in the research design (Bostley, 2019). Bostley (2019) further argued that research design helps avoid frustration by connecting the research through a structured plan that shows how all of the major parts of the research work together to answer the research questions. Research design determines the types of analyses that must be performed to achieve the desired results (Mühl, 2014).

According to Bostley (2019), there are three distinct approaches to research. These are the quantitative, qualitative and mixed method research approach. Qualitative research emphasizes exploring and comprehending the meaning that a person or group of people ascribes to a social or human problem (Bostley, 2019; Creswell, 2014). Denzin & Lincoln (2011) indicated that qualitative research approach produces data that is not quantifiable and uses observations, interviews and participation in generating data. The mixed method research approach integrates the qualitative and quantitative research approaches (Bostley, 2019; Creswell, 2014). Heigham (2009) states that researchers collect both numeric and textual data for analysis in the mixed methods approach.

The quantitative research approach uses techniques and measurements that produce discrete and quantifiable values (Denzin & Lincoln, 2011). Bostley (2019) revealed that in quantitative studies, the relationships between variables is objectively determined and allows the researcher to generate data or test hypotheses using various data collection methods. Al-Ababneh (2020) posited that the quantitative research method investigates the relationships between variables to explain, predict, and control a phenomenon. Quantitative research involves collecting numeric data and then analyzing the data using mathematical and statistical models (Marvasti, 2018). This study adopted the quantitative research method.

The choice of a quantitative research approach will enable the use of mathematical and statistical analysis (Ofori-Amanfo et al. 2022), in assessing the adoption of Industry 4.0 technologies among Ghanaian manufacturing firms. However, apart from the quantitative method being appropriate for the context of this study, another reason for selecting it over the other approaches is to unearth conclusive evidence of the study rather than simply providing information. Prior studies indicated that, because quantitative research involves numbers and values, statistical tools and software packages such as SPSS, PLS-SEM, AMOS, STATA, and others are essential for the study (Cooksey, 2020; Rasoolimanesh et al., 2021).

4.5 Research Population

A research population is referred to the total number of items or situations that make up the subject of a study (Etikan, 2016). The targeted population of the research were the manufacturing firms in Ghana. It covered the manufacturing industry in Ghana but largely concentrated on firms located in the Greater Accra region of Ghana. The respondents of the questionnaire were the CEOs, General Managers, Operations Managers, IT Managers, Supply Chain Managers, Financial Controllers and the Procurement Managers from manufacturing firms. These individuals are presumed to be actively involved in the adoption of new technology hence, would be in the capacity to provide the needed data for the research.

4.5.1 Sampling Technique and Procedure

Mühl (2014) indicated that a sample is a subset of a population chosen for observation and analysis. Mühl (2014) further adds that a sample is a collection consisting of a portion or subset of the population's objects or individuals chosen for the express purpose of representing the population. Creswell (2014) indicated that in statistical practice, sampling is the process of choosing a set predetermined number of individual observations from a population in order to learn about the population's concerns and create predictions using the sample. Fielding et al. (2012) postulated that the outcomes of data collected and analyzed from a sample of the population should be consistent with the outcomes obtained if data were collected from the entire population.

The convenience sampling technique was used for the selection of the participating manufacturing firms. Convenience sampling is a type of non-probability sampling technique where the target population is selected for the study if it fits specified practical requirements, such as simple accessibility, geographic proximity, availability at a specific time, or willingness to participate (Chiu & Cho, 2021; Etikan, 2016). Convenience sampling is a type of non-probability sampling technique where the respondents are willing to participate in the study and are also readily accessible (Lamm & Lamm, 2019).

The non-systematic approach of purposive sampling was employed as the sampling technique after identifying the minimal sample size required for the study to select the individual respondents from the firms. Purposive sampling was employed for this study because samples were chosen with the notion that each participant would provide the study with unique and useful information in accordance with the study's objectives. Tongco (2007) observe that the use of the purposive sample technique is essential to the accuracy of the data collected; as a result, the informant's dependability and competency must be guaranteed and can be employed by both quantitative and qualitative researchers. The purposive sampling technique according to Etikan (2016), is a non-probability sampling that works well when one wishes to research a specific cultural subject with informed experts inside.

4.5.2 Sample Size Determination

A sample refers to a part of a larger population (Etikan, 2016). The number of study participants or observations is referred to as the sample size (Malterud et al., 2016). Goodhue et al. (2012) argued that to obtain consistent and reliable sample results, researchers must consider the sample size of their study. The number of people who exhibit a particular feature is referred to as its prevalence in technical terms (Gupta, 2022). How precisely a researcher wishes to estimate the prevalence will determine the sample size required for your study. “Precision is the amount of error in a measurement” (Conroy, 2021 p.8). The greater the sample size, the lower the likelihood of measurement error and, thus, the greater the likelihood that the prevalence you detect in your sample will be near to the actual prevalence in the population (Riley et al., 2020). Researchers must closely evaluate the size of the sample being utilized in the study to obtain consistency and reliability of the results (Bagozzi, 2013).

The Ghana Living Standard Survey's (GLSS 7, 2016-2017) served as the source of population for the manufacturing firm in Ghana. The study focused on manufacturing companies that were registered and active in the Greater Accra region of Ghana. The GLSS 7 reported that 12,500 there are registered manufacturing firms in the Greater Accra region (Ghana Statistical Service, 2019). The sample size was estimated from the study population, following the Slovin's Sample Size formula to calculate the sample size.

$$\text{Sample Size} = \frac{N}{(1 + N * e^2)}$$

$$= \frac{12500}{(1 + 12500 * 0.1^2)}$$

$$= 101$$

Where:

N is the population (Number of manufacturing firms in the Greater Accra region)

'e' is the margin of the error. A margin of error at 10% was used.

The estimated sample size for the study was 101 manufacturing firms. This indicates that the minimum sample size for this study was determined to be 101 manufacturing firms. 120 firms were however used to cater for non-responses. Two respondents were purposively selected from each participating firm to yield a total of 240 responses.

Table 4.1 Conroy Sample Size Determination

Acceptable margin of error	Size of population					
	Large	**5000**	**2500**	**1000**	**500**	**200**
±20%	24	24	24	23	23	22
±15%	43	42	42	41	39	35
±10%	96	94	93	88	81	65
±7.5%	171	165	160	146	127	92
±5%	384	357	333	278	217	132
±3%	1067	880	748	516	341	169

Source: (Conroy, 2021)**.**

The Table 4.1 above guides the determination of sample size sizes that are required for a study based on the population and acceptable margin of error. From the GLSS 7 report, there are about 12500 manufacturing firm registered in the Greater Accra region. This indicates that the population for this study fall within large on table. Based on this, at the margin error of 10%, 96 firms can be used as the minimum sample size for this study without bias. However, this study employed 120 firms to enhance the response rate.

4.6 Design of Data Collection Instrument

Data for the study was collected through the use of questionnaire (see Appendix A). The questionnaires were administered to obtain relevant data from the respondents. For reliability and validity, Straub (1989) guideline for designing a survey instrument was used. Bostley (2019) postulated that a survey is a technique for gathering large amounts of data, usually in statistical form, from a large number of people in a relatively short period by using closed-ended questions. The questionnaire was developed following a review of literature on Industry 4.0 and the theory underpinning the study, that is the Technology Readiness and Acceptance Model (TRAM).

4.6.1 Survey Questionnaire Design

The questionnaires were developed based on the research questions, conceptual framework and the hypotheses of the study which were all informed by the literature on Industry 4.0 and TRAM. The questionnaire was designed into three sections. The first section was purposely designed to collect demographic data, which included age, gender, educational level, position at work, the number of years of experience and the type of industry the respondent operates. The second section was focused on seeking answers to the research questions and the third and final section of the questionnaire was based on the constructs presented in the conceptual framework. The constructs were measured using a 5-point Likert type scale. The interpretation of the scale is given in Table 4.1

Table 4.2 Likert Type Scale

NO.	Rating
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

Source: Researcher

According to Maher et al. (2018), the 5-point Likert scale questions are regarded as the type that provides consistent and accurate outcomes for multivariate analysis.

Table 4.3 Number of measurement items per each construct and sources

Constructs	No. of Questions	Sources
Optimism	5	Flavián et al. (2022), Hasan & Bao (2022), Parasuraman (2000)
Innovativeness	5	Flavián et al. (2022), Parasuraman (2000), Park et al. (2021)
Discomfort	5	Flavián et al. (2022), Hasan & Bao (2022) Kamble et al. (2019), Parasuraman (2000)
Insecurity	5	Flavián et al. (2022) Kamble et al. (2019) Parasuraman, (2000), Park et al. (2021)
Awareness	3	Flavián et al. (2022), Hasan & Bao (2022)
Perceived ease to use	5	Davis (1989), Park et al. (2021), Kamble et al. (2019)
Perceived usefulness	5	Davis (1989), Kamble et al. (2019), Park et al. (2021)

Intention to adopt	5	Kamble et al. (2019), Park et al. (2021)
Support resources	5	Akgün et al. (2012), Son (2010)

Source: Researcher

4.7 Data Collection Process

Data collection is the act of acquiring data and pertinent information that is important to answering the questions posed in a research (Flick, 2018). Boateng (2016) revealed two data collection sources, being primary and secondary data sources. Primary data refers to information that researchers get directly from sources (Rabianski S., 2003). Primary data is any information that is gathered directly from a source of information rather than through an existing source (Goel, 2022; Granger, 2014; Hox & Boeije, 2004). The primary data are usually researcher-generated data, such as results from surveys, interviews, and experiments (Goel, 2022). Rabianski (2003) identified the sources of primary data to include personal interviews, observation, focus group discussions and questionnaire administration. Secondary data is information that has been obtained from sources other than the primary source and has not been directly compiled by the researcher (Granger, 2014). Secondary data sources can include published or unpublished works. Secondary data sources on the other hand include archival records, documentation and physical artifacts (Boateng, 2016) and other published data from firms, institutions and government agencies.

This study mainly depended on primary data by collecting data through the design and use of a survey instrument. Questionnaires were administered in gathering data using google forms. The data was gathered from manufacturing firms. The selected industries were visited, and when access was granted, the audience of the sought and there and then the link to the questionnaire were sent through the email of the participants. The gathering of data was done between October to November, 2022.

4.8 Methods of Data Analysis

After the responses from survey participants have provided, the study's next phase involved organizing, summarizing, and analyzing the data that has been collected to draw conclusions. Chu & Ke (2017) indicated that data analysis involves searching through the data to extricate irrelevant information, modifying and re-modelling the collected data to communicate significant information that contributes to answering the research questions. With this knowledge, the questionnaire was double-checked to make sure all the responses have been submitted accurately and that all the pertinent questions have been answered. Data was then transmitted to the Smart-PLS software for additional analysis after being coded and structured into integrated constructs using the Statistical Package for Social Sciences (SPSS) programme.

There are many different types of data analysis. Dash and Paul (2021) stated that Structural Equation Modeling (SEM) is a statistical framework that models intricate interactions between direct and indirect observable variables. It consists of a variety of multiple regression models that can show variables as both predictors and outcomes. Other forms of quantitative analysis as specified by Taherdoost (2021) include correlation, multiple regression, analysis of variance (ANOVA), and multivariate analysis of variance (MANOVA).

Prior studies showed that, there are two primary approaches to the Structural Equation Modelling (SEM) (Kolog et al., 2018; Owusu et al., 2022; Sarstedt et al., 2016). Covariance Based-SEM (CB-SEM) is a compelling and flexible data analysis technique where hypothetical constructions are anticipated to cause their indicators as common variables (Dash & Paul, 2021). The CB-SEM uses computer software packages like AMOS, LISREL, MPLUS for analyzing data. The Partial Least Square SEM (PLS-SEM), is one of the key SEM techniques that enables the estimation of complex cause-and-effect relationship models using the latent constructs (Sarstedt et al., 2016). PLS-SEM concentrates on the analysis of variance using software packages such as ADANCO and SmartPLS (Legate et al., 2021).

The PLS-SEM approach is employed for this study on the bases that, the PLS-SEM procedures help to describe the facts of the study. PLS-SEM enables detection of patterns within the broad data and develop explanations as well as testing the hypotheses (Russo & Stol, 2021). Furthermore, PLS-SEM can analyze the relationship between dependent and independent constructs utilizing effect size and predictive relevance, which are not present in other quantitative analysis (Hair et al., 2019). PLS-SEM is a component of the standard set of multivariate analytic techniques (Shiau et al., 2019).

According to Sarstedt et al. (2022), in PLS-SEM, composite variables are created by linearly combining the indicators of a measurement model. The composite variables are considered to be complete depictions of the constructs and, as a result, are reliable substitutes for the conceptual variables under consideration. Edeh et al. (2022) argued that the PLS-SEM method enables the use of a very small sample to get results that accurately reflect effects found in huge populations of several million elements or individuals. Rigdon (2016) further added that smaller sample sizes can certainly yield solutions when using PLS-SEM. However, these instances depend on the population's characteristics. Edeh et al. (2022) indicated that with no identification issues, PLS-SEM can handle both reflective and formative assessment models as well as single-item constructs. As a result, it can be used in a range of research settings.

When using PLS-SEM, the measurement model is evaluated before any further analysis (assessment of the structural model) procedures are carried out (Dash & Paul, 2021). This activity facilitates comparison between the established framework and the information obtained from respondents. In PLS-SEM, reflecting and formative constructs are measured using different criteria (Legate et al., 2021). The study included the assessment of the measurement model followed by the assessment of the structural model.

4.9 Ethical Considerations

All ethical requirements including confidentiality, informed consent and stating the consequences of the study were observed. The consent from respondents were sought and they participated voluntarily (see Appendix B). The survey was anonymous with very little personally identifying information collected from the participants such as age. Confidentiality was maintained throughout the study. This study did not cause any harm to participants. The researcher respected respondents' right to refuse to participate maintaining objectivity during the gathering of data, analyses of data and at the stage of reporting.

4.10 Chapter Summary

This chapter presented the discussed research methodology employed comprising methodological issues such as the research paradigm, research design, research population, sampling technique employed, sample size determination, design of the data collection instrument, the mode of data collection process, techniques for analyzing data collected and ethical considerations.

CHAPTER FIVE

DATA ANALYSIS AND DISCUSSION OF THE FINDINGS

5.1 Chapter Overview

This chapter presents the data analysis and the discussion of the findings. The analysis has been structured into sections. The first section analyzes the data on the demographic characteristics of the respondents. The second section includes the measurement model assessment, which evaluates the indicators' consistency reliability, convergent and discriminant validity and accuracy. The subsequent section focused on the evaluation of the structural model. The last section covers the moderation analyses.

5.2 Response Rate

120 manufacturing firms were sampled for the study. Two respondents were selected from each firm, thus a total of 240 questionnaires were administered. Out of the 240 questionnaires administered, 170 were received, yielding a response rate of 70.8%. 70.8% response rate is considered a fair and respectable participation level for large-scale surveys of this nature (Gordon, 2002).

5.2.1 The Demographic Characteristics of Respondents

The demographic characteristics of the respondents included gender, age, level of education, type of department, number of years working in the firm and the type of industry. A summary of the demographic analysis is presented in Table 5.1.

Table 5.1 Demographic Characteristics of Respondents

Demographic	Characteristics	Frequency (170)	Percentage (%)
Gender	Male	126	74.1
	Female	44	25.9
	Total	**170**	**100**
Age	25 – 34	66	38.8
	35 – 44	66	38.8
	45 and above	38	22.4
	Total	**170**	**100**
Education	Diploma	12	7.1
	HND	24	14.1
	Degree	70	41.2
	Masters	64	37.6
	Total	**170**	**100**
Department	Operations	44	25.9
	IT	36	21.1
	Procurement	28	16.5

	Supply chain management	34	20.0
	Logistics	28	16.5
	Total	**170**	**100**
No. of Years Worked	1 – 5	62	36.5
	6 – 10	45	26.5
	More than 10	63	37.0
	Total	**170**	**100**
Type of Industry	Food and beverage	47	27.6
	Pharmaceutical	40	23.5
	Textiles and Garment	27	15.9
	Chemical and cement	17	10
	Aluminium Smelting	17	10
	Mining	19	11.2
	Total	**170**	**100**

Table 5.1 summarizes the various demographic characteristics of the respondents. Out of the 170 responses, 126 (74.1%) were males with the remaining 44 (25.9%) being females. In terms of age, the age brackets, 25-34 and 35-44 recorded the same number of responses that is 66 representing

38.8% each whereas ages 45 and above recorded 38 responses representing 22.4%. With the level of education, those with a degree recorded the majority with 70 responses representing 41.2%, followed by those with postgraduate degrees recording 64 (37.6%). Those with an HND and Diploma also accounted for 36 responses representing 21.2%.

With respect to the type of department, the highest department that responded to the questionnaire is the operations department with a total of 44 responses representing 25.9%. The IT department also recorded 36 (21.1%) responses whilst 28 people responded from both the procurement and logistics departments representing 16.5% each. The response from the supply chain department was 34 which represented 20% of the total responses. In respect of the number of years worked, the data collected shows that 63 respondents have worked more than 10 years representing 37%. For respondents who have worked for 1-5 years, there were 62 responses representing 36.5%. The least was 6-10 years which represents 45(26.5%). The manufacturing firms were divided into six categories. These categories were Food and beverages, Pharmaceuticals, Textiles and garments, Chemicals and cement, and Aluminium smelting and Mining. Most of the respondents to this study came from the Food and beverages category representing 27%. The Pharmaceutical industry followed with 23.5%. Textiles and garments were next with 15.9%. The Aluminium smelting industry recorded the least response with a percentage of 10%.

5.3 Awareness of the Concept of Industry 4.0

From the Figure 5.1, out of the 170 responses gathered, the majority of the respondents representing 93.5% responded “yes” to being familiar with the term Industry 4.0.

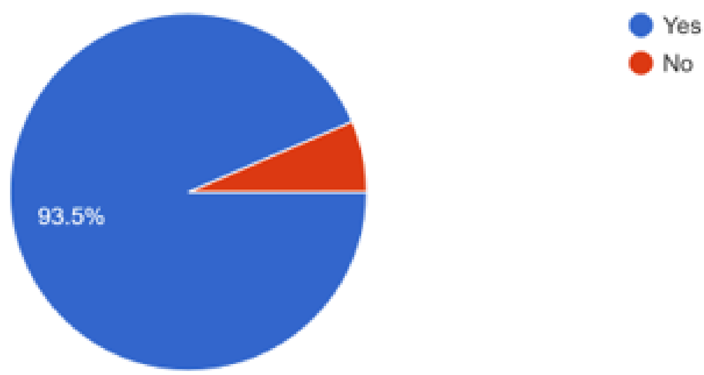

Figure 5.1 Familiarity with the term Industry 4.0

5.3.1 Dominant Industry 4.0 Technologies

As reflected in the Figure 5.2, out of the 170 responses, 141 respondents associated the most with Internet of Things as an Industry 4.0 technology accounting for 82.9% of the total responses. Blockchain technology recorded the least response (97) that respondents associate with Industry 4.0 representing 57.1%.

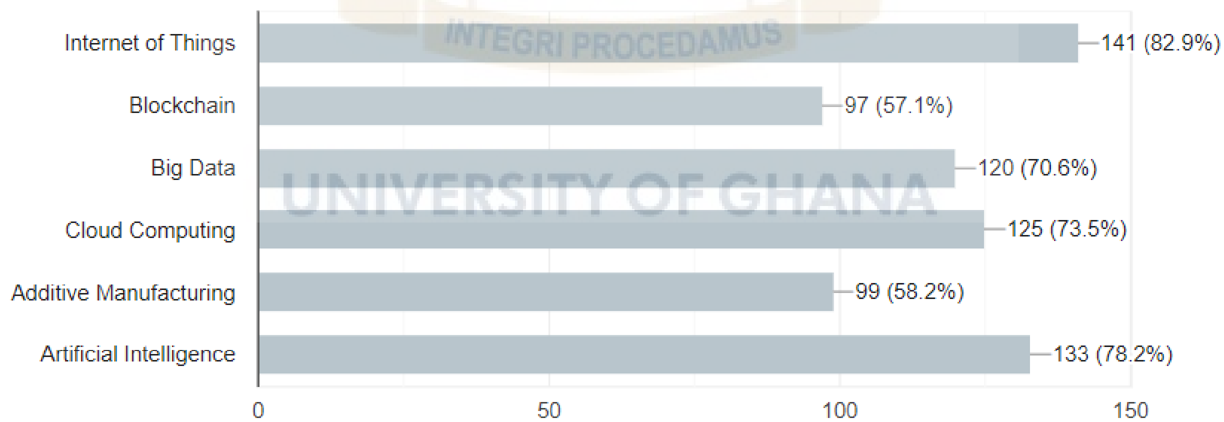

Figure 5.2 Dominant Industry 4.0 Technologies

5.3.2 Descriptive Statistics

The data stack's mean (average) is calculated by adding up the values of each component and dividing the results by the number of data inputs. The position of the dataset or its overall picture is measured using the mean (Paliy & Shankar, 2016). Table 5.2 provides the mean scores of the extent to which the manufacturing firms in Ghana are aware of Industry 4.0 technologies. Based on the Likert scale employed for the study where; 1- highly unaware, 2- unaware, 3- neutral, 4– aware and 5- highly aware. The questions were designed so that mean values below 3.5 indicate that Ghanaian manufacturing firms are unaware of Industry 4.0 technologies, while mean values of 3.5 and above indicate awareness of these technologies among Ghanaian manufacturing firms. Table 5.2 displays the mean values for all six types of Industry 4.0 technologies that are greater than 3.5. From Table 5.2, the least mean score is 3.59. The outcome from Table 5.2 indicates that Ghanaian manufacturing firms are aware of Industry 4.0 technologies.

Table 5.3 Extent of Awareness of Industry 4.0 Technologies

Industry 4.0 Technologies	**Mean Values**
Internet of Things	4.15882
Artificial Intelligence	4.082353
Cloud Computing	3.817647
Big Data	3.729412
Addictive Manufacturing	3.605882
Blockchain	3.594118

Table 5.3 provides the means values of the extent to which the manufacturing firms in Ghana have adopted Industry 4.0 technologies in their manufacturing operations. Given the scale used, where

1-Not adopted, 2- Adoption process initiated, 3- Don't know, 4- Partially adopted and 5- Fully adopted. The results reveal the mean value 3.95 for Internet of Things suggests that manufacturing firms in Ghana have partially adopted Internet of Things. Artificial Intelligence mean value is 3.50 which also implies that, Ghanaian manufacturing firms have partially adopted this Industry 4.0 technology (Artificial Intelligence). The mean value 3.41 for Cloud Computing indicated that, the adopting state of the technology was not known by the manufacturing firms. Again, Big Data had a mean value of 3.18 which also implies that, the adopting state of Big Data is not known by manufacturing firms in Ghana. For Addictive Manufacturing, the mean value is 3.08 which also indicates that the adopting state of the technology is not known. Lastly, Block chain also with the mean value of 2.84 also signifies that, the adopting state of the technology is not known.

Table 5.4 Extent of Adoption of Industry 4.0 Technologies

Industry 4.0 Technologies	**Mean Values**
Internet of things	3.952941
Artificial Intelligence	3.505882
Cloud Computing	3.417647
Big Data	3.188235
Addictive Manufacturing	3.082353
Block chain	2.841176

5.4 Model Assessment

5.4.1 Measurement Model Assessment

In PLS-SEM, evaluating the indicator loadings is the first step in evaluating the measurement model (Sarstedt et al., 2022). The assessment model's measurement provides the researcher the opportunity to evaluate the data gathered for the study with the adopted theory. The evaluation of the measurement model is a prerequisite for the first stage of Structural Equation Modeling (SEM) (Sarstedt et al., 2014). Among the criteria used to evaluate the reflective measurement model in SEM are indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2020).

5.4.2 Indicator Reliability

Urbach (2010 p. 18) defined the reliability of an indicator as "the degree to which a variable or set of variables is consistent with what it intends to measure". Reflective indicator loadings are monitored to ensure the indicator reliability. Hair et al. (2019) indicated that, indicators that load 0.70 and above are usually recommended because they offer adequate construct reliability, hence they are suggested for acceptance. Once more, variables having a variance of at least 0.70 constitute more than 50% (0.70) of the variation of the indicator. Indicators that had an insignificant correlation between their associated variables and the indicators themselves were eliminated (Roemer et al., 2021). As a result, following the first run of the analysis on SmartPLS, indicators that were below the minimum level of 0.70 were eliminated. The indicator, SUP1 was eliminated since its loading of 0.58 was below the acceptable threshold of 0.70. All other indicators exceeded the minimum requirement of 0.70, showing that they accurately measure the variables assigned.

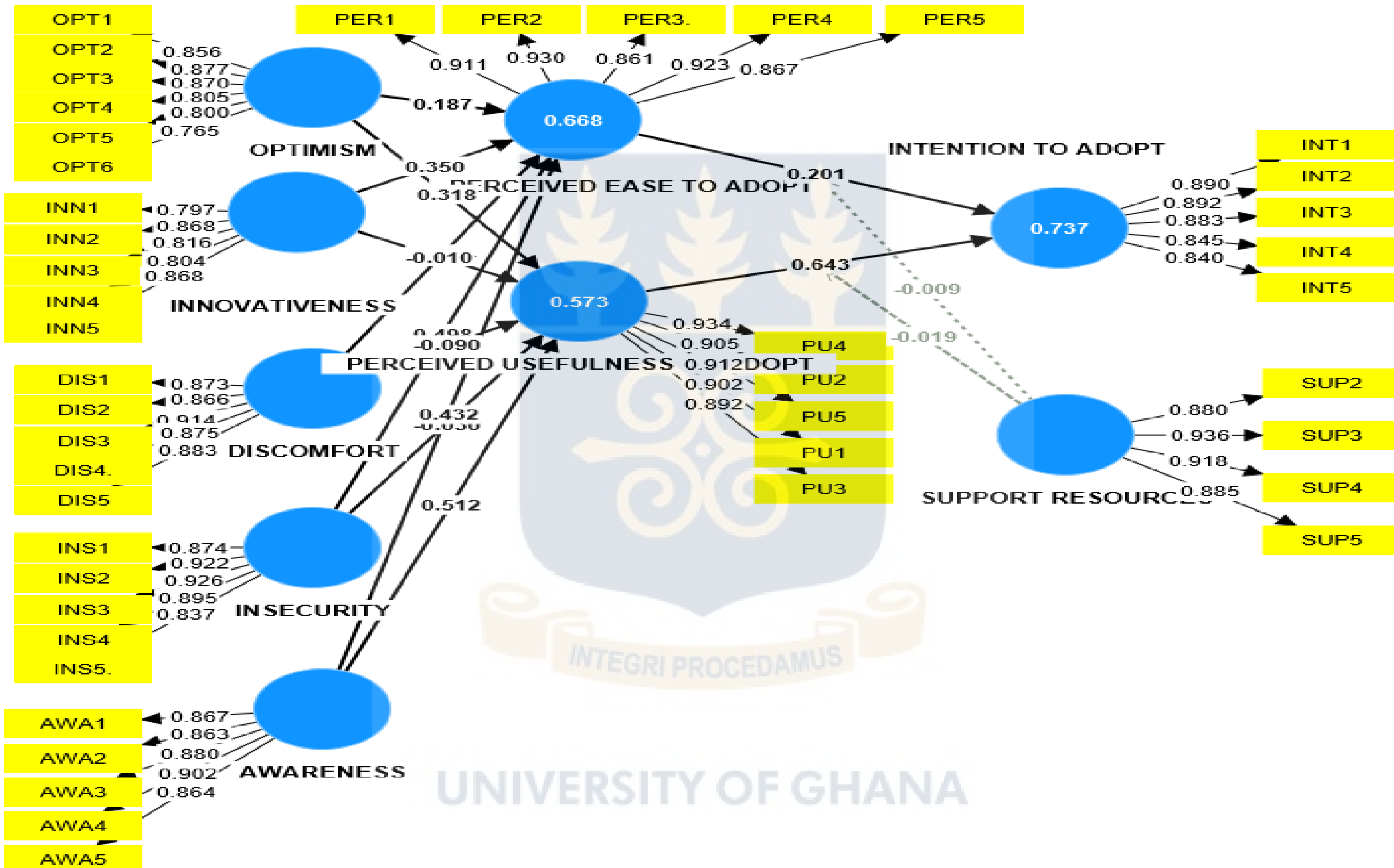

Figure 5.3 Results of PLS Analysis

5.4.3 Construct Reliability and Consistency

Cronbach's alpha is a widely used metric for assessing internal consistency and reliability based on the cross-correlation of observable variables. After assessing the indicators' accuracy, the next step includes assessing Cronbach's alpha's internal reliability (Cronbach, 1951). Taber (2018) postulated that, values below the minimum criterion of 0.70 do not indicate a favorable outcome from the model because the Cronbach's alpha values shouldn't be lower than 0.70. Since the average values of the elements are not recovered, previous research has critiqued the low reliability accuracy and values of Cronbach's alpha (Hair et al., 2019). As a result, composite reliability was proposed as a substitute for evaluating indicator reliability (Hair et al., 2019; Kumar et al., 2018).

Cronbach's alpha, for instance, makes the assumption that all indicators have the same loading. The composite reliability, however, is the opposite, as all indicators must have varied loads in order to provide the most accurate measure of reliability (Sarstedt et al., 2022). In terms of composite reliability, items with greater values correspond to higher levels of dependability, and vice versa. In research, 0.60 and 0.70 are deemed as the reliability levels and are acceptable values. Values between 0.70 and 0.90 are deemed good indications, and values surpassing 0.95 as problematic since values above 0.95 are more than necessary and hence lead the model's reliability to decline (Malhi et al., 2022). With this study, the composite reliability values range from 0.90 to 0.948. which indicates a normal and good level of confidence of the data.

In addition to the composite reliability, the Rho_A is suggested as a good substitute for measuring reliability accuracy in the SEM-PLS model (Mehmood & Saeed, 2021). Variables with values of

0.70 and higher are proposed for inclusion and acceptance in the Rho_A. The summary of the analysis is presented in Table 5.4.

Table 5.5 Construct Reliability and Validity

Variables	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Awareness	0.924	0.927	0.942	0.766
Discomfort	0.929	0.936	0.946	0.778
Innovativeness	0.888	0.894	0.918	0.691
Insecurity	0.935	0.901	0.921	0.794
Intention to Adopt	0.92	0.925	0.94	0.757
Optimism	0.909	0.913	0.93	0.689
Perceived ease to adopt	0.94	0.943	0.935	0.808
Perceived Usefulness to adopt	0.947	0.948	0.90	0.826
Support Resource	0.926	0.928	0.948	0.819

5.4.4 Convergent Validity

Validity testing comes after the constructs have been established to be very reliable. Convergent validity and discriminant validity are the two types of validity used to assess how much variance is shared between items and their constructs. Convergent Validity is defined "as the extent to which a measure correlates positively with alternative measures of the same constructs" (Hair et al., 2017 p.137). Convergent validity enables the researcher to demonstrate that the items were capable of measuring the variance in their latent variables. The average variance extracted (AVE) is used to establish convergent validity. The AVE can be determined by averaging the measured construct's reliabilities. Hence, a measurement of 0.500 or higher is therefore considered acceptable (Hair et al., 2017). As demonstrated in Table 5.4, the AVE values were above the acceptable threshold that is 0.500 with values of 0.689 being the lowest and 0.826 being the highest. This indicates that at least 50% of the variability in the latent construct's indicators can be explained. The second type of validity, discriminant validity, is described next.

5.4.5 Discriminant Validity

The next step is to validate the discriminant validity after establishing the convergent validity. Discriminant Validity "is defined as the extent to which a construct is truly distinct from other constructs by empirical standards" (Hair et al. 2017 p. 138). Henseler et al., (2015) indicated that, for examining the relationships between latent variables in a structural model, the discriminant validity method has come to be accepted. Discriminant validity is to show how constructs are statistically distinct from one another (Hair et al., 2019). Cross loadings, the Fornell-Larcker criterion, and the heterotrait-monotrait correlation ratio (HTMT) are the three methods that are usually used to establish discriminant validity. Sarstedt et al. (2019) has revealed that cross loadings are the component scores of each latent construct compared to the scores of all other items to determine cross loadings. The constructs are considered to be distinct from one another if each item loads better or higher in its own items than it does for any other item and its associated latent construct, hence establishing discriminant validity. The values for the cross loadings are presented in Table 5.5.

Table 5.6 Indicator items Cross-loadings for assessing Discriminant Validity

	AWA	DIS	INN	INS	INT	OPT	PER	PU	SUP	SUP x PER	SUP x PU
AWA 1	0.867	-0.181	0.201	-0.161	0.654	0.35	0.502	0.571	0.406	-0.032	-0.177
AWA 2	0.863	-0.178	0.335	-0.184	0.607	0.423	0.565	0.542	0.479	-0.118	-0.15
AWA 3	0.88	-0.143	0.188	-0.144	0.617	0.442	0.497	0.616	0.498	-0.114	-0.289
AWA 4	0.902	-0.171	0.134	-0.179	0.602	0.361	0.551	0.583	0.405	-0.047	-0.14
AWA 5	0.864	-0.063	0.195	-0.076	0.734	0.585	0.616	0.685	0.499	-0.22	-0.43
DIS 1	-0.155	0.873	-0.159	0.733	-0.229	-0.191	-0.301	-0.208	-0.239	0.206	0.061
DIS 2	-0.05	0.866	-0.081	0.722	-0.23	-0.142	-0.21	-0.209	-0.228	0.107	0.039
DIS 3	-0.153	0.914	-0.142	0.823	-0.283	-0.261	-0.297	-0.269	-0.324	0.2	0.009
DIS 4	-0.201	0.875	0.055	0.758	-0.212	-0.15	-0.289	-0.219	-0.256	0.108	0.008

DIS 5	-0.149	0.883	-0.011	0.769	-0.275	-0.208	-0.309	-0.27	-0.297	0.166	0.034
INN 1	0.191	-0.113	0.797	-0.1	0.253	0.287	0.466	0.188	0.26	-0.192	-0.037
INN 2	0.335	-0.178	0.868	-0.188	0.367	0.359	0.476	0.306	0.328	-0.236	-0.069
INN 3	0.161	0.052	0.816	0	0.271	0.406	0.372	0.187	0.275	-0.304	-0.21
INN 4	0.108	0.091	0.804	0.123	0.217	0.341	0.461	0.142	0.33	-0.226	-0.102
INN 5	0.176	-0.124	0.868	-0.095	0.294	0.397	0.475	0.23	0.354	-0.254	-0.154
INS 1	-0.142	0.781	-0.041	0.874	-0.211	-0.237	-0.115	-0.24	-0.223	0.104	-0.019
INS 2	-0.184	0.81	0.03	0.922	-0.211	-0.226	-0.183	-0.255	-0.276	0.194	0.038
INS 3	-0.178	0.755	-0.068	0.926	-0.248	-0.3	-0.139	-0.296	-0.24	0.284	0.16
INS 4	-0.146	0.777	-0.14	0.895	-0.249	-0.293	-0.218	-0.286	-0.322	0.308	0.14
INS 5	-0.076	0.737	-0.092	0.837	-0.211	-0.235	-0.157	-0.17	-0.225	0.232	0.097
INT 1	0.68	-0.312	0.312	-0.299	0.89	0.605	0.615	0.753	0.581	-0.295	-0.387

INT 2	0.696	-0.186	0.289	-0.194	0.892	0.562	0.555	0.811	0.584	-0.264	-0.398
INT 3	0.629	-0.205	0.339	-0.166	0.883	0.537	0.558	0.708	0.477	-0.305	-0.396
INT 4	0.595	-0.246	0.234	-0.239	0.845	0.54	0.451	0.698	0.49	-0.227	-0.428
INT 5	0.598	-0.281	0.309	-0.21	0.84	0.514	0.526	0.607	0.499	-0.227	-0.35
OPT 1	0.482	-0.22	0.436	-0.276	0.558	0.856	0.517	0.495	0.494	-0.361	-0.406
OPT 2	0.394	-0.245	0.427	-0.312	0.56	0.877	0.477	0.493	0.474	-0.45	-0.428
OPT 3	0.45	-0.1	0.344	-0.205	0.555	0.87	0.336	0.562	0.462	-0.253	-0.47
OPT 4	0.429	-0.158	0.342	-0.189	0.488	0.805	0.548	0.507	0.475	-0.388	-0.41
OPT 5	0.427	-0.186	0.357	-0.206	0.524	0.8	0.461	0.442	0.386	-0.318	-0.487
OPT 6	0.289	-0.183	0.202	-0.273	0.474	0.765	0.323	0.477	0.479	-0.407	-0.506
PER 1	0.536	-0.229	0.54	-0.098	0.541	0.481	0.911	0.384	0.512	-0.324	-0.202

PER 2	0.553	-0.315	0.493	-0.196	0.557	0.516	0.93	0.448	0.573	-0.309	-0.177
PER 3	0.661	-0.301	0.49	-0.194	0.632	0.514	0.861	0.606	0.562	-0.457	-0.36
PER 4	0.565	-0.29	0.505	-0.143	0.553	0.468	0.923	0.488	0.54	-0.312	-0.22
PER 5	0.483	-0.316	0.411	-0.202	0.508	0.448	0.867	0.48	0.566	-0.349	-0.187
PU 1	0.666	-0.218	0.239	-0.239	0.749	0.502	0.453	0.902	0.498	-0.141	-0.377
PU 2	0.6	-0.277	0.221	-0.29	0.718	0.573	0.507	0.905	0.497	-0.237	-0.483
PU 3	0.615	-0.203	0.22	-0.228	0.752	0.498	0.437	0.892	0.503	-0.212	-0.449
PU 4	0.603	-0.293	0.259	-0.274	0.753	0.55	0.534	0.934	0.548	-0.223	-0.464
PU 5	0.642	-0.233	0.231	-0.266	0.784	0.592	0.513	0.912	0.515	-0.258	-0.519
SUP 2	0.547	-0.303	0.277	-0.277	0.585	0.474	0.489	0.548	0.88	-0.319	-0.328
SUP 3	0.476	-0.212	0.358	-0.192	0.546	0.528	0.548	0.5	0.936	-0.396	-0.359

SUP 4	0.442	-0.213	0.333	-0.222	0.499	0.495	0.561	0.495	0.918	-0.382	-0.359
SUP 5	0.425	-0.376	0.386	-0.362	0.558	0.519	0.621	0.491	0.885	-0.495	-0.36
SUP x PER	-0.126	0.182	-0.288	0.258	-0.304	-0.438	-0.392	-0.236	-0.44	1	0.552
SUP x PU	-0.279	0.034	-0.133	0.098	-0.45	-0.539	-0.259	-0.505	-0.388	0.552	1

On Table 5.5 the constructs are represented by the following abbreviations AWA- Awareness, DIS-discomfort, INN- innovativeness, INS- insecurity, INT-intention to adopt, OPT- optimism, PER-perceived ease to adopt, PU- perceived usefulness to adopt, SUP-support resource, SUP x PER-support resource and perceived ease to adopt and SUP x PU- support resource and perceived usefulness to adopt.

5.4.6 The Fornell-Larcker Criterion

The second method for evaluating discriminant validity is the Fornell-Larcker criterion. It analyzes the correlations between the latent variable and the square root of the AVE values (Hair et al., 2017). Particularly, the square root of each construct's AVE should be more than the construct's highest correlation (Shiau et al., 2019). The Fornell-Larcker method is predicated on the notion that a construct exhibits greater variance with its linked indicators than with any other construct (Sarstedt et al., 2022). As presented in Table 5.6, the AVE values are 0.875, 0.882, 0.831, 0.891, 0.87, 0.83, 0.899, 0.909 and 0.905 respectively. The AVE are higher than their respective correlations with the other variables in the model. This indicates that the model has proven discriminant validity.

Table 5.7 The Fornell-Larcker Criterion

VARIABLES	AWA	DIS	INN	INS	INT	OPT	PER	PU	SUP
AWA	0.875								
DIS	-0.165	0.882							
INN	0.239	-0.076	0.831						
INS	-0.167	0.865	-0.071	0.891					
INT	0.738	-0.281	0.34	-0.255	0.87				
OPT	0.5	-0.22	0.428	-0.293	0.635	0.83			
PER	0.627	-0.323	0.545	-0.185	0.624	0.542	0.899		
PU	0.689	-0.269	0.258	-0.285	0.827	0.598	0.538	0.909	
SUP	0.525	-0.308	0.374	-0.293	0.607	0.557	0.613	0.564	0.905

5.4.7 Heterotrait-Monotrait Ratio (HTMT)

Cross-loadings and the Fornell-Larcker criterion have both been used to test discriminant validity, however recent studies indicate that neither the Cross-loadings nor the Fornell-Larcker criterion consistently identifies problems with discriminant validity (Henseler et al., 2015). Particularly, cross-loadings do not demonstrate a lack of discriminant validity when two variables are completely correlated, making this criterion ineffective for empirical study (Hair et al., 2017). According to Henseler et al. (2015), the Fornell-Larcker criterion has a deficiency, particularly when the indicator loadings of the structures under examination only slightly differ. The Fornell-

Larcker criterion performs better at detecting discriminant validity errors when indicator loadings differ more widely, but overall performance is still relatively weak (Roemer et al., 2021).

Henseler et al. (2015) proposed measuring the relationships' heterotrait-monotrait ratio (HTMT) as a remedy. The between-trait correlation to within-trait correlation ratio is known as HTMT. HTMT "is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the heterotrait-heteromethod correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (i.e., the monotrait-heteromethod correlations; for a formal definition of the HTMT statistic)" (Hair et al., 2017 p. 140).

Technically, the HTMT technique is an estimation of the true correlation between two constructs, if it were possible to measure them precisely (i.e., if they were perfectly reliable) (Roemer et al., 2021). Henseler et al. (2015) proposed a threshold value of 0.90 if the path model contains constructs that are conceptually extremely comparable. In other words, a value of the HTMT greater than 0.90 denotes a lack of discriminant validity (Hair et al., 2017). A lower and therefore more conservative threshold value of 0.85 seems justified when the path model's constructs are conceptually more different (Roemer et al., 2021). From the values of Table 5.7, it can be said that a discriminant validity is established since the HTMT values falls under the threshold of 0.90 according to (Henseler et al., 2015).

Table 5.8 Heterotrait-Monotrait Ratio (HTMT)

VARIABLES	AWA	DIS	INN	INS	INT	OPT	PER	PU	SUP	SUP PER	SUP PU
AWA											
DIS	0.177										

INN	0.259	0.159									
INS	0.178	0.897	0.151								
INT	0.793	0.303	0.373	0.273							
OPT	0.535	0.235	0.473	0.315	0.693						
PER	0.665	0.341	0.591	0.194	0.665	0.577					
PU	0.732	0.284	0.276	0.297	0.88	0.644	0.567				
SUP	0.562	0.325	0.411	0.308	0.652	0.606	0.657	0.6			
SUP PER	0.126	0.185	0.309	0.26	0.316	0.459	0.402	0.242	0.457		
SUP PU	0.282	0.036	0.146	0.105	0.469	0.571	0.263	0.518	0.404	0.552	

5.5 Structural Model Assessment

Urbach (2010 p.10) indicated that, "the statistical evaluation criterion for reflective measurement scales cannot be transferred directly to structural measurement models, where indicators are likely to represent the independent causes of the construct and thus do not necessarily correlate strongly". Studies Legate et al. (2021) and Sarstedt et al. (2014) reveal that many researchers inaccurately assess the structural measurement quality in PLS-SEM data analysis by using the reflective measurement model (Sarstedt et al., 2014). Prior research has shown that structural indicators, unlike reflective measurement, are error-free, and as a result, the internal consistency reliability notion is incorrect (H. Lin et al., 2020). Sarstedt et al., (2019) proposed five key procedures to evaluate the structural measurement model.

5.5.1 Assessing Multicollinearity Statistics

Collinearity is the strong correlation between two formative indicators (Hair et al., 2020). Multicollinearity is the correlation among more than two indicators (Sarstedt et al., 2019). The most significant type of collinearity is when two (or more) formative indicators with the exact same data are included in the same block of indicators (i.e., they are perfectly correlated) (Hair et al., 2017). The variance inflation factor (VIF) is used to evaluate the Multicollinearity of each independent construct (Sarstedt et al., 2019). Collinearity between a group of predictor constructs is shown by VIF values lower than 5.0. (Sarstedt et al., 2022). The VIF values generated from the PLS-SEM analysis are less than 5.0, which is the standard threshold. This suggests that the variables that are independent of the construct being observed are combined in a seamless linear manner. Table 5.8 displays a VIF of less than 5.0 for each number.

Table 5.8: Multicollinearity Statistics (Inner VIF)

Constructs	AWA	DIS	INN	INS	INT	OPT	PER	PU
AWA							1.345	1.345
DIS							4.033	4.033
INN							1.236	1.236
INS							4.197	4.197
INT								
OPT							1.668	1.668
PER					1.909			
PU					2.077			
SUP					1.983			

SUP PER					1.791			
SUP PU					1.929			

5.5.2 Assessing structural Model Path Coefficients

The term "path coefficients" refers to the hypothesized relationships between constructs in the analysis of the PLS-SEM algorithm. The path coefficients' standardized values typically lie between a value of -1 and +1. High positive correlations exist between the constructs' estimated path coefficient values, which are close to 1, and the reverse is typically statistically significant but less strongly correlated. However, a coefficient's significance is determined by the standard errors that were generated through bootstrapping the model. It is recommended that the coefficient has a significant level of reduced errors in the model if the t-values following the bootstrap are more than the critical value (Hair et al., 2017). Choosing the p-values, several researchers recommend using a significance level of 0.05. Therefore, the 5% (0.05) significance threshold was applied in this study.

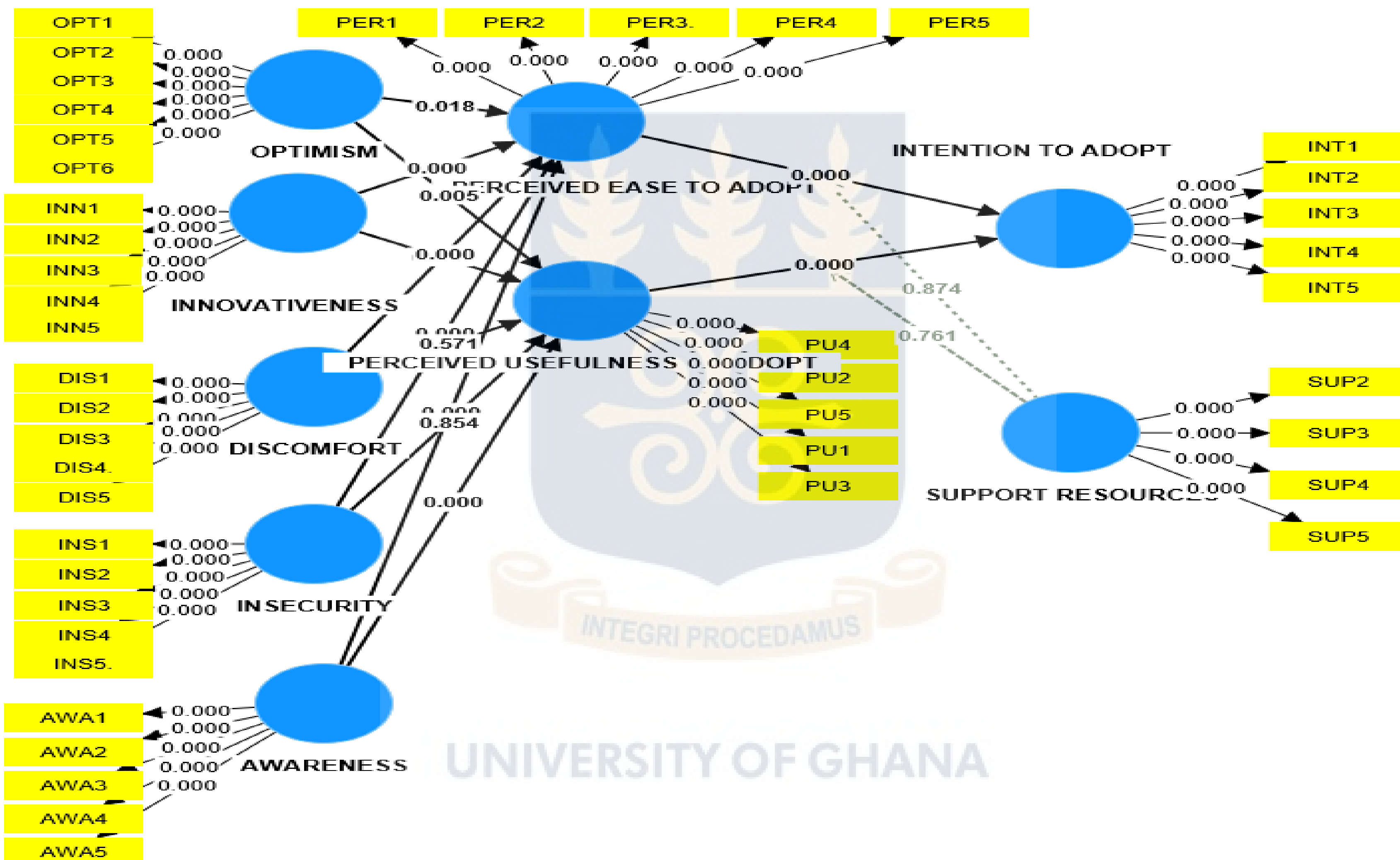

Figure 5.4 Direct Effect of Hypothesis (Bootstrapping)

Path Coefficients and Hypotheses

Regarding the correlation or structural path between the constructs, assessment of the path coefficients' strength and significance is conducted. The significance of the path coefficient was evaluated and examined using the Bootstrapping method in the Smart-PLS software (Sundram et al., 2016). Bootstrapping is a non-parametric resampling technique which is used to evaluate the statistical variability (Sarstedt et al., 2019). The bootstrapping is used to assess the accuracy of the estimates; it examines the variability in the sample data. A path coefficient is considered significant at the 5% probability of error level. We can therefore infer that the path coefficient is substantially different from zero at a significance level of 5% (= 0.05; two-tailed test) when the size of the resulting empirical t statistic is above 1.96 (Sarstedt et al., 2019). Most often, researchers decide on a significance level of 5%, which means that the relationship under study must have a p value that is less than 0.05 (Hair et al., 2017). Based on the assumption, H2b, H3b, H4b, H8a and H8b are not supported since the p- values are higher than the threshold of 5%. H1a, H1b, H2a, H3a, H4a, H5a, H5b, H6 and H7 with p-values less than or equal to 0.05 were supported.

Table 5.9: Path Coefficients and Hypotheses

Hypothesis	**Relationship**	**Decision**	**Original Mean**	**t-statistic**	**P-Value**
H1a	OPT -> PER	SUPPORTED	0.187	2.359	0.018
H1b	OPT -> PU	SUPPORTED	0.318	2.831	0.005
H2a	INN -> PER	SUPPORTED	0.35	4.952	0.000
H2b	INN -> PU	NOT SUPPORTED	-0.01	0.177	0.859
H3a	DIS -> PER	SUPPORTED	-0.614	4.945	0.000
H3b	DIS -> PU	NOT SUPPORTED	-0.09	0.566	0.571

H4a	INN -> PER	SUPPORTED	0.498	3.824	0.000
H4b	INS -> PU	NOT SUPPORTED	-0.01	0.177	0.859
H5a	AWA -> PER	SUPPORTED	0.432	5.944	0.000
H5b	AWA -> PU	SUPPORTED	0.512	7.6	0.000
H6	PER -> INT	SUPPORTED	0.201	3.583	0.000
H7	PU -> INT	SUPPORTED	0.643	8.425	0.000
H8a	SUP x PER -> INT	NOT SUPPORTED	-0.009	0.158	0.874
H8b	SUP x PU -> INT	NOT SUPPORTED	-0.019	0.305	0.761

5.5.3 Coefficient of Determination (R2 Value)

The most typical measuring criterion for assessing a structural model's fitness is its R^2 value (Hair et al., 2020). The variance between the endogenous and exogenous constructs in the model is represented by the coefficient. Rigdon (2016) revealed that the endogenous latent variables and the exogenous latent variables in the model are both impacted by the R^2 value. R^2 is utilized as a measurement criterion for predictive power for model estimation since it is the squared correlation values of actual and estimated (Sarstedt et al., 2016). The R^2 values are in the range of 0 to 1. Predictive accuracy increases with increasing value, and vice versa. It is challenging to offer standardized acceptable guidelines for R^2 because of the intricacy of some models and the variety of study disciplines. However, studies have characterized R^2 values of 0.75, 0.50, and 0.25 for endogenous variables as substantial, moderate, and weak, respectively, and advised researchers to take 0.75 values or above into consideration (Henseler et al., 2015; Sarstedt et al., 2022). The exogenous variables Optimism, Innovativeness, Discomfort, Insecurity and Awareness explains 66.8% of the variance of the endogenous variable Perceived Ease to adopt. Similarly, exogenous variables Optimism, Innovativeness, Discomfort, Insecurity and Awareness explains 57.3% of the variance of the endogenous variable Perceived Usefulness to adopt.

Table 5.10: Coefficient of Determination (R-square)

Constructs	R- square	R-square adjusted
INTENTION TO ADOPT	0.737	0.729
PERCEIVED EASE TO ADOPT	0.668	0.658
PERCEIVED USEFULNESS TO ADOPT	0.573	0.560

5.5.4 Determining the Effects Size (f Square Value)

The f^2 effect size is used to determine or measure the influence of the change in R^2 when a specific construct of exogenous variables in the model is being ignored. It was suggested that f^2 values below 0.020 have no impact, those between 0.150 and 0.350 have a medium impact, and those over 0.350 have a significant impact on the model (Cohen, 1988). Cohen (1988) further indicated that f^2 values below 0.020 imply a weak impact on the model's modifications. From Table 5.11, it can be said that, awareness has a significant effect on perceived ease to adopt and perceived usefulness to adopt. Discomfort has a medium effect on perceived ease to adopt and has no effect on perceive usefulness to adopt. Innovativeness has medium effect on perceived ease to adopt and has no effect on perceived usefulness to adopt. Insecurity has a medium effect on perceived ease to adopt and has no effect on perceived usefulness to adopt. Optimism has weak effect on perceived ease to adopt and on perceived usefulness to adopt. Perceived ease to adopt has no effect on intention to adopt. Perceive usefulness to adopt has a significant effect on intention to adopt.

Support resources has a weak effect on intention to adopt. Support resource did not have a moderating effect on perceived ease to adopt. Support resource did not have a moderating effect on perceived usefulness to adopt Industry 4.0 technologies. Support resources did not moderate perceived ease and perceived usefulness on intention to adopt Industry 4.0 technologies.

Table 5.11: Assessing effect size using f-square values

Constructs	AWA	DIS	INN	INS	INT	OPT	PER	PU
AWA							0.418	0.457
DIS							0.282	0.005
INN							0.299	0.000
INS							0.178	0.001
INT								
OPT							0.063	0.141
PER					0.080			
PU					0.758			
SUP					0.022			
SUP x PER					0.000			
SUP x PU					0.001			

5.5.5 Assessing the Predictive Relevance (q-square value)

The model's ability to accurately forecast the endogenous latent variables depends on its predictive significance (Hair Jr et al., 2014). The application of Stone-Q^2 Geisser's value was proposed to be examined as part of determining the size of the R^2 values to forecast accuracy (Geisser, 1974). The predictive relevance of the path model for a given dependent construct is indicated in the structural model by Q^2 values greater than zero for a particular reflective endogenous latent variable. In other words, the Q^2 measures how well the model predicts the future. Per the values of the Q-predict illustrated on the Table 5.12, there is a predictive relevance in the model. This is because the Q-predict values are above the threshold of 0 (zero). If Q^2 is less than 0, the model is regarded weak and has no predictive value, and all of the independent variables are insufficient to explain the dependent variable (s). All of the Q2 values in table 5.12 were over the threshold of 0.350, indicating that the model had a high level of predictive relevance.

Table 5.12 Q-Square

Constructs	**Q predict**	**RMSE**	**MAE**
Intention to adopt	0.629	0.622	0.475
Perceived ease to adopt	0.630	0.618	0.472
Perceived Usefulness to adopt	0.518	0.707	0.537

5.5.6 Moderating Variable

This section of the study focused on analyzing the role of the moderator (support resource) on the relationship between the variable of perceived ease of adoption and perceived usefulness to intention to adopt. The study assessed the moderating role of support resource on the relationship between Perceived ease to adopt, perceived usefulness to adopt and Intention to adopt. It was hypothesized that support resources moderate the relationship between perceived ease to adopt Industry 4.0 technologies and the intention to adopt Industry 4.0 technologies. Again, support resources were hypothesized to moderate the relationship between perceived usefulness to adopt

Industry 4.0 and the intention to adopt Industry 4.0 technologies. However, from Table 5.13 the p-values 0.874 and 0.761 indicates that support resource does not moderate the relationship between perceived ease to adopt Industry 4.0 technologies and Intention to adopt, neither does it moderate the relationship between perceived usefulness to adopt Industry 4.0 technologies and Intention to adopt Industry 4.0 technologies.

Table 5.13 Moderation Analysis

Hypothesis	Relationship	Decision	Original Mean	t-statistic	P-Value
H8a	SUP x PER -> INT	NOT SUPPORTED	-0.009	0.158	0.874
H8b	SUP x PU -> INT	NOT SUPPORTED	-0.019	0.305	0.761

5.6 Discussion of Results

There are two parts to the following section; the first part discusses the awareness of the dominant Industry 4.0 technologies among the Ghanaian manufacturing firms. The second part discusses the effects of Industry 4.0 awareness and technology readiness and acceptance factors on the adoption of Industry 4.0 technologies by manufacturing firms.

5.6.1 Awareness of Dominant Industry 4.0 Technologies

The need to determine the awareness of the dominant Industry 4.0 technologies is in response to request in the literature for research that aims to address the question "What are the dominant Industry 4.0 technologies that manufacturing firms in Ghana are aware of?" In literature dominant Industry 4.0technologies includes; Internet of things, Blockchain, Big Data, Cloud computing, Additive Manufacturing and Artificial Intelligence (Baygin et al., 2016; Oztemel & Gursev, 2020;

Vinitha et al., 2020). The results of the study demonstrate that Ghanaian manufacturing firms are aware about Industry 4.0 technologies. Fig 5.1 demonstrates an awareness level of 93.5% of the Industry 4.0 technologies among a total of 170 respondents. Again, Figure 5.2 also demonstrates the level of awareness for the dominant Industry 4.0 technologies among the Ghanaian manufacturing firms. The outcome indicates that, out of the 170 responses, 141 respondents associated the most with Internet of Things as an Industry 4.0 technology accounting for 82.9% of the total responses. Blockchain technology recorded the least response (97) that respondents associate with Industry 4.0 representing 57.1%.

The results showed that respondents were aware of the dominant technologies of Industry 4.0, based on the comparison of the mean value of replies for each of the six dominant technologies with the firms' level of awareness. From the study it was discovered that, the mean values of the responses for the awareness of the dominant Industry 4.0 technologies were scored on the scale of 1-5 as displayed on Table 5.2. The findings reflected a general awareness of the Industry 4.0 technologies from the respondents. The Internet of Things had the highest score of 4.15 indicating that it has the highest level of awareness. Artificial Intelligence also had a score of 4.08 which implies that the awareness of the technology. The awareness score for Cloud Computing showed a 3.81 level of awareness. The response showed a mean score of 3.72 for the awareness level for Big Data. Additive Manufacturing had a mean score of 3.60 which also implies that there is awareness of such technology. The Block Chain had a score of 3.59 which also indicated an awareness. In accordance with this results, it is evident that the manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies.

The extent to which a firm has adopted the dominant Industry 4.0 technologies was another finding from the study. Table 5.3 presented the mean results of the extent of adoption of Industry 4.0

technologies among the manufacturing firms in Ghana. The scale for assessment were represented as 1-Not adopted, 2- Adoption process initiated, 3- Don't know, 4- Partially adopted and 5- Fully adopted. Based on the scale given, it can be evident that the Internet of Things and Artificial Intelligence are the technologies that are partially adopted by the manufacturing firms in Ghana with the mean values of 3.95 and 3.50. On the other hand, based on the scale of assessment, it can be said that the other technologies that is Cloud Computing, Big Data, Additive Manufacturing and Block Chain their state of adoption appear not to have been adopted by the respondents. This is evident that, extent of adoption of Industry 4.0 technologies are on a minimal.

5.6.2 Awareness, and Technology Readiness and Acceptance Factors

The study was embarked with the purpose of examining the awareness of Industry 4.0 technologies among manufacturing firms in Ghana and to ascertain their readiness for accepting and embracing such technologies examined the extent of readiness and acceptance of Industry 4.0 technologies. To accomplish this purpose, the Technology Readiness and Acceptance Model (TRAM) was used to test the validity of the readiness and acceptance of industry 4.0 technologies among manufacturing firms in Ghana. Nine (9) of the fourteen (14) hypotheses were fully supported, whereas five (5) others were not. The thresholds of the t-statistic are used as the basis for discussion. The t-statistic results on Table 5.9 is used as the basis. The empirical t-statistic for significance is a value greater than 1.96 (Sarstedt et al., 2014).

5.6.3 Optimism

Optimism is the positive attitude people have about technology, including how in control they feel, how flexible, convenient, and how effective the technology is (Parasuraman, 2000). The proposed hypotheses for Optimism are *H1a: "Optimism about Industry 4.0 technologies positively* *influences manufacturing firms perceived ease to adopt Industry 4.0". H1b: "Optimism about Industry 4.0 technologies positively influences manufacturing firms perceived usefulness to adopt Industry 4.0 technologies".* H1a was supported with a t-statistic of 2.35. This implies that there is a significant correlation between optimism and perceived ease of adopting Industry 4.0 technologies. With the results from the t-statistic it can be said that optimism has a positive influence on manufacturing firms adopting Industry 4.0 technology. Previous studies have shown that optimism has a significant impact on the readiness to adopt a new technology (Hasan & Bao, 2022; Parasuraman, 2000; Raman & Aashish, 2021). Further, H1b was also supported with a t-value of 2.83 which indicates a significant influence of optimism on perceived usefulness to adopt Industry 4.0 technologies. The results indicate that, optimism has a positive influence on the perceived usefulness for manufacturing firms to adopt Industry 4.0 technologies. The current findings of the study support the existing literature evidence that optimism influences a firm's readiness to adopt a technology (Parasuraman, 2000). Optimism is a key factor in a firm's readiness and acceptance decision to adopt Industry 4.0 technology.

5.6.4 Innovativeness

Innovativeness is referred to "as a propensity of being a technology pioneer and influencer" Parasuraman 2000 p.311). The following hypotheses were tested in relation to innovativeness and adoption of Industry 4.0 technologies. *H2a was proposed that, "innovativeness of manufacturing firms positively influences their perceived ease to adopt Industry 4.0 technologies". H2b also proposed that, "innovativeness of manufacturing firms positively influences their perceived usefulness to adopt Industry 4.0 technologies"*. H2a was supported. In testing H2a, the statistical results from the study confirmed that innovativeness positively influences manufacturing firms' perceived ease to adopt Industry 4.0 technologies. The statistical results displayed on Table 5.9

showed a t-value of 4.95 for H2a. This finding confirms existing literature knowledge that, innovativeness have positive influence on adopting a new technology (Omotayo & Adekunle, 2021; Pai & Alathur, 2019). No statistically significant relationship was established between innovativeness and perceived usefulness to adopt Industry 4.0 (t-value = 0.177) hence, hypothesis H2b was not supported. The finding may be so because, manufacturing firms may frequently find it difficult to discover the information pertaining to the benefits of adopting Industry 4.0 technology. This may be as a result of the lack of professional training and knowledge in the use of advanced technology in manufacturing. This result contradicts a study by Lin et al. (2007) that found that innovativeness positively influences perceived usefulness to adopt a new technology.

5.6.5 Discomfort

Discomfort is defined as "a perceived lack of control over technology and a feeling of being overwhelmed by it"(Parasuraman & Colby, 2001 p. 44). Two hypotheses were proposed, H3a and H3b. *H3a states that "the discomfort of manufacturing firms about Industry 4.0 technologies negatively influences their perceived ease to adopt the technologies". H3b on the other hand states that, "the discomfort of manufacturing firms about Industry 4.0 technologies negatively influences perceived usefulness of adopting the technologies"*. The t-value for H3a was 4.94 signifying that the hypothesis is supported. This suggests that discomfort of manufacturing firms negatively influence the perceived ease to adopt Industry 4.0. The finding is in line with prior studies which also established that, the ease of adoption of a new technology is negatively impacted by the uncertainties of doing so (Chen & Lin, 2018). This implies that firms will not be ready and willing to adopt Industry 4.0 technologies if they perceive its features are not easy to use, and the technology is not clear and easy to understand. H3b was not supported (t-value = 0.56), which is below the threshold point. This results contradict a previous study's finding which stipulated that discomfort of a new technologies negatively influences perceived usefulness to adopt them (Parasuraman, 2000).

5.6.6 Insecurity

Insecurity is defined as "a distrust of technology and skepticism about its ability to work properly" (Parasuraman & Colby, 2001 p. 44). *H4a proposes that, "manufacturing firms' feeling of Insecurity about Industry 4.0 technologies negatively influences their perceived ease to adopt these technologies". H4b on the other hand states; "manufacturing firms' feeling of Insecurity about Industry 4.0 technologies negatively influences their perceived usefulness to adopt these technologies.* There is a statistically significant correlation between insecurity and perceived ease to adopt Industry 4.0 technologies. The t-value for H4a is 3.82 which implies that the proposed hypothesis is supported. It shows that manufacturing firms' feeling of Insecurity about Industry 4.0 technologies negatively influences their perceived ease to adopt Industry 4.0 technologies. The finding affirms the study by Omar et al. (2021) who established that when one's level of insecurity is high, there is a minimal chance that one will trust, feel safe, and overlook the risks, consequently causing one not to adopt and use a new technology. Another finding by Ali et al. (2021) also indicated that the perceived ease to adopt a technology is adversely affected by insecurity. It can be said, as though people are aware of the easy use of new technology, but will fail to adopt due to the fear of losing some confidential over the internet. H4b was not supported. H4b showed a statistical insignificant relationship with perceived usefulness to adopt industry 4.0 technologies (t-statistic = 0.17). This suggests that a firm's perceived usefulness of a new technology, is not affected by the insecurity that is associated with the technology. The finding does not support prior studies which revealed that, insecurity negatively influences perceived usefulness to adopt (Omar et al., 2021; Parasuraman, 2000).

5.6.7 Awareness

Studies have revealed that, the factors that influence the adoption of new technologies is based on the level of awareness or knowledge the firm has on that technology (Kinkel et al., 2022). In support of the aforementioned, H5a predicted that *"manufacturing firms' awareness of Industry 4.0 technologies positively influences their perceived ease to adopt these technologies"*. H5b also predicted that "*manufacturing firms' awareness of Industry 4.0 positively influences their perceived usefulness to adopt such technologies"*. H5a was supported with a significant t-value of 5.94. This indicates a positive correlation between awareness and perceived ease to adopt. Literature has it that, firms must be aware of the characteristics of the technology in order to adopt new technology in manufacturing (Ardito et al., 2019). H5b was also supported. The results of H5b shows a positive correlation between awareness and perceived usefulness to adopt Industry 4.0 with a t-value of 7.6 as displayed on Table 5.9. Awareness has a positive correlation with perceived usefulness. This implies that if firms are aware of a technology, this could potentially influence their perceived ease of use of that technology and subsequently facilitate its adoption. This finding suggests that manufacturing firms that are aware of a technology and find it valuable would embrace Industry 4.0 technology, which will enhance them in their production operations. This evidence aligns with the finding of a previous study by Pai & Alathur (2019) which did established a correlation between awareness and perceived usefulness to adopt a new technology.

5.6.8 Perceived Ease to Adopt

Perceived ease of use "is the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989 p. 320). H6 states that, *"Manufacturing firms' perceived ease of Industry 4.0 technologies positively influences their intention to adopt such technologies"*. H6 was support with t-value of 3.58. Findings from prior studies revealed that, that perceived ease of use of a new technology has key effects on adoption and use of the new technology (Acheampong et al., 2017). For instance, if the features of Industry 4.0 are easy to use and are easier to use as compared to the traditional way of manufacturing, it will facilitate the firms' intention to adopt the technologies.

5.6.9 Perceived Usefulness to Adopt

Perceived usefulness is the of the idea that adopting a technology would enhance a user's ability to execute a particular task (Park et al., 2021). According to Lin et al. (2007), technology readiness and people's intentions to adopt a new technology are entirely mediated by its perceived usefulness. Technologies enable manufacturing with direct communication systems, thereby allowing the making of adaptive decisions and helping challenges to be solved in real-time (Tangahu et al., 2021). In line with this, hypothesis 7 (H7) states: *"Manufacturing firms' perceived usefulness to adopt of Industry 4.0 positively influences their intention to adopt such technologies".* H7 was supported with a significant t-value of 8.42. There is a positive correlation between perceived usefulness to adopt and intention to adopt. This implies that, firms will adopt or use a technology to the extent that it will improve their ability to enhance their performance (Mensah, 2020; Rojas-Méndez et al., 2017). Perceived usefulness of Industry 4.0 technologies will positively influence the intention to adopt Industry 4.0 technologies (Parasuraman, 2000).

5.6.10 Support Resources

H8a and H8b explores the moderating effect of support resources. The H8a proposed that, "*Support resources moderate the relationship between perceived ease to adopt Industry 4.0 technologies".* H8b on the other hand, proposed that, *"Support resources moderate the* *relationship between perceived usefulness of Industry 4.0 technologies and the intention to adopt Industry 4.0 technologies".* H8a was not supported. The t-value for H8a is 0.15 which signifies statistically insignificant relationship. A firm's intention to adopt Industry 4.0 technologies would be dependent on the existing support resources such as IT infrastructure, IT capability and financial resource. Support resources are anticipated to moderate the effect of perceived ease to use and perceived usefulness on a firm's intention to adopt a new technology (Faqih & Jaradat, 2015). Contrary to this position in the literature, the current finding indicates that, support resources do not have any moderating effect on the relationship between perceived ease to adopt a technology. H8b was also not supported with a t-value of 0.30 as shown on Table 5.9. This implies that support resources do not moderate manufacturing firms' perceived usefulness to adopt and intention to adopt Industry 4.0 technologies. This finding of the study revealed that support resources do not moderate the relationship between perceived usefulness and intention to adopt industry 4.0 technologies.

5.7 Chapter Summary

This chapter sought to determine the extent of awareness of dominant Industry 4.0 among firms in Ghana. The mean values of the level of awareness of manufacturing firms in Ghana about Industry 4.0 technologies were higher than 3.5. Based on the mean values obtained, it gives an indication that manufacturing firms in Ghana. On the other hand, this shows that, manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies. Again, the structural equation modelling was used to analyze the relationship between dependent and independent variables. Nine (9) of the fourteen (14) hypotheses stated were supported, whereas five (5) were not. The supported hypotheses included H1a, H1b, H2a, H3a, H4a, H5a, H5b, H6 and H7. The hypotheses H2b, H3b, H4b, H8a and H8b however, were not supported.

CHAPTER SIX

SUMMARY, CONCLUSIONS AND CONTRIBUTIONS OF THE STUDY

6.1 Chapter Overview

This chapter presents a summary of the previous chapters, a summary of findings, conclusions, the study's contributions, the study's limitations, and future research directions.

6.2 Summary of Previous Chapters

The study aimed to examine the awareness of Industry 4.0 technologies among manufacturing firms in Ghana and to ascertain their readiness for accepting and embracing such technologies. The current study examined the readiness and awareness of the manufacturing sector of Ghana in embracing Industry 4.0 technologies. Concerning the scope, the study covered only the manufacturing firms in the Greater Accra of Ghana. The significance of the study relative to research, practice and policy was also discussed in the first chapter.

Chapter two presented the general idea of Industry 4.0 by discussing how the manufacturing sector has evolved over the years. The chapter also reviewed relevant literature on Industrial evolution, digital technologies, importance, implementation challenges, barriers, and benefits of Industry 4.0. The second chapter also examined relevant literature regarding the composition and the principles of Industry 4.0 which are made up of interoperability, decentralization, virtualization, real-time capability, modularity and service orientation.

The third chapter discussed the theory underpinning the study which formed the basis for the development of the proposed theoretical framework and the development of the hypotheses. The study is theoretically anchored on the foundations of the Technology Readiness and Acceptance

Model (TRAM). The research variables were borrowed from the TRAM to ascertain the factors influencing manufacturing firms' adoption of Industry 4.0 technologies. TRAM helps in evaluating a user's viewpoint on any generic technology using the constructs, optimism, innovativeness, discomfort and insecurity. Awareness was added to the existing constructs of the TRAM and support resources as a moderating factor.

The fourth chapter discussed the research methodology employed. This comprised methodological issues such as the research paradigm, research design, research population, sampling technique employed, sample size determination, design of the data collection instrument, the description of the data collection process, techniques for analyzing data collected and ethical considerations.

The data was analyzed in chapter five, and the results were then presented. Before data analysis, the data was cleaned to weed out any missing or incorrect data sets. The demographic components were illustrated. Excel was used to find the means from the Likert scale on the extent of awareness and extent to which Industry 4.0 technologies have been adopted by the manufacturing firms in Ghana. The Smart-PLS software was then used to analyze the relationships between the research variables. The findings showed that the majority of the research hypotheses were accepted. Additionally, the moderating variable's impact was also evaluated. This chapter also discussed findings relative to the existing literature.

The final chapter presented a summary of the previous chapters, a summary of the findings, a conclusion, the contributions of the study as well as the limitations. The summary of the findings was divided into three in line with the objectives. The first finding of the first objective revealed that the manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies. The second finding of the second summary of the objective showed the theoretical framework used Technology Readiness and Acceptance Model (TRAM). It was found that the variables of the model helped in determining the Industry 4.0 readiness and acceptance among manufacturing firms in Ghana. In the third summary, it was found that the findings of H5a and H5b confirmed awareness influencing perceived ease and perceived usefulness to adopt Industry 4.0. It was concluded from the results of the study that manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies. In addition, it was concluded that among the dominant Industry 4.0 technology: The Internet of Things, Artificial Intelligence, Cloud Computing, Big Data Analytics, Additive Manufacturing and Blockchain. The Internet of Things and Artificial Intelligence were partially adopted. The sixth chapter also presented the contributions of the study to research, practice and policy. In research, it contributed to the existing body of knowledge by introducing awareness and support resources to the already existing variables. In practice, the results would help practitioners to focus on making decisions that will enable the firms to be innovative and optimistic to facilitate the adoption of Industry 4.0. The knowledge discovered would help policymakers and relevant government agencies to enact policies to reduce the insecurity of firms in adopting Industry 4.0 technologies. The study was limited by scope. Also, further studies could use other readiness and acceptance models to determine the adoption of Industry 4.0 technologies.

6.3 Summary of Findings

The study's findings are divided into three categories by the objectives of the study. The findings on the awareness of dominant Industry 4.0 technologies among manufacturing firms in Ghana, the findings on Industry 4.0 technologies readiness and acceptance among manufacturing firms in Ghana and the effects of the awareness, technology readiness and acceptance factors on the adoption of Industry 4.0 technologies by manufacturing firms in Ghana.

6.3.1 Determine the awareness of the dominant Industry 4.0 technologies among manufacturing firms in Ghana.

Findings from the studies revealed that manufacturing firms are aware of the dominant Industry 4.0 technologies. The dominant Industry 4.0 technologies are the Internet of things, Blockchain, Big Data, Cloud Computing, Additive Manufacturing and Artificial Intelligence. The results of the study indicated awareness of Industry 4.0 technologies among manufacturing firms in Ghana. From the responses gathered for the study, 93.5% of the total respondents were aware of Industry 4.0 technologies.

6.3.2 Determine Industry 4.0 technologies' readiness and acceptance among manufacturing firms in Ghana.

The second objective of the study was to determine firms' readiness and acceptance of Industry 4.0 technologies among manufacturing firms in Ghana. The PLS-SEM was used to analyze the hypotheses developed for the study. The theoretical framework was developed from the Technology Readiness and Acceptance Model (TRAM) and the constructs helped in assessing the Industry 4.0 technologies' readiness and acceptance among manufacturing firms in Ghana. From the findings of 14 tested hypotheses, nine (9) of the hypotheses were accepted whereas the remaining five (5) were rejected. However, it was revealed that the moderator which is the support resource does not moderate the relationship between perceived ease to adopt and intention to adopt Industry 4.0 and the relationship between perceived usefulness to adopt and intention to adopt Industry 4.0 technologies.

6.3.3 Examine the effect of Industry 4.0 awareness and technology readiness and acceptance factors on its adoption among manufacturing firms in Ghana

Extant literature has reported that relations exist between awareness and technology readiness and the adoption of Industry 4.0 technologies. The study discovered that when firms are aware of technology, its perceived ease to adopt and perceived usefulness, there is a tendency to be ready and accept such technology. The findings of hypotheses H5a and H5b confirm the position that awareness which was an addition to complement the original framework (TRAM) influences perceived ease and perceived usefulness to adopt Industry 4.0 technologies. Other studies such as Shareef et al. (2009) and Sinha et al. (2019) support this position.

6.4 Mapping Research Objectives to Findings and Conclusions

Table 6.1 Summary of the study findings

Research Objectives	**Research Findings**	**Supported Literature**	**Conclusions**
Determine the awareness of the dominant Industry 4.0 technologies among manufacturing firms in Ghana.	The Internet of things dominated the Industry 4.0 techno that dominates among the Ghanaian manufacturing with a total response of 141 out of the sample of 170. Artificial Intelligence happens to be the second dominant Industry 4.0 technology, which was also followed by Cloud Computing.	Sinha et al. (2019), Kinkel et al. (2022), Shareef et al. (2009)	Relating to the findings of the study, it can be concluded that, the manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies.

	The analyses revealed that the Blockchain happens to record the least with level of awareness the dominant Industry 4.0 technologies among manufacturing firms in Ghana.		
Determine Industry 4.0 technologies' readiness and acceptance among manufacturing firms in Ghana.	The findings of this study showed the factors that influence firms' readiness to accept new technology (Industry 4.0). These factors were examined using Technology Readiness and Acceptance Model (TRAM) and Awareness: i. Optimism ii. Innovativeness iii. Discomfort iv. Insecurity v. Awareness vi. Perceived ease of use	Mensah, (2020), Pai & Alathur (2019), Raman & Aashish (2021), Rojas-Méndez et al. (2017), Zhong et al. (2017), Parasuraman & Colby (2015), Shareef et al. (2009)	It can be concluded that the factors of Technology readiness and acceptance model (TRAM) and awareness can be used to determine the readiness and acceptance of Industry 4.0 technologies among manufacturing firms in Ghana.

	vii. Perceived usefulness viii. Intention to adopt There is a perception that technologies that would be easy to use significantly influences firms' readiness and acceptance to adopt. Firms perceive that Industry 4.0 will be easy to understand, use and flexible, hence, favorable to adopt it. Any technology that is difficult to use irrespective of the benefits will not be easily acceptable and adopted. Similarly, there is a notion that technologies that would improve the performance of a firm will significantly influence firms' readiness and acceptance to adopt. Firms perceive that Industry 4.0 will help improve their performance and		

	production processes hence, favorably ready to adopt it.		
Examine the effect of Industry 4.0 awareness and technology readiness and acceptance factors on the adoption of Industry 4.0 technologies by manufacturing firms in Ghana.	Firms were optimistic in adopting Industry 4.0 as revealed by the results of the study. It was revealed that innovativeness has a positive influence on a firm adopting a new technology. Innovativeness can as well have a negative influence on a firm adopting a new technology that is; if the manufacturing firms find it difficult to discover the information pertaining to the benefits of adopting Industry 4.0 technology. The finding showed that, the discomfort of manufacturing firms negatively influences	(Omotayo & Adekunle (2021) Parasuraman, (2000), Kim & Chiu (2019)	There should be infrastructure and opportunities should be provided to assist firms acquire computing skills and also become technology savvy. The government should also put strategies and measures in place to help firms migrate into the use of advanced manufacturing technologies.

	firms' readiness to adopt Industry 4.0 technologies. It was further revealed that perceived insecurity has a negative influence on the readiness of firms to adopt Industry 4.0. Awareness and knowledge a firm has on the technology has an influence on the adoption of new technologies in manufacturing firms in Ghana.		

6.5 Conclusions

In relation to the results of the study it can be said that, manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies. It can be established that the factors of Technology readiness and acceptance model (TRAM) and awareness can be used to determine the readiness and acceptance of Industry 4.0 technologies among manufacturing firms in Ghana. There can be a conclusion from the study that, manufacturing firms in Ghana are aware of the dominant Industry 4.0 technologies. Based on the results of the study, it can be concluded that Internet of Things and Artificial Intelligence are partially adopted by manufacturing firms in Ghana whiles the other dominant Industry 4.0 technologies such as Cloud computing, Big Data, Additive Manufacturing and Blockchain are not adopted.

6.6. Study Contributions

6.6.1 Contribution to Research

Studies have revealed that, Industry 4.0 technologies are emerging advancements in the manufacturing sector globally. Due to this, there are calls for productive research to uncover further discoveries that support the body of literature and theories for effective implementation. Theoretically, this study adds to the body of knowledge already known about the readiness in accepting a new technology. The study added that awareness of a technology will influence the readiness to adopt a new technology and the results from H5a and H5b confirmed that. In addition to the TRAM variables, support resource was introduced as a moderating factor in examining the readiness and acceptance of new technologies. The study discovered that support resource does not moderate a firms' readiness in adopting a technology.

6.5.2 Contribution to Practice

The findings of the study will help management to focus on making decisions to be innovative in their firms to help in adopting new technologies. H2a revealed that, when firms are innovative, it influences their intention to adopt new technology. With the results from optimism as a readiness variable in adopting a new technology, it will help practitioners to focus of formulating policies that will enable them to be optimistic to influence the adoption new technology. H1a and H1b revealed that being optimistic influences the adoption of Industry 4.0 technology. Discomfort is defined as "a perceived lack of control over technology and a feeling of being overwhelmed by it" (A. Parasuraman, 2000). The results of the study (H3a) specified that, discomfort influences firms in adopting Industry 4.0. This discovery of the studies will enable management to focus on the usefulness of a technology rather that its ease of use.

6.5.3 Contribution for Policy

In policy, this study will serve as a piece of knowledge that will enable policymakers and relevant government agencies to enact policies that serve as a curb to insecurity of firms adopting Industry 4.0 technologies. Insecurity is defined as "a distrust of technology and skepticism about its ability to work properly" (Parasuraman, 2000). The results (H4a) of the study showed that insecurity influences firms' intention to adopt Industry 4.0 technologies. This knowledge discovered will help policymakers and its relevant stakeholders make decision on making internet use policies that will help to reduce the level of insecurity in adopting new technology. Also, another finding of the study (H5a and H5b) postulated that awareness influences firms' intention in adopting Industry 4.0 technologies. This knowledge discovered will enable policymakers in making decision of creating awareness of new technologies among firms to facilitate the consideration to adopt such new technologies.

6.6 Limitations and Future Research Directions

The study however has some limitation regarding its scope. The study focused on manufacturing firms located in the Greater Accra region of Ghana. This research might be replicated to examine how ready firms are, in different regions to adopt Industry 4.0 technologies. Similarly, the Technology Readiness and Acceptance Model (TRAM) was used as the theoretical foundation. Future researchers may think about employing a new technological acceptance model that takes additional characteristics or circumstances into consideration that may have an impact on readiness. Furthermore, research has demonstrated that, based on their scores on the four characteristics of technological readiness, people may be functionally divided into five distinct clusters (explorers, pioneers, skeptics, paranoids, and laggards, in that order) (Parasuraman & Colby, 2015). The psychographic and demographic characteristics of these groups are diverse, and they range significantly in terms of their technological attitudes and behaviors as well as in how long it takes each category to enter the technology market. Future research might attempt to study how the diversity of the people in technology acceptance will influence their readiness to adopt Industry 4.0 technologies.

REFERENCES

Aburiro, N. Ednut, Z., & Khatoon. (2021). *Philosophical Underpinning and Phenomenology Approach in*. *38*(January 2020), 237–254.

Abdallah, A. B., Rawadiah, O. M., Al-Byati, W., & Alhyari, S. (2021). Supply chain integration and export performance: the mediating role of supply chain performance. *International Journal of Productivity and Performance Management*, *70*(7), 1907–1929. https://doi.org/10.1108/IJPPM-02-2021-0076

Abimbola, B. (2021). *Cloud Computing Concept and Roots*. http://arxiv.org/abs/2102.00981

Achaw, O.W., & Danso-Boateng, E. (2021). Chemical and Process Industries. *Springer International Publishing.* https://doi.org/10.1007/978-3-030-79139-1

Acheampong, P., Zhiwen, L., Asante Antwi, H., Akai, A., Otoo, A., Mensah, W. G., & Sarpong, P. B. (2017). Hybridizing an Extended Technology Readiness Index with Technology Acceptance Model (TAM) to Predict E-Payment Adoption in Ghana. *American Journal of Multidisciplinary Research © 2017 Americanajournals* |, *2*(5), 172–184. http://onlinejournal.org.uk/index.php/ajmur/index

Acioli, C., Scavarda, A., & Reis, A. (2021). Applying Industry 4.0 technologies in the COVID–19 sustainable chains. *International Journal of Productivity and Performance Management*, *70*(5), 988–1016. https://doi.org/10.1108/IJPPM-03-2020-0137

Addo-Tenkorang, R., & Helo, P. T. (2016). Big data applications in operations/supply-chain management: A literature review. *Computers and Industrial Engineering*, *101*, 528–543. https://doi.org/10.1016/j.cie.2016.09.023

Adeyeri, M. (2018). From Industry 3.0 to Industry 4.0: Smart Predictive Maintenance System as Platform for Leveraging. *Arctic*, *71*(December), 64–81.

Agag, G., & El-Masry, A. A. (2016). Understanding the determinants of hotel booking intentions and moderating role of habit. *International Journal of Hospitality Management*, *54*, 52–67. https://doi.org/10.1016/j.ijhm.2016.01.007

Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision Sciences*, *30*(2), 361–391. https://doi.org/10.1111/j.1540-5915.1999.tb01614.x

Agrawal, P., & Narain, R. (2018). Digital supply chain management: An Overview. *IOP Conference Series: Materials Science and Engineering*, *455*(1). https://doi.org/10.1088/1757-899X/455/1/012074

Aguiar, A. A., Silva, L., Parente, C., & Costa, C. A. (2020). Organizational innovation in the context of family farms: Lean diagnosis. *Journal of Innovation Management*, *8*(2), 68–86. https://doi.org/10.24840/2183-0606_008.002_0006

Akanmu, A. A., Anumba, C. J., & Ogunseiju, O. O. (2021). Towards next generation cyber-physical systems and digital twins for construction. *Journal of Information Technology in Construction*, *26*(June), 505–525. https://doi.org/10.36680/j.itcon.2021.027

Akgün, A. E., Keskin, H., & Byrne, J. (2012). Antecedents and contingent effects of organizational adaptive capability on firm product innovativeness. *Journal of Product Innovation Management*, *29*, 171–189. https://doi.org/10.1111/j.1540-5885.2012.00949.x

Akkermans, H. A., Bogerd, P., & Wassenhove, L. N. Van. (2011). Structured Analysis, Design, and Implementation of Information System. *SpringerReference*, *146*, 284–301. https://doi.org/10.1007/springerreference_25823

Al-Ababneh, M. M. (2020). Linking Ontology, Epistemology and Research Methodology. *Science & Philosophy*, *8*(1), 75–91. https://doi.org/10.23756/sp.v8i1.500

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating Technology Acceptance Model with Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems. *IEEE Access*, *7*, 26797–26809. https://doi.org/10.1109/ACCESS.2019.2899368

Albach, H., Meffert, H., Pinkwart, A., & Ralf, R. (2015). Management of permanent change—new challenges and opportunities for change management. In *Management of Permanent Change*. https://doi.org/10.1007/978-3-658-05014-6_1

Ali Akbar, M. K. (2019). Cloud computing in libraries. *Library Philosophy and Practice*, *2019*. https://doi.org/10.1515/9783110608915

Ali, M., Raza, S. A., Khamis, B., Puah, C. H., & Amin, H. (2021). How perceived risk, benefit and trust determine user Fintech adoption: a new dimension for Islamic finance. *Foresight*, *23*(4), 403–420. https://doi.org/10.1108/FS-09-2020-0095

Allen, R. C. (2003). Progress and poverty in early modern Europe. *Economic History Review*, *56*(3), 403–443. https://doi.org/10.1111/j.1468-0289.2003.00257.x

Almada-Lobo, F. (2015). The Industry 4.0 revolution and the future of Manufacturing Execution Systems (MES). *Journal of Innovation Management*, *3*(4), 16–21. https://doi.org/10.24840/2183-0606_003.004_0003

AlMuhayfith, S., & Shaiti, H. (2020). The impact of enterprise resource planning on business performance: With the discussion on its relationship with open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(3). https://doi.org/10.3390/JOITMC6030087

Anand, G., Larson, E. C., & Mahoney, J. T. (2020). Thomas Kuhn on Paradigms. *Production and Operations Management*, *29*(7), 1650–1657. https://doi.org/10.1111/poms.13188

Anitah, J. N., Onserio Nyamwange, S., Obara Magutu, P., Chirchir, M., & Mose, J. M. (2019). Industry 4.0 Technologies and Operational Performance of Unilever Kenya and L'Oreal East Africa. *Noble International Journal of Business and Management Research ISSN*, *03*(10), 125–134.

Apte, S., & Petrovsky, N. (2016). Will blockchain technology revolutionize excipient supply chain management? *Journal of Excipients and Food Chemicals*, *7*(3), 76–78.

Ardito, L., Petruzzelli, A. M., Panniello, U., & Garavelli, A. C. (2019). Towards Industry 4.0: Mapping digital technologies for supply chain management-marketing integration. *Business Process Management Journal*, *25*(2), 323–346. https://doi.org/10.1108/BPMJ-04-2017-0088

Attaran, M. (2007). RFID: An enabler of supply chain operations. *Supply Chain Management*, *12*(4), 249–257. https://doi.org/10.1108/13598540710759763

Attaran, M. (2020). Digital technology enablers and their implications for supply chain management. *Supply Chain Forum*, *21*(3), 158–172. https://doi.org/10.1080/16258312.2020.1751568

Banerjee, M., Lee, J., & Choo, K. K. R. (2018). A blockchain future for internet of things security: a position paper. *Digital Communications and Networks*, *4*(3), 149–160. https://doi.org/10.1016/j.dcan.2017.10.006

Barreto, L., Amaral, A., & Pereira, T. (2017). Industry 4.0 implications in logistics: an overview. *Procedia Manufacturing*, *13*, 1245–1252. https://doi.org/10.1016/j.promfg.2017.09.045

Bartodziej, C. J. (2017). The Concept Industry 4.0. *The Concept Industry 4.0*, *2011*, 142–143. https://doi.org/10.1007/978-3-658-16502-4

Baryshnikova, N., Kiriliuk, O., & Klimecka-Tatar, D. (2021). Enterprises' strategies transformation in the real sector of the economy in the context of the COVID-19 pandemic. *Production Engineering Archives*, *27*(1), 8–15. https://doi.org/10.30657/pea.2021.27.2

Basl, J. (2017). Pilot Study of Readiness of Czech Companies to Implement the Principles of Industry 4.0. *Management and Production Engineering Review*, *8*(2), 3–8. https://doi.org/10.1515/mper-2017-0012

Baygin, M., Yetis, H., Karakose, M., & Akin, E. (2016). An effect analysis of industry 4.0 to higher education. *2016 15th International Conference on Information Technology Based Higher Education and Training, ITHET 2016*, 14–17. https://doi.org/10.1109/ITHET.2016.7760744

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2021). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *0123456789*. https://doi.org/10.1007/s10479-021-03956-x

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and supply chain management: a literature review. In *International Journal of Production Research* (Vol. 57, Issues 15–16). https://doi.org/10.1080/00207543.2017.1402140

Benešová, A., & Tupa, J. (2017). Requirements for Education and Qualification of People in Industry 4.0. *Procedia Manufacturing*, *11*(June), 2195–2202. https://doi.org/10.1016/j.promfg.2017.07.366

Bhushan, D., & Agrawal, R. (2020). The Internet of Things: Looking beyond the hype. In *An Industrial IoT Approach for Pharmaceutical Industry Growth: Volume 2*. INC. https://doi.org/10.1016/B978-0-12-821326-1.00008-5

Bi, Z., Jin, Y., Maropoulos, P., Zhang, W. J., & Wang, L. (2021). Internet of things (IoT) and big data analytics (BDA) for digital manufacturing (DM). *International Journal of Production Research*, *0*(0), 1–18. https://doi.org/10.1080/00207543.2021.1953181

Boateng, R. (2016). *Research made easy*. CreateSpace Independent Publishing Platform.

Bostley, M. A. (2019). Basics of research design: A guide to selecting appropriate research design. *International Journal of Contemporary Applied Researches*, *Vol. 6*, *No*(5), 76–89. https://www.researchgate.net/publication/342354309 _Basics_of_Research_Design_A_Guide_to_selecting_appropriate_research_design.

Briggs, A., & Coleman, M. (2019). Research methodology in educational leadership and management. In *Oxford Research Encyclopedia of Education*.

Bruland, K., & Mowery, D. (2006). Innovation in time. *The Oxford Handbook of Innovation*, 349–379.

Butner, K. (2010). The smarter supply chain of the future. *Strategy and Leadership*, *38*(1), 22–31. https://doi.org/10.1108/10878571011009859

Büyüközkan, G., & Göçer, F. (2018). Digital Supply Chain: Literature review and a proposed framework for future research. *Computers in Industry*, *97*, 157–177. https://doi.org/10.1016/j.compind.2018.02.010

Cardinale, I., & Scazzieri, R. (2021). Structures and transformations: Heuristics of economic change. *Structural Change and Economic Dynamics*, *xxxx*. https://doi.org/10.1016/j.strueco.2021.09.012

Carvalho, N., Chaim, O., Cazarini, E., & Gerolamo, M. (2018). Manufacturing in the fourth industrial revolution: A positive prospect in Sustainable Manufacturing. *Procedia Manufacturing*, *21*, 671–678. https://doi.org/10.1016/j.promfg.2018.02.170

Castellacci, F., & Natera, J. M. (2013). The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. *Research Policy*, *42*(3), 579–594. https://doi.org/10.1016/j.respol.2012.10.006

Castillo S, M. J., & Bigne, E. (2021). A model of adoption of AR-based self-service technologies: a two country comparison. *International Journal of Retail and Distribution Management*, *49*(7), 875–898. https://doi.org/10.1108/IJRDM-09-2020-0380

Cecez-Kecmanovic M.A., D. & K. (2013). The methodological landscape: Information systems and knowledge management. *Research Methods: Information, Systems, and Contexts*, *February 2015*, 113–138.

Cegielski, C. G., Jones-Farmer, L. A., Wu, Y., & Hazen, B. T. (2012). Adoption of cloud computing technologies in supply chains: An organizational information processing theory approach. *The International Journal of Logistics Management*, *23*(2), 184–211. https://doi.org/10.1108/09574091211265350

Charro, A., Schaefer, D., Charro, A., & Schaefer, D. (2018). Cloud Manufacturing as a new type of Product- Service System. *International Journal of Computer Integrated Manufacturing*, *31*(10), 1018–1033. https://doi.org/10.1080/0951192X.2018.1493228

Chauhan, C., & Singh, A. (2020). A review of Industry 4.0 in supply chain management studies. *Journal of Manufacturing Technology Management*, *31*(5), 863–886. https://doi.org/10.1108/JMTM-04-2018-0105

Chawla, R. N., & Goyal, P. (2022). Emerging trends in digital transformation: a bibliometric analysis. *Benchmarking*, *29*(4), 1069–1112. https://doi.org/10.1108/BIJ-01-2021-0009

Chen, M. F., & Lin, N. P. (2018). Incorporation of health consciousness into the technology readiness and acceptance model to predict app download and usage intentions. *Internet Research*, *28*(2), 351–373. https://doi.org/10.1108/IntR-03-2017-0099

Cheng, F. T., Tieng, H., Yang, H. C., Hung, M. H., Lin, Y. C., Wei, C. F., & Shieh, Z. Y. (2016). Industry 4.1 for Wheel Machining Automation. *IEEE Robotics and Automation Letters*, *1*(1), 332–339. https://doi.org/10.1109/LRA.2016.2517208

Chiappetta Jabbour, C. J., Fiorini, P. D. C., Ndubisi, N. O., Queiroz, M. M., & Piato, É. L. (2020). Digitally-enabled sustainable supply chains in the 21st century: A review and a research agenda. *Science of the Total Environment*, *725*, 138177. https://doi.org/10.1016/j.scitotenv.2020.138177

Lin, C.H., Shih, H.Y., & Sher, P. J. (2007). Integrating Technology Readiness into Technology Acceptance: The TRAM Model. *Psychology & Marketing*, *24*(6), 641–657. https://doi.org/10.1002/mar

Chiu, W., & Cho, H. (2021). The role of technology readiness in individuals' intention to use health and fitness applications: a comparison between users and non-users. *Asia Pacific Journal of Marketing and Logistics*, *33*(3), 807–825. https://doi.org/10.1108/APJML-09-2019-0534

Chodha, V., Dubey, R., Kumar, R., Singh, S., & Kaur, S. (2022). Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques. *Materials Today: Proceedings*, *50*, 709–715. https://doi.org/10.1016/j.matpr.2021.04.487

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big Data Analytics in Operations Management. *Production and Operations Management*, *27*(10), 1868–1883. https://doi.org/10.1111/poms.12838

Chu, H., & Ke, Q. (2017). Research methods: What's in the name? *Library and Information Science Research*, *39*(4), 284–294. https://doi.org/10.1016/j.lisr.2017.11.001

Codini, A. P., Abbate, T., & Messeni Petruzzelli, A. (2022). Business Model Innovation and exaptation: A new way of innovating in SMEs. *Technovation*, *December 2020*, 102548. https://doi.org/10.1016/j.technovation.2022.102548

Coenen, L., Benneworth, P., & Truffer, B. (2012). Toward a spatial perspective on sustainability transitions. *Research Policy*, *41*(6), 968–979. https://doi.org/10.1016/j.respol.2012.02.014

Cohen, J. (1988). Set correlation and contingency tables. *Applied Psychological Measurement*, *12*(4), 425–434.

Cole, R., Stevenson, M., & Aitken, J. (2019). Blockchain technology: implications for operations and supply chain management. *Supply Chain Management*, *24*(4), 469–483. https://doi.org/10.1108/SCM-09-2018-0309

Colli, M., Berger, U., Bockholt, M., Madsen, O., Møller, C., & Wæhrens, B. V. (2019). A maturity assessment approach for conceiving context-specific roadmaps in the Industry 4.0 era. *Annual Reviews in Control*, *48*, 165–177. https://doi.org/10.1016/j.arcontrol.2019.06.001

Conroy, R. M. (2021). The RCSI Sample Size Handbook. *Beaumont Hospital Ethics Committee*, *May*, 1–79. https://doi.org/10.13140/RG.2.2.30497.51043

Cooksey, R. W. (2020). Computer Programs for Analysing Quantitative Data. In *Illustrating Statistical Procedures: Finding Meaning in Quantitative Data* (pp. 33–49). Springer.

Crafts, N. (2021). the Sources of British Economic Growth Since the Industrial Revolution: Not the Same Old Story. *Journal of Economic Surveys*, *35*(3), 697–709. https://doi.org/10.1111/joes.12349

Creswell, J. W. (2014). *A concise introduction to mixed methods research*. SAGE publications.

Creswell, J. W., & Creswell, J. (2003). *Research design*. Sage publications Thousand Oaks, CA.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555

da Rosa Righi, R., Alberti, A. M., & Singh, M. (2019). *Blockchain Technology for Security*. https://www.researchgate.net/profile/Victoria_Lemieux/publication/333659272_Blockchain

_Technology_Recordkeeping/links/5cfadaaf299bf13a3845866e/Blockchain-Technology-Recordkeeping.pdf

Dahmani, N., Benhida, K., Belhadi, A., Kamble, S., Elfezazi, S., & Jauhar, S. K. (2021). Smart circular product design strategies towards eco-effective production systems: A lean eco-design industry 4.0 framework. *Journal of Cleaner Production*, *320*(May), 128847. https://doi.org/10.1016/j.jclepro.2021.128847

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018a). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*(July), 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018b). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*(December 2017), 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*(August), 121092. https://doi.org/10.1016/j.techfore.2021.121092

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

de Vass, T., Shee, H., & Miah, S. J. (2021). Iot in supply chain management: a narrative on retail sector sustainability. *International Journal of Logistics Research and Applications*, *24*(6), 605–624. https://doi.org/10.1080/13675567.2020.1787970

Denzin, N. K., & Lincoln, Y. S. (2011). *The Sage handbook of qualitative research*. sage.

Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: applications, challenges and opportunities. *Journal of Data, Information and Management*, *2*(2), 67–74. https://doi.org/10.1007/s42488-020-00023-1

Douglas, K. M., & Sutton, R. M. (2018). RE-INTERPRETING THE KUHNIAN PARADIGM IN INFORMATION SYSTEMS. *Journal of the Association for Information Systems*, *40*(2), 568–599.

Dubey, R., Gunasekaran, A., & Childe, S. J. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision*, *57*(8), 2092–2112. https://doi.org/10.1108/MD-01-2018-0119

Edeh, E., Lo, W.-J., & Khojasteh, J. (2022). Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. In *Structural Equation Modeling: A Multidisciplinary Journal*. https://doi.org/10.1080/10705511.2022.2108813

Ekonomist, N., & Trebinje, H. M. (2020). *INNOVATION AND COMPETITIVE ADVANTAGE IN*. *14*(28), 29–35. https://doi.org/10.7251/NOEEN2028029G

ElMaraghy, H. (2019). Smart changeable manufacturing systems. *Procedia Manufacturing*, *28*, 3–9. https://doi.org/10.1016/j.promfg.2018.12.002

Erboz, G., Yumurtacı Hüseyinoğlu, I. Ö., & Szegedi, Z. (2021). The partial mediating role of supply chain integration between Industry 4.0 and supply chain performance. *Supply Chain Management*, *April*. https://doi.org/10.1108/SCM-09-2020-0485

Erdoğmu, N., & Esen, M. (2011). An investigation of the effects of technology readiness on technology acceptance in e-HRM. *Procedia - Social and Behavioral Sciences*, *24*, 487–495. https://doi.org/10.1016/j.sbspro.2011.09.131

Esmaeilian, B., Sarkis, J., Lewis, K., & Behdad, S. (2020). Blockchain for the future of sustainable supply chain management in Industry 4.0. *Resources, Conservation and Recycling*, *163*. https://doi.org/10.1016/j.resconrec.2020.105064

Etikan, I. (2016). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, *5*(1), 1. https://doi.org/10.11648/j.ajtas.20160501.11

Falwadiya, H., & Dhingra, S. (2022). Blockchain technology adoption in government organizations: a systematic literature review. *Journal of Global Operations and Strategic Sourcing*, *15*(3), 473–501. https://doi.org/10.1108/JGOSS-09-2021-0079

Faqih, K. M. S., & Jaradat, M. I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *Journal of Retailing and Consumer Services*, *22*, 37–52. https://doi.org/10.1016/j.jretconser.2014.09.006

Fatorachian, H., & Kazemi, H. (2021a). Impact of Industry 4.0 on supply chain performance. *Production Planning and Control*, *32*(1). https://doi.org/10.1080/09537287.2020.1712487

Fatorachian, H., & Kazemi, H. (2021b). Impact of Industry 4.0 on supply chain performance. *Production Planning and Control*, *32*(1), 63–81. https://doi.org/10.1080/09537287.2020.1712487

Ferreira, A., Silva, G. M., & Dias, Á. L. (2021). Determinants of continuance intention to use mobile self-scanning applications in retail. *International Journal of Quality and Reliability Management*. https://doi.org/10.1108/IJQRM-02-2021-0032

Fielding, N., Lee, R., & Blank, G. (2012). The SAGE Handbook of Online Research Methods. *The SAGE Handbook of Online Research Methods*, 195–216. https://doi.org/10.4135/9780857020055

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293–320. https://doi.org/10.1108/JOSM-10-2020-0378

Flick, U. (2018). *Designing qualitative research*. Sage.

Frank, A. G., Cortimiglia, M. N., Ribeiro, J. L. D., & Oliveira, L. S. de. (2016). The effect of innovation activities on innovation outputs in the Brazilian industry: Market-orientation vs. technology-acquisition strategies. *Research Policy*, *45*(3), 577–592. https://doi.org/10.1016/j.respol.2015.11.011

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, *210*, 15–26. https://doi.org/10.1016/J.IJPE.2019.01.004

Frederico, Guilherme F., Garza-Reyes, J. A., Anosike, A., & Kumar, V. (2020). Supply Chain 4.0: concepts, maturity and research agenda. *Supply Chain Management*, *25*(2), 262–282. https://doi.org/10.1108/SCM-09-2018-0339

Frederico, Guilherme Francisco, Garza-Reyes, J. A., Kumar, A., & Kumar, V. (2021).

Performance measurement for supply chains in the Industry 4.0 era: a balanced scorecard approach. *International Journal of Productivity and Performance Management*, *70*(4). https://doi.org/10.1108/IJPPM-08-2019-0400

Gannon, M. J., Taheri, B., & Azer, J. (2022a). Contemporary Research Paradigms and Philosophies. *Contemporary Research Methods in Hospitality and Tourism*, *July*, 5–19. https://doi.org/10.1108/978-1-80117-546-320221002

Gannon, M. J., Taheri, B., & Azer, J. (2022b). Contemporary Research Paradigms and Philosophies. In F. Okumus, S. M. Rasoolimanesh, & S. Jahani (Eds.), *Contemporary Research Methods in Hospitality and Tourism* (pp. 5–19). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80117-546-320221002

Garay-Rondero, C. L., Martinez-Flores, J. L., Smith, N. R., Caballero Morales, S. O., & Aldrette-Malacara, A. (2020). Digital supply chain model in Industry 4.0. *Journal of Manufacturing Technology Management*, *31*(5). https://doi.org/10.1108/JMTM-08-2018-0280

Geisser, S. (1974). Biometrika Trust A Predictive Approach to the Random Effect Model Author (s): Seymour Geisser Published by : Oxford University Press on behalf of Biometrika Trust Stable URL : http://www.jstor.org/stable/2334290. *Biometrika Trust*, *61*(1), 101–107.

Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020a). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, *31*(4), 669–686. https://doi.org/10.1108/JMTM-10-2019-0368

Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020b). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, *31*(4). https://doi.org/10.1108/JMTM-10-2019-0368

Ghana Investment Promotion Centre (GIPC). (2022). Highlight on Ghana's Manufacturing Sector. *Manufacturing-Spotlight-Brochure*, 1–7.

Ghana Statistical Service. (2019). Ghana Living Standards Survey round 7 (GLSS7), Main Report. *Ghana Statistical Service*, 1–343. https://statsghana.gov.gh/gsspublications.php?category=MTAwMjg3Mzk3NC4zMDc=/webstats/1opr93rn57

Ghobakhloo, M. (2018). The future of manufacturing industry: a strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management*, *29*(6), 910–936. https://doi.org/10.1108/JMTM-02-2018-0057

Goel, A. (2022). Using secondary data in research on social sustainability in construction project management: a transition from "interview society" to "project-as-practice." *Engineering, Construction and Architectural Management*. https://doi.org/10.1108/ECAM-10-2021-0905

Gohil, D., & Thakker, S. V. (2021). Blockchain-integrated technologies for solving supply chain challenges. *Modern Supply Chain Research and Applications*, *3*(2), 78–97. https://doi.org/10.1108/mscra-10-2020-0028

Gökalp, E., Şener, U., & Eren, P. E. (2017). Development of an assessment model for industry 4.0: Industry 4.0-MM. *Communications in Computer and Information Science*, *770*(November), 128–142. https://doi.org/10.1007/978-3-319-67383-7_10

Goodhue, D. L., Lewis, W., Thompson, R., & Thompson, R. (2012). *QÍarterjy*. *36*(3), 981–1001.

Gordon, N. (2002). A Question of Response Rate. *Science Editor*, *25*(1), 25–26.

https://www.councilscienceeditors.org/wp-content/uploads/v25n1p025-026.pdf

Govindan, K., Cheng, T. C. E., Mishra, N., & Shukla, N. (2018). Big data analytics and application for logistics and supply chain management. *Transportation Research Part E: Logistics and Transportation Review*, *114*(March), 343–349. https://doi.org/10.1016/j.tre.2018.03.011

Granger, S. (2014). The computer learner corpus: a versatile new source of data for SLA research. In *Learner English on computer* (pp. 3–18). Routledge.

Griffith, R., & Tengnah, C. (2011). Adoption law: A district nurse's guide. *British Journal of Community Nursing*, *16*(4), 196–199. https://doi.org/10.12968/bjcn.2011.16.4.196

Guba, E. G., & yvonna s. Lincoln. (1990). Competing Paradigms in Quualitative Research. In *Handbook of Qualitative Research* (pp. 105–117).

Gupta, A., Mazumdar, B. D., Mishra, M., Shinde, P. P., Srivastava, S., & Deepak, A. (2021). Role of cloud computing in management and education. *Materials Today: Proceedings*, *xxxx*. https://doi.org/10.1016/j.matpr.2021.07.370

Gupta, B. N. (2022). *Business statistics*. SBPD Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks. *Sage*, 165.

Hair, Joe F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*(August 2019), 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*.

Harryanto, Muchran, M., & Ahmar, A. S. (2018). Application of TAM model to the use of information technology. *International Journal of Engineering and Technology(UAE)*, *7*(2.9 Special Issue 9), 37–40.

Hasan, N., & Bao, Y. (2022). A mixed-method approach to assess users' intention to use mobile health (mHealth) using PLS-SEM and fsQCA. In *Aslib Journal of Information Management* (Vol. 74, Issue 4). https://doi.org/10.1108/AJIM-07-2021-0211

Helo, P., & Shamsuzzoha, A. H. M. (2020). Real-time supply chain—A blockchain architecture for project deliveries. *Robotics and Computer-Integrated Manufacturing*, *63*(December 2019), 101909. https://doi.org/10.1016/j.rcim.2019.101909

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Herceg, I. V., Kuč, V., Mijušković, V. M., & Herceg, T. (2020). Challenges and driving forces for industry 4.0 implementation. *Sustainability (Switzerland)*, *12*(10), 1–22. https://doi.org/10.3390/su12104208

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for industrie 4.0 scenarios.

Proceedings of the Annual Hawaii International Conference on System Sciences, *2016-March*, 3928–3937. https://doi.org/10.1109/HICSS.2016.488

History, W. E., Clark, G., & Zealand, N. (2005). *2 . The British Industrial Revolution , 1760-1860*.

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, *89*, 23–34. https://doi.org/10.1016/j.compind.2017.04.002

Hofmann, E., & Rutschmann, E. (2018). Big data analytics and demand forecasting in supply chains: a conceptual analysis. *International Journal of Logistics Management*, *29*(2), 739–766. https://doi.org/10.1108/IJLM-04-2017-0088

Holl, A., & Mariotti, I. (2021). An empirical study of drivers for the adoption of logistics innovation. *Industry and Innovation*, *00*(00), 1–32. https://doi.org/10.1080/13662716.2021.1990020

Hopkins, J. L. (2021). An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia. *Computers in Industry*, *125*, 103323. https://doi.org/10.1016/j.compind.2020.103323

Horváth, D., & Szabó, R. Z. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, *146*(June), 119–132. https://doi.org/10.1016/j.techfore.2019.05.021

Hox, J. J., & Boeije, H. R. (2004). Data Collection, Primary vs. Secondary. In *Encyclopedia of*

Social Measurement (pp. 593–599). https://doi.org/10.1016/B0-12-369398-5/00041-4

Hoyer, C., Gunawan, I., & Reaiche, C. H. (2020). The Implementation of Industry 4.0 – A Systematic Literature Review of the Key Factors. *Systems Research and Behavioral Science*, *37*(4), 557–578. https://doi.org/10.1002/sres.2701

Huang, J. M., Ho, T. K., Liu, Y. C., & Lin, Y. H. (2015). A discussion on the user intention of golfers toward golf GPS navigation. *Journal of Hospitality and Tourism Technology*, *6*(1), 26–39. https://doi.org/10.1108/JHTT-02-2015-0013

Industrial Revolution Stages From Steam Power To Cyber Physical Systems, Automation And Internet Of Things Royalty Free SVG, Cliparts, Vectors, And Stock Illustration. Image 68697111. (n.d.). Retrieved June 3, 2022, from https://www.123rf.com/photo_68697111_industrial-revolution-stages-from-steam-power-to-cyber-physical-systems-automation-and-internet-of-t.html?vti=o82ryk6sj9l12o3c5w-1-3

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

J. Heigham, R. A. C. (2009). Qualitative Research in Applied Linguistics. In *Syria Studies* (Vol. 7, Issue 1). https://www.researchgate.net/publication/269107473_What_is_governance/link/548173090cf22525dcb61443/download%0Ahttp://www.econ.upf.edu/~reynal/Civilwars_12December2010.pdf%0Ahttps://think-asia.org/handle/11540/8282%0Ahttps://www.jstor.org/stable/41857625

Jahani, N., Sepehri, A., Vandchali, H. R., & Tirkolaee, E. B. (2021). Application of industry 4.0

in the procurement processes of supply chains: A systematic literature review. *Sustainability (Switzerland)*, *13*(14), 1–25. https://doi.org/10.3390/su13147520

Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2021). Upgrading the manufacturing sector via applications of Industrial Internet of Things (IIoT). *Sensors International*, *2*(August), 100129. https://doi.org/10.1016/j.sintl.2021.100129

Jede, A., & Teuteberg, F. (2015). Integrating cloud computing in supply chain processes: A comprehensive literature review. *Journal of Enterprise Information Management*, *28*(6), 872–904. https://doi.org/10.1108/JEIM-08-2014-0085

Jiang, Z., Yuan, S., Ma, J., & Wang, Q. (2022). The evolution of production scheduling from Industry 3.0 through Industry 4.0. *International Journal of Production Research*, *60*(11), 3534–3554. https://doi.org/10.1080/00207543.2021.1925772

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations and Production Management*, *37*(1), 10–36. https://doi.org/10.1108/IJOPM-02-2015-0078

Sundram, V. P.K., Chandran, V. G. R., & Bhatti, M. A(2016). Supply chain practices and performance: the indirect effects of supply chain integration. *Benchmarking*, *23*(6), 1445–1471. https://doi.org/10.1108/BIJ-03-2015-0023

Kamble, S., Gunasekaran, A., & Arha, H. (2019). Understanding the Blockchain technology adoption in supply chains-Indian context. *International Journal of Production Research*, *57*(7), 2009–2033. https://doi.org/10.1080/00207543.2018.1518610

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*, 408–425. https://doi.org/10.1016/j.psep.2018.05.009

Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. (2021). A machine learning based approach for predicting blockchain adoption in supply Chain. *Technological Forecasting and Social Change*, *163*(August 2019), 120465. https://doi.org/10.1016/j.techfore.2020.120465

Kasim, H., & Antwi, S. K. (2015). Qualitative and quantitative research paradigms in business research: A philosophical reflection. *European Journal of Business and ManagementOnline)*, *7*(3), 217–225. https://www.researchgate.net/profile/Hamza-Kasim/publication/295087782_Qualitative_and_Quantitative_Research_Paradigms_in_Business_Research_A_Philosophical_Reflection/links/56c7587108ae5488f0d2cd62/Qualitative-and-Quantitative-Research-Paradigms-in-Busine

Kaushik, A. K., & Rahman, Z. (2017). An empirical investigation of tourist's choice of service delivery options: SSTs vs service employees. *International Journal of Contemporary Hospitality Management*, *29*(7), 1892–1913. https://doi.org/10.1108/IJCHM-08-2015-0438

Kerin, M., & Pham, D. T. (2019). A review of emerging industry 4.0 technologies in remanufacturing. *Journal of Cleaner Production*, *237*, 117805. https://doi.org/10.1016/j.jclepro.2019.117805

Kim, H. M., & Laskowski, M. (2018). Toward an ontology-driven blockchain design for supply-chain provenance. *Intelligent Systems in Accounting, Finance and Management*, *25*(1), 18–

27. https://doi.org/10.1002/isaf.1424

Kim, S., & Garrison, G. (2009). Investigating mobile wireless technology adoption: An extension of the technology acceptance model. *Information Systems Frontiers*, *11*(3), 323–333. https://doi.org/10.1007/s10796-008-9073-8

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: the role of technology readiness. *International Journal of Sports Marketing and Sponsorship*, *20*(1), 109–126. https://doi.org/10.1108/IJSMS-06-2017-0050

Kinkel, S., Baumgartner, M., & Cherubini, E. (2022). Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation*, *110*(August 2021), 102375. https://doi.org/10.1016/j.technovation.2021.102375

Kolog, E. A., Montero, C. S., & Tukiainen, M. (2018). Development and Evaluation of an Automated e-Counselling System for Emotion and Sentiment Analysis. *The Electronic Journal Information Systems Evaluation*, *21*(1), 1–19. www.ejise.com

Koren, Y., & Shpitalni, M. (2010). Design of reconfigurable manufacturing systems. *Journal of Manufacturing Systems*, *29*(4), 130–141. https://doi.org/10.1016/j.jmsy.2011.01.001

Krauss, S. (2015). Research Paradigms and Meaning Making: A Primer. *The Qualitative Report*. https://doi.org/10.46743/2160-3715/2005.1831

Kumar, D. S., Purani, K., & Viswanathan, S. A. (2018). Influences of 'appscape' on mobile app adoption and m-loyalty. *Journal of Retailing and Consumer Services*, *45*(September), 132–141. https://doi.org/10.1016/j.jretconser.2018.08.012

Kumar, S., Balaji, M. S., Quazi, A., & Quaddus, M. (2018). Journal of Retailing and Consumer Services Predictors of customer acceptance of and resistance to smart technologies in the retail sector. *Journal of Retailing and Consumer Services*, *42*(November 2017), 147–160. https://doi.org/10.1016/j.jretconser.2018.02.005

Kumari, P., & Kaur, P. (2021). A survey of fault tolerance in cloud computing. *Journal of King Saud University - Computer and Information Sciences*, *33*(10), 1159–1176. https://doi.org/10.1016/j.jksuci.2018.09.021

Kurt, R. (2019). Industry 4.0 in Terms of Industrial Relations and Its Impacts on Labour Life. *Procedia Computer Science*, *158*, 590–601. https://doi.org/10.1016/j.procs.2019.09.093

Lamm, A. J., & Lamm, K. W. (2019). Journal of International Agricultural and Extension Education: From the Editors. *Journal of International Agricultural and Extension Education*, *26*(1), 8. https://doi.org/10.5191/jiaee.2019.26105

Lan, P. (2018). A review of advantages and disadvantages of three paradigms : positivism , interpretivism and critical inquiry. *The University of ADELAIDE*, *April*, 0–7. https://doi.org/10.13140/RG.2.2.13995.54569

Larasati, N. (2017). Technology Readiness and Technology Acceptance Model in New Technology Implementation Process in Low Technology SMEs. *International Journal of Innovation, Management and Technology*, *8*(2), 113–117. https://doi.org/10.18178/ijimt.2017.8.2.713

Larsen, G. D. (2011). Understanding the early stages of the innovation diffusion process: Awareness, influence and communication networks. *Construction Management and Economics*, *29*(10), 987–1002. https://doi.org/10.1080/01446193.2011.619994

Legate, A. E., Hair, J. F., Chretien, J. L., & Risher, J. J. (2021). PLS-SEM: Prediction-oriented solutions for HRD researchers. *Human Resource Development Quarterly*, 1–19. https://doi.org/10.1002/hrdq.21466

Leukel, J., Kirn, S., & Schlegel, T. (2011). Supply chain as a service: A cloud perspective on supply chain systems. *IEEE Systems Journal*, *5*(1), 16–27. https://doi.org/10.1109/JSYST.2010.2100197

Li, K., Zhou, T., & Liu, B. hai. (2020). Internet-based intelligent and sustainable manufacturing: developments and challenges. *International Journal of Advanced Manufacturing Technology*, *108*(5–6), 1767–1791. https://doi.org/10.1007/s00170-020-05445-0

Liao, Y., Deschamps, F., Loures, E. de F. R., & Ramos, L. F. P. (2017). Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. *International Journal of Production Research*, *55*(12), 3609–3629. https://doi.org/10.1080/00207543.2017.1308576

Lin, D., Lee, C. K. M., Lau, H., & Yang, Y. (2018). Strategic response to Industry 4.0: an empirical investigation on the Chinese automotive industry. *Industrial Management and Data Systems*, *118*(3), 589–605. https://doi.org/10.1108/IMDS-09-2017-0403

Lin, H., Lee, M., Liang, J., Chang, H., Huang, P., & Tsai, C. (2020). A review of using partial least square structural equation modeling in e-learning research. *British Journal of Educational Technology*, *51*(4), 1354–1372.

Lin, K. C., Shyu, J. Z., & Ding, K. (2017). A cross-strait comparison of innovation policy under industry 4.0 and sustainability development transition. *Sustainability (Switzerland)*, *9*(5). https://doi.org/10.3390/su9050786

Lin, W. D., Low, Y. H., Chong, Y. T., & Teo, C. L. (2019). Integrated Cyber Physical Simulation Modelling Environment for Manufacturing 4.0. *IEEE International Conference on Industrial Engineering and Engineering Management*, *2019-Decem*, 1861–1865. https://doi.org/10.1109/IEEM.2018.8607696

Lincoln, Y. S., & Guba, E. g. (2011). Paradimatic controvercies\ contradictions\ and emerging confluencies Related papers Dialogical principles for qualit at ive inquiry: a nonfoundat ional pat h. *The Sage Handbook of Qualitative Research*, *4*(2), 163–188.

Liu, Y., Li, H., Kostakos, V., Goncalves, J., Hosio, S., & Hu, F. (2014). An empirical investigation of mobile government adoption in rural China: A case study in Zhejiang province. *Government Information Quarterly*, *31*(3), 432–442. https://doi.org/10.1016/j.giq.2014.02.008

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, *6*, 1–10. https://doi.org/10.1016/j.jii.2017.04.005

Maher, C., Hadfield, M., Hutchings, M., & de Eyto, A. (2018). Ensuring Rigor in Qualitative Data Analysis: A Design Research Approach to Coding Combining NVivo With Traditional Material Methods. *International Journal of Qualitative Methods*, *17*(1), 1–13. https://doi.org/10.1177/1609406918786362

Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research*, *59*(6), 1875–1900. https://doi.org/10.1080/00207543.2020.1793011

Maity, M., Bagchi, K., Shah, A., & Misra, A. (2019). Explaining normative behavior in information technology use. *Information Technology and People*, *32*(1), 94–117. https://doi.org/10.1108/ITP-11-2017-0384

Malhi, A. S., Kovid, R. K., Dutta, A., & Sijariya, R. (2022). What Drives Adoption of Cloud-Based Online Games in an Emerging Market? An Investigation Using Flow Theory. In *Machine Intelligence and Data Science Applications* (pp. 775–787). Springer.

Malik, A., Manusia,B.P.S.D.M, & Timur, P. J. (2019). Creating Competitive Advantage through Source Basic Capital Strategic Humanity in the Industrial Age 4.0. *International Research Journal of Advanced Engineering and Science*, *4*(1), 209–215.

Malterud, K., Siersma, V. D., & Guassora, A. D. (2016). Sample Size in Qualitative Interview Studies: Guided by Information Power. *Qualitative Health Research*, *26*(13), 1753–1760. https://doi.org/10.1177/1049732315617444

Martens, M., Roll, O., & Elliott, R. (2017). Testing the technology readiness and acceptance model for mobile payments across Germany and South Africa. *International Journal of Innovation and Technology Management*, *14*(06), 1750033.

Marvasti, A. (2018). Research methods. *The Cambridge Handbook of Social Problems*, *1*(3), 23–37. https://doi.org/10.1017/9781108656184.003

Masood, T., & Sonntag, P. (2020). Industry 4.0: Adoption challenges and benefits for SMEs. *Computers in Industry*, *121*, 103261. https://doi.org/10.1016/j.compind.2020.103261

McFarland, D. J., & Hamilton, D. (2006). Adding contextual specificity to the technology acceptance model. *Computers in Human Behavior*, *22*(3), 427–447. https://doi.org/10.1016/j.chb.2004.09.009

Mehmood, K. K., & Saeed, S. (2021). Exploring the nexus between Empowering Leadership and Work Engagement through Employee Resilience during times of Covid 19. *Sustainable Business and Society in Emerging Economies*, *3*(3), 375–387.

Meindl, B., Ayala, N. F., Mendonça, J., & Frank, A. G. (2021). The four smarts of Industry 4.0: Evolution of ten years of research and future perspectives. *Technological Forecasting and Social Change*, *168*(March). https://doi.org/10.1016/j.techfore.2021.120784

Mensah, I. K. (2020). Impact of performance expectancy, effort expectancy, and citizen trust on the adoption of electronic voting system in Ghana. *International Journal of Electronic Government Research (IJEGR)*, *16*(2), 19–32.

Mick, D. G., & Fournier, S. (1998). Paradoxes of Technology : Consumer. *Journal of Consumer Research*, *25*(September), 123–143.

Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *International Journal of Logistics Research and Applications*, *13*(1), 13–39. https://doi.org/10.1080/13675560902736537

Miragliotta, G., Sianesi, A., Convertini, E., & Distante, R. (2018). *Data driven management in Industry 4.0: a method to measure Data Productivity*. *51*(11), 19–24. https://doi.org/10.1016/j.ifacol.2018.08.228

Mohajan, H. K. (2020). The Second Industrial Revolution has Brought Modern Social and Economic Developments. In *Journal of Social Sciences and Humanities* (Vol. 6, Issue 1).

Mourtzis, D. (2022). Introduction to cloud technology and Industry 4.0. *Design and Operation of Production Networks for Mass Personalization in the Era of Cloud Technology*, 1–12.

https://doi.org/10.1016/b978-0-12-823657-4.00011-7

Mühl, J. K. (2014). Research methodology. In *Contributions to Management Science*. https://doi.org/10.1007/978-3-319-04069-1_4

Mukwawaya, G. F., Emwanu, B., & Mdakane, S. (2018). Assessing the readiness of South Africa for Industry 4.0 - Analysis of government policy, skills and education. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, *2018*(NOV), 1587–1604.

Müller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability (Switzerland)*, *10*(1). https://doi.org/10.3390/su10010247

Musyaffi, A. M., Mulyani, S., & Suraida, I. (2021). Lack of readiness of digital banking channel acceptance: Study on TAM 3 and technology readiness. *Academy of Strategic Management Journal*, *20*(Special Issue 4), 1–18.

Nagy, J., Ol, J., & Erdei, E. (n.d.). The Role and Impact of Industry 4 . 0 and the Internet of Things on the Business Strategy of the Value Chain — The Case of Hungary. *Journal of Manufacturing Technology Management*. https://doi.org/10.3390/su10103491

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018

Nantee, N., & Sureeyatanapas, P. (2021). The impact of Logistics 4.0 on corporate sustainability: a performance assessment of automated warehouse operations. *Benchmarking*, *28*(10), 2865–2895. https://doi.org/10.1108/BIJ-11-2020-0583

Nascimento, D. L. M., Alencastro, V., Quelhas, O. L. G., Caiado, R. G. G., Garza-Reyes, J. A., Lona, L. R., & Tortorella, G. (2019). Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal. *Journal of Manufacturing Technology Management*, *30*(3), 607–627. https://doi.org/10.1108/JMTM-03-2018-0071

Nasiri, M., Ukko, J., Saunila, M., & Rantala, T. (2020). Managing the digital supply chain: The role of smart technologies. *Technovation*, *96–97*(March), 102121. https://doi.org/10.1016/j.technovation.2020.102121

Nederveen, A. A. J., Konings, J. W., & Stoop, J. A. (2003). Globalization, international transport and the global environment: Technological innovation, policy making and the reduction of transportation emissions. *Transportation Planning and Technology*, *26*(1), 41–67. https://doi.org/10.1080/03081060309908

Nguyen, T., ZHOU, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers and Operations Research*, *98*, 254–264. https://doi.org/10.1016/j.cor.2017.07.004

Norouzi, N. (2021). Post-COVID-19 and globalization of oil and natural gas trade: Challenges, opportunities, lessons, regulations, and strategies. *International Journal of Energy Research*, *45*(10), 14338–14356. https://doi.org/10.1002/er.6762

Nurdiana, N., & Pandin, M. G. R. (2021). Industrial Revolution: A History of Industrial Revolution and Its Influence in Manufacturing Companies. *Historia Madania: Jurnal Ilmu Sejarah*, *5*(2), 137–151. https://doi.org/10.15575/hm.v5i2.13063

Ofori-Amanfo, J., Akonsi, S. W., & Agyapong, G. K. Q. (2022). The impact of organisational capabilities on the performance of small- and medium-sized enterprises (SMEs). *European Business Review*. https://doi.org/10.1108/EBR-06-2021-0139

Okot-Uma, R. W., & Caffrey, L. (2000). *Trusted Services and Public Key Infrastructure (PKI)*. Commonwealth Secretariat.

Olsen, T. L., & Tomlin, B. (2020). Industry 4.0: Opportunities and challenges for operations management. *Manufacturing and Service Operations Management*, *22*(1), 113–122. https://doi.org/10.1287/msom.2019.0796

Omar, Q., Yap, C. S., Ho, P. L., & Keling, W. (2021). Can technology readiness predict farmers' adoption intention of the e-AgriFinance app? *Journal of Agribusiness in Developing and Emerging Economies*. https://doi.org/10.1108/JADEE-04-2021-0090

Omotayo, F. O., & Adekunle, O. A. (2021). Adoption and use of electronic voting system as an option towards credible elections in Nigeria. *International Journal of Development Issues*, *20*(1), 38–61. https://doi.org/10.1108/IJDI-03-2020-0035

Onileowo, T. T., Muharam, F. M., Ramily, M. K., & Khatib, S. F. A. (2021). *The Nexus between Innovation and Business Competitive Advantage : A Conceptual Study*. *9*(3), 352–361. https://doi.org/10.13189/ujaf.2021.090309

Otchere, S. K., Nyamewaa, E. B., & Hammond, F. (2022). Big Data Characteristics and Innovation Performance in Ghanaian Manufacturing Firms: The Role of the Big Data Team? *Open Access Library Journal*, *9*(2), 1–13.

Owusu, A., Akpe-Doe, C. E., & Taana, I. H. (2022). Assessing the effectiveness of e-government services in Ghana: A case of the registrar general's department. *International Journal of Electronic Government Research (IJEGR)*, *18*(1), 1-23. https://doi.org/10.4018/IJEGR.289827

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. *Journal of Intelligent Manufacturing*, *31*(1), 127–182. https://doi.org/10.1007/s10845-018-1433-8

Pai, R. R., & Alathur, S. (2019). Determinants of individuals' intention to use mobile health: insights from India. *Transforming Government: People, Process and Policy*, *13*(3–4), 306–326. https://doi.org/10.1108/TG-04-2019-0027

Paliy, O., & Shankar, V. (2016). Application of multivariate statistical techniques in microbial ecology. *Molecular Ecology*, *25*(5), 1032–1057. https://doi.org/10.1111/mec.13536

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Parasuraman, Ananthanarayanan, & Colby, C. L. (2001). *Techno-ready marketing: How and why your customers adopt technology*. Free Press New York.

Park, J. S., Ha, S., & Jeong, S. W. (2021). Consumer acceptance of self-service technologies in fashion retail stores. *Journal of Fashion Marketing and Management*, *25*(2), 371–388.

https://doi.org/10.1108/JFMM-09-2019-0221

Park, Y. S., Konge, L., & Artino, A. R. (2020). The Positivism Paradigm of Research. *Academic Medicine*, *95*, 690–694. https://doi.org/10.1097/ACM.0000000000003093

Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. *Procedia Manufacturing*, *13*, 1206–1214. https://doi.org/10.1016/j.promfg.2017.09.032

Pfeiffer, S. (2016). Robots, industry 4.0 and humans, or why assembly work is more than routine work. *Societies*, *6*(2). https://doi.org/10.3390/soc6020016

Pfeiffer, S. (2017). The Vision of "Industrie 4.0" in the Making—a Case of Future Told, Tamed, and Traded. *NanoEthics*, *11*(1), 107–121. https://doi.org/10.1007/s11569-016-0280-3

Phillips, R. J. (2000). Digital technology and institutional change from the gilded age to modern times: The impact of the telegraph and the internet. *Journal of Economic Issues*, *34*(2), 267–289. https://doi.org/10.1080/00213624.2000.11506266

Piccarozzi, M., Aquilani, B., & Gatti, C. (2018). Industry 4.0 in management studies: A systematic literature review. *Sustainability (Switzerland)*, *10*(10), 1–24. https://doi.org/10.3390/su10103821

Pivoto, D. G. S., de Almeida, L. F. F., da Rosa Righi, R., Rodrigues, J. J. P. C., Lugli, A. B., & Alberti, A. M. (2021). Cyber-physical systems architectures for industrial internet of things applications in Industry 4.0: A literature review. *Journal of Manufacturing Systems*, *58*(PA), 176–192. https://doi.org/10.1016/j.jmsy.2020.11.017

Plasch, M., Pfoser, S., Gerschberger, M., Gattringer, R., & Schauer, O. (2021). Why Collaborate in a Physical Internet Network?—Motives and Success Factors. *Journal of Business Logistics*, *42*(1), 120–143. https://doi.org/10.1111/jbl.12260

Qin, J., Liu, Y., & Grosvenor, R. (2016). A Categorical Framework of Manufacturing for Industry 4.0 and beyond. *Procedia CIRP*, *52*, 173–178. https://doi.org/10.1016/j.procir.2016.08.005

Queiroz, M. M., Pereira, S. C. F., Telles, R., & Machado, M. C. (2019). Industry 4.0 and digital supply chain capabilities: A framework for understanding digitalisation challenges and opportunities. *Benchmarking*, *28*(5), 1761–1782. https://doi.org/10.1108/BIJ-12-2018-0435

Rabianski S., J. (2003). *68Bfe6580297494936F0126Ed5D3D017.Pdf*.

Rafdinal, W., & Senalasari, W. (2021). Predicting the adoption of mobile payment applications during the COVID-19 pandemic. *International Journal of Bank Marketing*, *39*(6), 984–1002. https://doi.org/10.1108/IJBM-10-2020-0532

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics*, *224*(November 2019). https://doi.org/10.1016/j.ijpe.2019.107546

Ralston, P., & Blackhurst, J. (2020). Industry 4.0 and resilience in the supply chain: a driver of capability enhancement or capability loss? *International Journal of Production Research*, *58*(16). https://doi.org/10.1080/00207543.2020.1736724

Raman, P., & Aashish, K. (2021). Gym users: an enabler in creating an acceptance of sports and fitness wearable devices in India. *International Journal of Sports Marketing and*

Sponsorship. https://doi.org/10.1108/IJSMS-08-2021-0168

Raman, R., Sairam, B., Veena, G., Vachharajani, H., & Nedungadi, P. (2021). Adoption of online proctored examinations by university students during COVID-19: Innovation diffusion study. *Education and Information Technologies*, *26*(6), 7339–7358. https://doi.org/10.1007/s10639-021-10581-5

Ras, E., Wild, F., Stahl, C., & Baudet, A. (2017). Bridging the skills gap of workers in industry 4.0 by human performance augmentation tools - Challenges and roadmap. *ACM International Conference Proceeding Series*, *Part F1285*, 428–432. https://doi.org/10.1145/3056540.3076192

Rashid, A., & Chaturvedi, A. (2019). Cloud Computing Characteristics and Services A Brief Review. *International Journal of Computer Sciences and Engineering*, *7*(2), 421–426. https://doi.org/10.26438/ijcse/v7i2.421426

Rasoolimanesh, S. M., Wang, M., Mikulić, J., & Kunasekaran, P. (2021). A critical review of moderation analysis in tourism and hospitality research toward robust guidelines. *International Journal of Contemporary Hospitality Management*, *33*(12), 4311–4333. https://doi.org/10.1108/IJCHM-02-2021-0272

Razali, N. A. M., Muhamad, W. N. W., Ishak, K. K., Saad, N. J. A. M., Wook, M., & Ramli, S. (2021). Secure Blockchain-Based Data-Sharing Model and Adoption among Intelligence Communities. *IAENG International Journal of Computer Science*, *48*(1).

Rejeb, A., Keogh, J. G., & Treiblmaier, H. (2019). Leveraging the Internet of Things and blockchain technology in Supply Chain Management. *Future Internet*, *11*(7), 1–22. https://doi.org/10.3390/fi11070161

Richard P. Bagozzi, Y. Y. and L. W. P. (2013). Bogazzi_Assesing Construct Validity in Organiational Research. *Administrative Science Quarterly*, *36*(3), 421–458. http://www.jstor.org/stable/2393203

Rigdon, E. E. (2016). Choosing PLS path modeling as analytical method in European management research: A realist perspective. *European Management Journal*, *34*(6), 598–605. https://doi.org/10.1016/j.emj.2016.05.006

Riley, R. D., Ensor, J., Snell, K. I. E., Harrell, F. E., Martin, G. P., Reitsma, J. B., Moons, K. G. M., Collins, G., & Van Smeden, M. (2020). Calculating the sample size required for developing a clinical prediction model. *The BMJ*, *368*. https://doi.org/10.1136/bmj.m441

Robert, S. R. A. W. K. (n.d.). *Transitioning to a Smart Industry with Open Innovation*.

Roblek, V., Meško, M., & Krapež, A. (2016). A Complex View of Industry 4.0. *SAGE Open*, *6*(2). https://doi.org/10.1177/2158244016653987

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management and Data Systems*, *121*(12), 2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082

Rogers, E. M. (2003). Diffusion networks. *Networks in the Knowledge Economy*, 130–179.

Rojas-Méndez, J. I., Parasuraman, A., & Papadopoulos, N. (2017). Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation. *Marketing Intelligence and Planning*, *35*(1), 18–39. https://doi.org/10.1108/MIP-08-2015-0163

Rüßmann, M. et al. (2015). Future of Productivity and Growth in Manufacturing. *Boston Consulting*, *April*. https://doi.org/10.1007/s12599-014-0334-4

Russo, D., & Stol, K. J. (2021). PLS-SEM for software engineering research: An introduction and survey. *ACM Computing Surveys*, *54*(4). https://doi.org/10.1145/3447580

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). *Blockchain technology and its relationships to sustainable supply chain management*. *7543*. https://doi.org/10.1080/00207543.2018.1533261

Sahoo, S. (2021). Big data analytics in manufacturing: a bibliometric analysis of research in the field of business management. *International Journal of Production Research*, *0*(0), 1–29. https://doi.org/10.1080/00207543.2021.1919333

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology and Marketing*, *39*(5), 1035–1064. https://doi.org/10.1002/mar.21640

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research*, *69*(10), 3998–4010. https://doi.org/10.1016/j.jbusres.2016.06.007

Sarstedt, M., Hair Jr, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ)*, *27*(3), 197–211.

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115. https://doi.org/10.1016/j.jfbs.2014.01.002

Saste, A., & Files, A. W. L. (2017). Predicting Demographic Attributes from Web. *International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*, 381–386.

Savin-Baden, M., & Major, C. M. (2013). Qualitative Research: An Essential Guide to Theory and Practice. *Routledge*, 96–97.

Schlick, J., Stephan, P., Loskyll, M., & Lappe, D. (2017). Industrie 4.0 in der praktischen Anwendung. In *Handbuch Industrie 4.0 Bd. 2* (pp. 3–29). Springer.

Schumacher, A., Nemeth, T., & Sihn, W. (2019). Roadmapping towards industrial digitalization based on an Industry 4.0 maturity model for manufacturing enterprises. *Procedia CIRP*, *79*, 409–414. https://doi.org/10.1016/j.procir.2019.02.110

Schwab, K. (2016). The Fourth Industrial Revolution: what it means and how to respond. *World Economic Forum*, 1–7.

Shamout, M., Ben-Abdallah, R., Alshurideh, M., Alzoubi, H., Al Kurdi, B., & Hamadneh, S. (2022). A conceptual model for the adoption of autonomous robots in supply chain and logistics industry. *Uncertain Supply Chain Management*, *10*(2), 577–592. https://doi.org/10.5267/j.uscm.2021.11.006

Shareef, M. A., Kumar, V., Kumar, U., & Hasin, A. A. (2009). Diffusion of innovation and capability theory in the context of e-government. *Handbook of Research on Contemporary Theoretical Models in Information Systems*, 193–211. https://doi.org/10.4018/978-1-60566-659-4.ch011

Sharma, M., Gupta, R., Acharya, P., & Jain, K. (2021). Systems approach to cloud computing adoption in an emerging economy. *International Journal of Emerging Markets*.

https://doi.org/10.1108/IJOEM-04-2021-0501

Sheel, A., & Nath, V. (2019). Effect of blockchain technology adoption on supply chain adaptability, agility, alignment and performance. *Management Research Review*, *42*(12), 1353–1374. https://doi.org/10.1108/MRR-12-2018-0490

Shi, Z., Xie, Y., Xue, W., Chen, Y., Fu, L., & Xu, X. (2020). Smart factory in Industry 4.0. *Systems Research and Behavioral Science*, *37*(4), 607–617. https://doi.org/10.1002/sres.2704

Shiau, W. L., Sarstedt, M., & Hair, J. F. (2019). Internet research using partial least squares structural equation modeling (PLS-SEM). *Internet Research*, *29*(3), 398–406. https://doi.org/10.1108/IntR-10-2018-0447

Shrouf, F., Ordieres, J., & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. *IEEE International Conference on Industrial Engineering and Engineering Management*, *2015-Janua*, 697–701. https://doi.org/10.1109/IEEM.2014.7058728

Siderska, J., & Jadaan, K. S. (2018). *Cloud manufacturing : a service-oriented manufacturing paradigm . A review paper*. *10*(1). https://doi.org/10.1515/emj-2018-0002

Singh, S., & Aggarwal, Y. (2022). In search of a consensus definition of innovation: a qualitative synthesis of 208 definitions using grounded theory approach. *Innovation: The European Journal of Social Science Research*, *35*(2), 177–195. https://doi.org/10.1080/13511610.2021.1925526

Sinha, M., Majra, H., Hutchins, J., & Saxena, R. (2019). Mobile payments in India: the privacy factor. *International Journal of Bank Marketing*, *37*(1), 192–209. https://doi.org/10.1108/IJBM-05-2017-0099

Son, T. (2010). *Section I Section I* (Issue Pica 1997).

Srivastava, D. K., Kumar, V., Ekren, B. Y., Upadhyay, A., Tyagi, M., & Kumari, A. (2022). Adopting Industry 4.0 by leveraging organisational factors. *Technological Forecasting and Social Change*, *176*(February 2021), 121439. https://doi.org/10.1016/j.techfore.2021.121439

Stănescu, D. F., & Romașcanu, M. C. (2022). an Explorative Study on Users' Motivation and Adoption of Wearables Technologies Using the Technology Acceptance Model (Tam). *Psychological Applications and Trends 2022*, *5*, 381–385. https://doi.org/10.36315/2022inpact087

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly: Management Information Systems*, *13*(2), 147–165. https://doi.org/10.2307/248922

Sung, T. K. (2018). Industry 4.0: A Korea perspective. *Technological Forecasting and Social Change*, *132*(October 2017), 40–45. https://doi.org/10.1016/j.techfore.2017.11.005

Szirmai, A. (2012). Industrialisation as an engine of growth in developing countries, 1950-2005. *Structural Change and Economic Dynamics*, *23*(4), 406–420. https://doi.org/10.1016/j.strueco.2011.01.005

Taalbi, J. (2019). Origins and pathways of innovation in the third industrial revolution. *Industrial and Corporate Change*, *28*(5), 1125–1148. https://doi.org/10.1093/icc/dty053

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education*, *48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Taghipour, M., & Mahboobi, M. (2020). Application of Cloud Computing in System Management in Order to Control the Process. *Management*, *3*(3), 35–55. https://doi.org/10.31058/j.mana.2020.33003

Taherdoost, H. (2021). Different Types of Data Analysis ; Data Analysis Methods and Techniques in Research Projects. *International Journal of Academic Research in Management (IJARM)*, *9*(May 2020), 10.

Tang, C. S., & Veelenturf, L. P. (2019). The strategic role of logistics in the industry 4.0 era. *Transportation Research Part E: Logistics and Transportation Review*, *129*(June), 1–11. https://doi.org/10.1016/j.tre.2019.06.004

Tangahu, W., Rahmat, A., & Husain, R. (2021). Novateur Publications International Journal of Innovations in Engineering Research and Technology [Ijiert] Modern Education in Revolution 4.0. *Website: Ijiert.Org VOLUME*, *8*.

Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. *Engineering*, *5*(4), 653–661. https://doi.org/10.1016/j.eng.2019.01.014

Terziyan, V., Gryshko, S., & Golovianko, M. (2018). Patented intelligence: Cloning human decision models for Industry 4.0. *Journal of Manufacturing Systems*, *48*(April), 204–217. https://doi.org/10.1016/j.jmsy.2018.04.019

Thames, L., & Schaefer, D. (2017). *Industry 4.0: An Overview of Key Benefits, Technologies, and Challenges* (Issue May). https://doi.org/10.1007/978-3-319-50660-9_1

Theorin, A., Bengtsson, K., Provost, J., Lieder, M., Johnsson, C., Lundholm, T., & Lennartson, B. (2017). An event-driven manufacturing information system architecture for Industry 4.0. *International Journal of Production Research*, *55*(5), 1297–1311. https://doi.org/10.1080/00207543.2016.1201604

Thomas, K. (1970). Logic of Discovery or Psychology of Research. *I. Lakatos & A. MuSGRAVE, Oe*, 1–23.

Tian, M., Huo, B., Park, Y., & Kang, M. (2021). Enablers of supply chain integration: a technology-organization-environment view. *Industrial Management and Data Systems*, *121*(8), 1871–1895. https://doi.org/10.1108/IMDS-09-2020-0564

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. *Mathematical Problems in Engineering*, *2021*(Ml). https://doi.org/10.1155/2021/1476043

Tiwari, A. (2013). Analysis Of Supply chain management in Cloud Computing. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, *3*, 2278–3075.

Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications*, *5*, 147–158. https://doi.org/10.17348/era.5.0.147-158

Tortorella, G. L., Giglio, R., & van Dun, D. H. (2019). Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement.

International Journal of Operations and Production Management, *39*, 860–886. https://doi.org/10.1108/IJOPM-01-2019-0005

Tsochev, G., & Sharabov, M. (2021). Artificial intelligence methods used in industry 4.0 in particular industrial control systems. *AIP Conference Proceedings*, *2333*(March), 0–7. https://doi.org/10.1063/5.0041610

Urbach, N., & Ahlemann, F. (2010). Structural Equation Modeling in Information Systems Research Using Partial Least Squares. *Journal of Information Technology Theory and Application (JITTA)*, *11*(2), 5–40. http://aisel.aisnet.org/jitta/vol11/iss2/2

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0 - A Glimpse. *Procedia Manufacturing*, *20*, 233–238. https://doi.org/10.1016/j.promfg.2018.02.034

Van Der Vorst, J., Beulens, A., & Van Beek, P. (2005). Innovations in logistics and ICT in food supply chain networks. *Innovation in Agri-Food Systems: Product Quality and Consumer*, *May 2014*, 245–290. https://doi.org/10.3920/978-90-8686-666-3

Vickers, C., & Ziebarth, N. L. (2019). Lessons for Today from Past Periods of Rapid Technological Change. *DESA Working Paper*, *2019/DWP*(158), 1–38. https://www.un.org/esa/desa/papers/2019/wp158_2019.pdf

Vinitha, K., Ambrose Prabhu, R., Bhaskar, R., & Hariharan, R. (2020). Review on industrial mathematics and materials at Industry 1.0 to Industry 4.0. *Materials Today: Proceedings*, *33*, 3956–3960. https://doi.org/10.1016/j.matpr.2020.06.331

Viriyasitavat, W., Anuphaptrirong, T., & Hoonsopon, D. (2019). When blockchain meets Internet of Things: Characteristics, challenges, and business opportunities. *Journal of*

Industrial Information Integration, *15*(February), 21–28. https://doi.org/10.1016/j.jii.2019.05.002

Viswanathan, M., Umashankar, N., Sreekumar, A., & Goreczny, A. (2021). Marketplace Literacy as a Pathway to a Better World: Evidence from Field Experiments in Low-Access Subsistence Marketplaces. *Journal of Marketing*, *85*(3), 113–129. https://doi.org/10.1177/0022242921998385

Wada, K. (2020). *The Evolution of the Toyota Production System*. Springer.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77–84. https://doi.org/10.1111/jbl.12010

Wang, B. (2018). The Future of Manufacturing: A New Perspective. *Engineering*, *4*(5), 722–728. https://doi.org/10.1016/j.eng.2018.07.020

Wang, H., Zheng, Z., Xie, S., Dai, H. N., & Chen, X. (2018). Blockchain challenges and opportunities: a survey. *International Journal of Web and Grid Services*, *14*(4), 352. https://doi.org/10.1504/ijwgs.2018.10016848

Wang, J., Lim, M. K., Wang, C., & Tseng, M. L. (2021). The evolution of the Internet of Things (IoT) over the past 20 years. *Computers and Industrial Engineering*, *155*(June 2020), 107174. https://doi.org/10.1016/j.cie.2021.107174

Wang, L., Törngren, M., & Onori, M. (2015). Current status and advancement of cyber-physical systems in manufacturing. *Journal of Manufacturing Systems*, *37*, 517–527. https://doi.org/10.1016/j.jmsy.2015.04.008

Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations. *Chest*, *158*(1), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012

WRIGLEY, E. A. (1962). The Supply of Raw Materials in the Industrial Revolution. *The Economic History Review*, *15*(1), 1–16. https://doi.org/10.1111/j.1468-0289.1962.tb02224.x

Xu, L. Da, & Duan, L. (2019). Big data for cyber physical systems in industry 4.0: a survey. *Enterprise Information Systems*, *13*(2), 148–169. https://doi.org/10.1080/17517575.2018.1442934

Xu, L. Da, Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. *International Journal of Production Research*, *56*(8), 2941–2962. https://doi.org/10.1080/00207543.2018.1444806

Yang, F., & Gu, S. (2021). Industry 4.0, a revolution that requires technology and national strategies. *Complex & Intelligent Systems*, *7*(3), 1311–1325. https://doi.org/10.1007/s40747-020-00267-9

Yin, Y., Stecke, K. E., & Li, D. (2018). The evolution of production systems from Industry 2.0 through Industry 4.0. *International Journal of Production Research*, *56*(1–2), 848–861. https://doi.org/10.1080/00207543.2017.1403664

Yu, Z., & Wang, T. N. (2012). Research on the visualization of equipment support based on the technology of Internet of Things. *Proceedings of the 2012 2nd International Conference on Instrumentation and Measurement, Computer, Communication and Control, IMCCC 2012*, 1352–1357. https://doi.org/10.1109/IMCCC.2012.318

Zailani, S., Iranmanesh, M., Nikbin, D., & Beng, J. K. C. (2015). Determinants of RFID

Adoption in Malaysia's Healthcare Industry: Occupational Level as a Moderator. *Journal of Medical Systems*, *39*(1). https://doi.org/10.1007/s10916-014-0172-4

Zekhnini, K., Cherrafi, A., Bouhaddou, I., Benghabrit, Y., & Garza-Reyes, J. A. (2021). Supply chain management 4.0: a literature review and research framework. *Benchmarking*, *28*(2), 465–501. https://doi.org/10.1108/BIJ-04-2020-0156

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering*, *3*(5), 616–630. https://doi.org/10.1016/J.ENG.2017.05.015

Zhou, K., Liu, T., & Zhou, L. (2016). Industry 4.0: Towards future industrial opportunities and challenges. *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery, FSKD 2015*, 2147–2152. https://doi.org/10.1109/FSKD.2015.7382284

Žukauskas, P., Vveinhardt, J., & Andriukaitienė, R. (2018). Philosophy and paradigm of scientific research. *Management Culture and Corporate Social Responsibility*, *121*.

APPENDIX A

MONICA BAFFOWAA

UNIVERSITY OF GHANA BUSINESS SCHOOL

DEPARTMENT OF OPERATIONS AND MANAGEMENT INFORMATION SYSTEMS

QUESTIONNAIRE

Dear Respondent,

I am a student at the University of Ghana Business School pursuing an MPhil in Management Information Systems. As part of the requirement for the award of this degree, I am undertaking research on the topic: *The Adoption of Industry 4.0 Technologies among Ghanaian Manufacturing Firms: A Technology Readiness and Acceptance Model Perspective*. I kindly seek your assistance and cooperation in completing this questionnaire. Any information provided will be used for the purpose of this research only. You are assured that all the information provided will be treated with the utmost confidentiality. It would take roughly 20 minutes to get the questionnaire completed.

SECTION A: DEMOGRAPHIC FACTORS (Kindly select the appropriate box)

1. Gender

Male [ ]   Female [ ]

2. Age of respondent

25 – 34years [ ] 35 – 44years [ ] 45years and above [ ]

3. Highest Educational Qualification

Diploma [ ]   HND [ ]   Degree [ ]   Masters and Above [ ]

4. Department of the respondent in the organization

Operations/Production [ ] IT [ ] Procurement [ ] Supply Chain Management [ ] Logistics [ ]

5. Number of years worked in this organization

1 – 5 years [ ] 6 – 10 years [ ] More than 10 years [ ]

6. Please tick the type of industry in which your firm is found

a. Food and beverage	[ ]	b. Pharmaceutical	[ ]
c. Textiles and garment	[ ]	d. Chemical and Cement	[ ]
e. Aluminum Smelting	[ ]	f. Mining	[ ]

SECTION B: Awareness of the concept of Industry 4.0 and its basics

Kindly answer by ticking the appropriate check box provided

7. Are you familiar with the term, Industry 4.0?

Yes [ ] No [ ]

8. Which of the following technologies do you associate with Industry 4.0? (Please tick all that apply)

a. Internet of Things	[ ]	b. Blockchain	[ ]
c. Big Data	[ ]	d. Cloud Computing	[ ]
e. Additive Manufacturing	[ ]	f. Artificial Intelligence	[ ]

Please indicate the extent to which you are aware of the under listed Industry 4.0 technologies using a Likert Scale of 1-5 where, 1= Highly unaware, 2= Unaware, 3=Neutral, 4=Aware, 5=Highly Aware.

INDUSTRY 4.0 TECHNOLOGIES	**1**	**2**	**3**	**4**	**5**
Internet of things					

Blockchain					
Big Data					
Cloud Computing					
Additive Manufacturing					
Artificial Intelligence					

Please indicate the extent to which your firm has adopted any of the under listed Industry 4.0 technologies using a Likert Scale of 1-5 where, 1= Not adopted, 2= Adoption process initiated, 3=Don't Know, 4=Partially adopted, 5=Fully adopted.

ADOPTED INDUSTRY 4.0 TECHNOLOGIES	**1**	**2**	**3**	**4**	**5**
Internet of things					
Blockchain					
Big Data					
Cloud Computing					
Additive Manufacturing					
Artificial Intelligence					

SECTION C Awareness and Readiness

Please indicate the extent to which you agree or disagree with the following statements using a Likert Scale of 1-5 where, 1= Strongly disagree, 2= Disagree, 3=Neutral, 4=Agree, 5=Strongly agree

	STATEMENTS	**1**	**2**	**3**	**4**	**5**
A	**OPTIMISM**					
OPT 1	Industry 4.0 gives more control over a firm's operations					
OPT 2	We prefer to use the most advanced technology available for manufacturing.					
OPT 3	Industry 4.0 technologies make the production processes convenient					
OPT 4	Industry 4.0 technologies give more freedom of mobility					
OPT 5	Technologies in manufacturing processes make the occupation efficient					

OPT 6	Using technologies is preferred because it does not limit regular business hours.					
B	**INNOVATIVENESS**					
INN 1	We usually figure out new high–technology products and services without help from others.					
INN 2	We keep up with the latest technological developments in our area of manufacturing					
INN 3	We are among the first to acquire new technology when it appears.					
INN 4	Other people come to us for advice on new technology.					
INN 5	We enjoy the challenge of figuring out high-technology gadgets to improve our operations.					
C	**DISCOMFORT**					
DIS 1	We have a feeling Industry 4.0 technologies may fail us					
DIS 2	There is no such thing as a manual for Industry 4.0 technologies					
DIS 3	The technical support lines of Industry 4.0 technology suppliers are not helpful					
DIS 4	The Industry 4.0 technologies make it easier for stakeholders to spy on our activities.					
DIS 5	Sometimes, we think that Industry 4.0 technologies are not designed to be user-friendly					
D	**INSECURITY**					
INS 1	Using Industry 4.0 technologies lowers the quality of relationships by reducing personal interaction					
INS 2	We are worried that in using Industry 4.0 technologies, the information we send over the internet can be accessed by other people.					
INS 3	We do not feel confident doing business with Industry 4.0 technologies.					
INS 4	We do not consider it safe to do any kind of financial business using Industry 4.0 technologies					
INS 5	When we provide information over Industry 4.0 technologies, we are never sure it really gets to the right place or person.					
E	**AWARENESS**					
AWS 1	We are aware of Industry 4.0 technologies					
AWS 2	We have a great deal of knowledge about Industry 4.0 technologies					
AWS 3	Using Industry 4.0 technologies will help improve decision-making with data-based tools					
AWS 4	We are knowledgeable about the capabilities of Industry 4.0 in manufacturing					

AWS 5	Using Industry 4.0 technologies will improve our manufacturing operations					
F	**PERCEIVED EASE TO ADOPT INDUSTRY 4.0**					
PE 1	The features of Industry 4.0 technologies are easy to use					
PE 2	Industry 4.0 technologies are understandable and clear					
PE 3	Using Industry 4.0 technologies in manufacturing is easier than the traditional process.					
PE 4	Learning to use Industry 4.0 in the production process is easy					
PE 5	It would be easy to become skillful at using Industry 4.0					
G	**PERCEIVED USEFULNESS**					
PU 1	Using Industry 4.0 would help improve performance					
PU 2	Industry 4.0 will help improve productivity					
PU 3	Industry 4.0 will help improve production effectiveness					
PU 4	Industry 4.0 will help minimize delays in production					
PU 5	Industry 4.0 enables quick accomplishment of tasks					
H	**INTENTION TO ADOPT**					
ITA 1	It is desirable to use Industry 4.0					
ITA 2	Industry 4.0 technologies are good for manufacturing					
ITA 3	Using Industry 4.0 is favorable within the context of manufacturing					
ITA 4	Using Industry 4.0 is a great idea towards enhancing our manufacturing process					
ITA 5	We will use Industry 4.0 technologies in our operations					

Please indicate the extent to which you agree or disagree with the following statements using a Likert Scale of 1-5 where, 1= Strongly disagree, 2= Disagree, 3=Neutral, 4=Agree, 5=Strongly agree

SUPPORT RESOURCE	**1**	**2**	**3**	**4**	**5**
Adequate technological infrastructure is necessary for Industry 4.0 adoption					
We have a competent IT support team to help in times of crisis					
We have the capacity to acquire new equipment for the adoption of Industry 4.0 technologies					

We have the financial resources to put in place the needed infrastructure for the adoption of Industry 4.0 technologies					
We have sufficient internet access and speed for operating with Industry 4.0					

APPENDIX B

UNIVERSITY OF GHANA
BUSINESS SCHOOL
DEPARTMENT OF OPERATIONS AND MANAGEMENT INFORMATION SYSTEMS

UGBS
University of Ghana Business School

Ref. No.: INTRO/OMIS/0822/25

30th September, 2022

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

LETTER OF INTRODUCTION – MONICA BAFFOWAA – 10875307

I write to kindly introduce to you the above-named second year MPhil student from the Operations and Management Information Systems department, University of Ghana Business School.

Monica is working on a dissertation titled **'The Adoption of Industry 4.0 Technologies Among Ghanaian Manufacturing Firms; A Technology Readiness and Acceptance Model Perspective.'.**

The thesis is being supervised by Dr. Joshua Ofori-Amanfo, a Lecturer in the department.

Monica intends to use your organization to enable him gather data on the list of enterprises and their respective contact numbers.

I would be very grateful if you could provide the necessary information and assistance for the successful completion of this thesis.

Thank you for your anticipated co-operation.

Yours faithfully,

Prof. Anthony Afful-Dadzie
Head of Department

COLLEGE OF HUMANITIES
P. O. Box LG 78, Legon, Accra, Ghana.
• Telephone: +233 (0) 303 963 755 • Email: omis@ug.edu.gh • Website: ugbs.ug.edu.gh