FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

STUDYING THE EXECUTIVE PERCEPTION OF INVESTMENT IN INTELLIGENT SYSTEMS AND THE EFFECT ON FIRM PERFORMANCE

A dissertation submitted in partial fulfillment of the

Requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

by

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2022

To: Dean William Hardin
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This dissertation, written by Noel R. Wijesinha and entitled Studying the Executive Perception of Investment in Intelligent Systems and the Effect on Firm Performance, having been approved in respect of style and intellectual content, is referred to you for judgement.

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

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Date of Defense: June 2, 2022

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Florida International University, 2022

DEDICATION

I dedicate this dissertation to my wife, Nadira Wijesinha, and my two daughters, Avaya Wijesinha and Mahalia Wijesinha, who have been supportive and patient during my doctoral journey. Additionally, I dedicate this dissertation to my father, Ranjit Wijesinha, my mother, Nalini Wijesinha, and my brother Anthony Wijesinha who have been supportive during my doctoral journey. Finally, I would like to dedicate this dissertation to my friend, the late Professor Hosea Perry (Winona State University), who always encouraged me to complete my doctoral degree.

ACKNOWLEDGMENTS

I want to thank all the dissertation committee members for their support and feedback on my dissertation. Additionally, I would like to thank Dr. Manjul Gupta for all the time, effort, and guidance as the committee chair and major professor during my dissertation process. Furthermore, I would like to thank Dr. Amin Shoja, Dr. Fred Walumbwa, and Dr. Miguel Aguirre-Urreta for all the guidance and encouragement during my dissertation proposal submission. Similarly, I would like to thank my DBA cohort 2 classmates, Clay Dickinson, David Freer, Fred White, Hernan Morales, Juan Rey, and Mauro Echeverri, for the feedback given to improve my dissertation. Finally, I would like to thank Dr. George Marakas for his leadership and guidance, the entire FIU DBA faculty, and Ms. Yasemin Shirazi for the guidance and support throughout my DBA program to develop my knowledge and skills to become a practitioner-scholar.

ABSTRACT OF THE DISSERTATION

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Florida International University, 2022

Miami, Florida

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This research study examines the relationship between investment in intelligent systems resources and capabilities (based on artificial intelligence and machine learning algorithms) and the effect on company performance. Despite existing research on the benefits of adopting intelligent systems, companies have been slow to adopt these technologies. For example, there is a lack of research on intelligent systems use-cases that will increase firm performance. This research study used resource-based view (RBV) and dynamic capabilities framework (DCF) to investigate firms' investment in intelligent systems resources that build intelligent systems capabilities and the association to organization performance dimensions: revenue and profitability. The study used an online survey administered and received responses from 165 participants from organizations in Canada and the USA. The study findings provide empirical evidence that intelligent systems infrastructure resources and intelligent systems IT human resources increase firm performance, but intelligent systems business resources constructs selected for the study do not contribute to firm performance.

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ABBREVIATIONS AND ACRONYMS

Item	Description
AI	Artificial Intelligence
BdaaS	Big Data as a Service
CB-SEM	Covariance based Structured Equitation Model
DCF	Dynamic Capabilities Framework
DOI	Diffusion of Innovation
IaaS	Infrastructure as a Service
IS	Intelligent Systems
IT	Information Technology
ML	Machine Learning
PA	Parallel Analysis
PaaS	Platform as a Service
PLS-SEM	Partial Least Square Structured Equitation Model
RBV	Resource-based View
SaaS	Software as a Service
SEM	Structured Equation Model
SKUs	Stock Keeping Units
TAM	Technology Acceptance Model
TOE	Technology Organization Environment Framework
VoWi-Fi	Voice Over Wi-Fi

1. INTRODUCTION

1.1 Problem Statement

Companies use information technology (IT) to lower costs, enhance product differentiation, and change the competitive scope by reaching customers worldwide. Porter and Millar (1985) identified that IT alters the disposition of products, processes, companies, industries, and even competition. The authors provided a practical framework for exploring the strategic importance of IT on innovation. Many companies use innovation as a competitive advantage to increase organizational performance, and in the current business environment, technology is used to innovate. Companies such as Apple, Amazon, Facebook, Google, and Starbucks use technology to innovate, build brands, and increase revenue and profitability (Pinto et al., 2017).

Companies in the United States have been using intelligent systems based on artificial intelligence (AI) and machine learning (ML) algorithm use-cases for personalized design and production, customer experience building, inventory, and supply chain management to increase firm performance. For example, the paper published by Vocke et al. (2019a) discussed the potential use of AI in enterprises across all industries and found that senior IT executives identified AI is used for language assistants (68%), automation (62%), and predictive analytics tools (58%) for business intelligence solutions. Gartner states that global AI and ML business value reached $1.2 trillion in 2018 and will reach $3.2 trillion in 2022 (Columbus, 2019a). According to a 2018 McKinsey Global Institute study, AI's annual impact on the world economy (1.2 percent) will outpace the introduction of the steam engine (0.3 percent), 1990s robots (0.4

percent), and the spread of IT in the 2000s (0.6 percent), while adding $13 trillion to the global economy by 2030 (Wladawsky-Berger, 2018).

Many companies have implemented AI and ML pilot projects by implementing artificial neural networks for merchandising, customer purchase prediction, and demand forecasting using single-hidden layer feed-forward neural networks. Research conducted by Cruz-Dominguez and Santos-Mayorga (2016) examined the option to improve the storage location assignment for merchandise in a warehouse using artificial neural systems by studying a spare parts distributor in Mexico that handles over 50,000 Stock Keeping Units (SKUs) in the warehouse. Their study confirmed that artificial neural systems could be trained to assign a product to a warehouse zone category just like a human warehouse management expert. The study by Martinez et al. (2018) explored ML algorithms to predict customer purchase demand increases within a certain time frame using Lasso regression (a logistic model that is one of the most common models used in context classification) and single-hidden layer feed-forward neural network. Their study compared both methods using transactional data from 10,136 customers. The study confirmed that both Lasso regression and single-hidden layer feed-forward neural network methods provided an accuracy rate of 88.98% based on the test data analyzed.

Adoption of technology varies among firms in different industries. Some firms are slow to adopt technology as the market, or the industry these companies compete in does not implement best-of-the-breed technology. The rival companies in the industry do not invest and adopt the latest technology. Porter (2007) identified that firms' technology adoption and evolution are different among industries based on the scale of change, learning, uncertainty reduction and imitation, technology diffusion, and diminishing return of technology innovation. Due to the industry, companies tend to adopt intelligent systems based on AI and ML beyond the pilot phase. Prior empirical research has proven successful implementation of ML framework for customer purchase predictions on business-to-business (B2B) eCommerce sites. These studies have used a smaller subset of sample data, but to effectively prove the models, companies have to run these models with a large volume of actual data (Martínez et al., 2018). Therefore, these models must be refined and tested for other applications beyond pilot projects (Bohanec et al., 2017).

Despite all the research on IT and innovation, such as big data platforms, which allow companies to process vast data streams through AI and ML, organizations in certain industries have been slow to adopt intelligent systems. As a result, there is a lack of understanding of intelligent systems use-cases that will increase firm performance. For example, Pantano and Vannucci (2019) examined the diffusion level of technologies in the retail environment that was completed at 208 stores in Oxford Street, London, UK. The authors' study demonstrated that retail companies had no more than three different digital technologies for business use-cases. As a result, the executives in these companies do not strive to invest and leverage technology systems that are cutting edge and complex to increase firm performance. Their research also indicated that the retail industry must invest more in technology to compete in the current economic environment.

Companies have struggled to move from the pilot phase to companywide adoption and use intelligent systems to increase firm performance. Adopting intelligent systems beyond a pilot is a challenge to many organizations as companies fail to align a firm's culture, structure, and work environment to support artificial intelligence adoption. For example, Fountaine et al. (2019) explored why companies have been slow to adopt

AI and ML to create a competitive advantage. The authors used literature review and case study analysis to illustrate how financial institutions implemented AI and analytics teams based on centralized (hub) and decentralized (spoke) structures. The authors identified ten ways AI programs fail and provided guidance to implement successful AI in organizations beyond the financial industry.

Many companies cannot measure or capture the impact on firm performance by implementing intelligent systems as pilot projects do not produce enough data to measure the impact of using intelligent systems due to a lack of companywide adoption. Nevertheless, research is lacking on the role of intelligent systems capabilities on firm performance. Therefore, this research will use resource-based view (RBV) and dynamic capabilities frameworks (DCF) to examine the mediating role of intelligent systems capabilities on the relationship between intelligent systems resources and firm performance.

There is widespread use of RBV in empirical literature to measure firm performance and IT investment. For example, Bharadwaj (2000) examined the association between organization IT capabilities and firm performances. The author identified that IT resources such as IT infrastructure, IT human resources, and IT intangible resources are used to develop IT capabilities. The author's study indicated that firms with high IT capabilities outperform those with low IT capabilities. Ravichandran and Lertwongsatien (2005) drew on the RBV theory and published evidence on how information systems assets and competencies impact firm performance. The authors' research provided strong evidence that variations in firm performance can be explained by the extent to which IT is used to support and enhance a firm's core competencies.

Zhuang and Lederer (2006) examined the investment in e-commerce technology resources and firm performance. The authors' used RBV theory for their theoretical model, and their study supported that eCommerce performance directly influences firm performance.

Dynamic capabilities framework (DCF) is another theoretical flamework academic scholars use to measure firm performance and investment in IT. For example, Lin and Wu (2014) investigated the role of DCF in the RBV framework and explored the relationships among different resources, dynamic capabilities, and firm performance. Their finding showed that dynamic capabilities mediate the firm's resources to improve performance. Wamba et al. (2017) study of big data analytics and firm performance used RBV and DCF to study the implementation of big data analytics platform capabilities at companies in China and its effect on firm performance. Their study confirmed, the organizations that built big data analytics capabilities had a higher firm performance. Santoro et al. (2021) explored the effects of knowledge management and dynamic capabilities on entrepreneurial intensity and firm performance. Their study confirmed that knowledge management orientation positively and significantly impacts entrepreneurial intensity and firm performance.

1.2 Research Relevance

This study aims to understand the investment in internal resources such as big data platforms to leverage intelligent systems (based on AI and ML algorithms) that provide a competitive advantage for organizations and impact to firm performance. Findings from this study will help the firms identify the investments in internal resources such as IT that helps companies rapidly innovate by leveraging intelligent systems, enabling AI and ML capabilities to increase firm performance against rivals. This research work has implications for managers responsible for consuming and implementing intelligent systems. This research work has implications for executives responsible for investments in intelligent systems to derive organization competitive advantage to surge firm performance. Findings from this study will benefit the firm's shareholders to ascertain the link between competitive advantage and investment in intelligent systems by the firm is the correct IT investment decisions to enhance organizational growth. This research will contribute to and expand on the current knowledge base of RBV and DCF that enable an increase in organization performance through the investment in intelligent systems.

1.3 Research Question(s)

This research study is organized as follows. Section 2 introduces the reader to the RBV and DCF of the firm, introduction to intelligent systems, and firm performance. The research model and hypothesis justifications are documented in section 3. Section 4 introduces the research study methodology and instrument. Research study data collection, methods used to validate the data, and analysis is highlighted in section 5. Section 6 discusses theoretical implications, practical implications, limitations, and future research. The structure of the study is to address the following research questions:

1. What effect do intelligent systems resources investment have on firm performance at organizations in Canada and the USA?
2. What effect do intelligent systems resources investment have on intelligent systems capabilities at organizations in Canada and the USA?

3. What is the effect of intelligent systems capability in mediating the relationship between intelligent systems resources and firm performance at organizations in Canada and the USA?

2. LITERATURE REVIEW

Edith Penrose was the first scholar to discuss and write about the importance of a firm's resources on its competitive position. She argued that a company's internal and external growth could be attributed to how the firm leverages its resources (Newbert, 2007; Penrose, 1959). Porter expanded on Penrose's work to define the five forces framework. Porter's five forces framework was originally used in strategic management to analyze a company's competitive advantage, and Porter extended the framework to measure technology and competitive advantage (Porter, 2007). Porter's model is based on how an organization implements strategies and capabilities to create a competitive advantage to counter five external competitive forces that shape every industry. A firm looks at external threats and opportunities, but it has to look at its strengths and weaknesses. When a firm analyses its strengths and weaknesses, the organization has to look at its available resources. A firm's resources are any physical and intangible assets the company uses, including brand names, knowledge, technology, employees, vendors, machinery, and efficient use of capital at any given moment in time (Wernerfelt, 1984).

2.1 Resourced-based View

Barney (1991) built on Porter's and Wernerfelt's research to define the resource-based view (RBV), which considers the firm's internal features and performance. RBV is based on the following assumptions, (a) companies within an industry have similar internal resources they control, and (b) internal assets are not fully organized by every company (J. Barney, 1991). RBV analyzes the foundation of competitive advantage at an organization by leveraging internal resources such as IT, manufacturing facilities, and skilled personnel (Shan et al., 2019). Figure 1 below, adapted from Grant (1991), depicts the resource-based view framework, which starts with (a) identifying the firm's resources, (b) identifying the firm's capabilities, (c) identifying the firm's competitive advantage, (d) identifying and selecting firms' strategy and (e) identifying the resource gap.

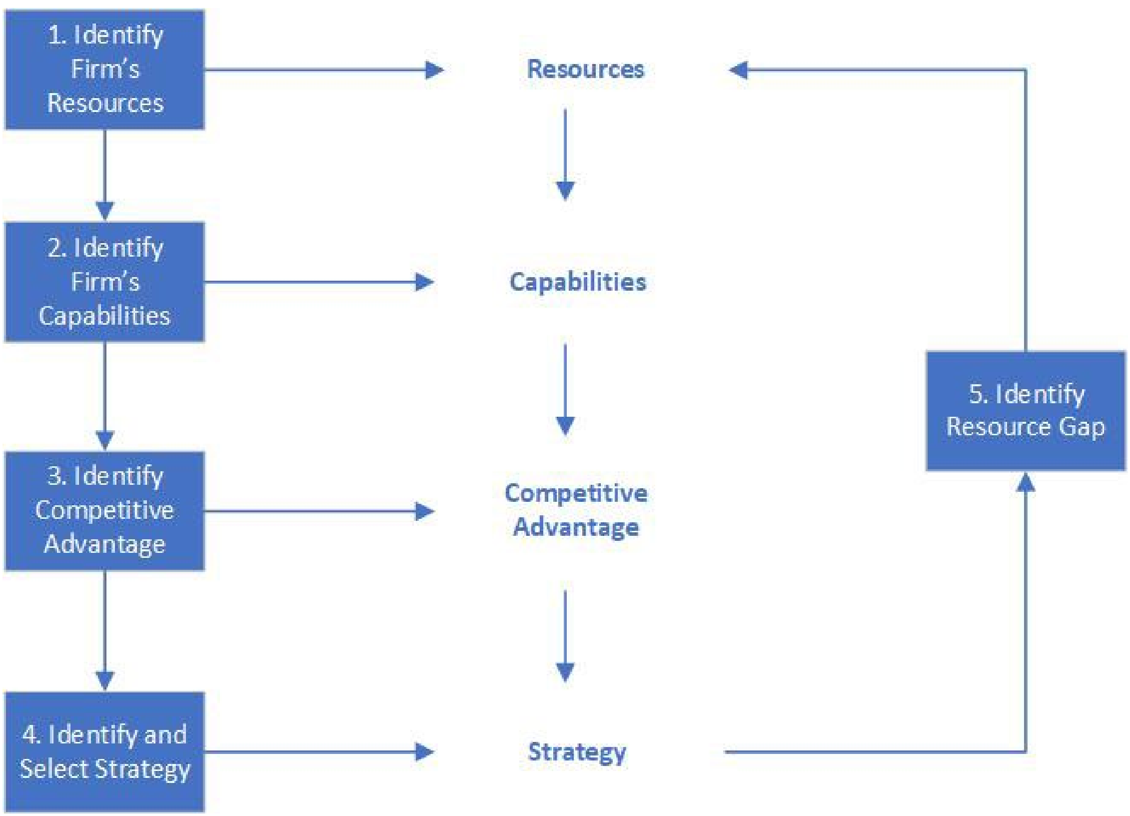

Figure 1 Resource-based view framework. Source: (Grant, 1991)

Firm resources include all assets, organization competencies, characteristics, data, and knowledge the firm controls to implement strategies to enhance the firm's efficiency and effectiveness. As per Barney (1991), a firm's resources can be categorized into the following three, (a) physical capital, (b) human capital, and (c) organization capital. Physical capital includes building, plants, equipment, and technology. Human capital includes training, experience, judgment, intelligence, relationships, and insight of individual managers and workers. Organization capital includes the firm's reporting structure, formal and informal planning, controlling and coordinating system, and informal relationships among groups within and between the firm and its environment.

2.2 Organization Resources

Grant (1991) identified six major organizational resource categories and these are financial, physical, human, technological, reputation, and organizational resources. Financial resources are the firm's cash, liquid securities, and line of credit. The firm's factories, distribution centers, office buildings, sales outlets, and warehouses are physical resources. Human resources are the firm's employees, managers, and senior executive team's knowledge and skills. Technology resources are systems and tools required to produce or create new products and services. Reputation resources are the firms' brand names and goodwill. The organizational resources of a firm are all assets that a corporation has available to use in the production process. Resources are the source of a firm's capabilities, and capabilities are the primary source of a company's competitive advantage (J. Barney, 1991). A firm can use all the six major categories of resources to implement an economic strategy, which has not been employed by any of its current or future competitors at that moment in time, thereby creating a competitive advantage to intensify growth (J. Barney, 1991; Grant, 1991).

2.3 Organization Capabilities

In order to innovate and build a competitive advantage, a company must develop its capabilities. A firm's capabilities can be identified when teams within the company employ all organizational resources, then select or identify a strategy to effectively and efficiently use these resources to create capabilities. For example, when discovering organization capabilities, a firm must look at the organization's functional capabilities: product development, market research, human resource management, financial control, and operation management (Grant, 1991). The functional capabilities are linked to the resources identified by RBV at many organizations. The firm creates valuable capabilities when individual functional capabilities are integrated into a core competency. Core competency is a central or strategic capability that enables a company to effectively and efficiently use its resources for competitive advantage (Grant, 1991; Teece et al., 1997).

Companies should form dynamic capabilities to achieve a competitive advantage as global competition heats up with a rapidly changing environment using technology. Dynamic capabilities are a company's ability to amalgamate, form, and tailor internal and external capabilities to address the hyper-competitive economic and technology environments (Teece et al., 1997). An organization must make rapid changes to its capabilities by investing in organization assets to stay ahead of its rivals. Dynamic capabilities within an organization have the following characteristics, (a) processes (coordination/integration, learning, and reconfiguration), (b) positions (financial assets, reputation assets, structural assets, institutional assets, market assets, and organization boundaries), and (c) paths (path reliance and technology prospects that help identify the effective, and efficient capabilities to create competitive advantage) (Helfat & Peteraf, 2003; Teece et al., 1997). Organization and dynamic capabilities help an organization create a competitive advantage to help the firm contend with its rivals. Holdford (2018) classified organization capabilities and dynamic capabilities into the following categories, (a) managerial, (b) marketing, (c) financial, and (d)technical.

2.4 Competitive Advantage

A firm has a competitive advantage when it executes an economic strategy that has not been utilized by any of its current or future competitors at that moment (J. Barney, 1991). Companies invest in strategic resources to create a competitive advantage. The firm has a sustained competitive advantage when the firm implements strategies that cannot be duplicated by current or future competitors to receive the same benefits (J. Barney, 1991; Grant, 1991). A sustained competitive advantage lasts a long period and cannot be duplicated by competitors (Grant, 1991). Competitive advantage does not last forever due to economic and technological changes that will disrupt and erode the competitive advantage. Some firms that had their competitive advantage eroded by economic and technological advances are Blackberry, Netscape, Apple (personal computer business), and Kodak. When there is resource homogeneity and mobility among all firms in the industry, one firm cannot attain a sustained competitive advantage as the same resources are available to all companies in the industry (J. Barney, 1991; Grant, 1991). That said, the first movers will create a competitive advantage over their rivals as these companies will be the first to market new products or services, but the competitive advantage is short-lived as its competitors will copy and introduce the same products (J. Barney, 1991; Lieberman & Montgomery, 1998). Rogers Communications out of Toronto, Ontario, Canada, was the first to implement Voice over WiFi (VoWi-Fi) giving Rogers a temporary competitive advantage as the first mover. However, Bell Canada and TELUS quickly followed by implementing VoWi-Fi, which eroded Rogers's competitive advantage.

Resource heterogeneity and immobility requirements are required for the company to sustain a competitive advantage (J. Barney, 1991; Grant, 1991). Not all organization resources will be heterogeneous and immobile. The resources should have the following characteristics to contribute to sustained competitive advantage, a) the resource has to be valuable, b) the resource must be rare, c) the resource has to be imperfectly imitable, and d) the resource cannot be a strategic substitute (J. Barney, 1991). The resources that enable a company to implement strategies that improve the organization's efficiency and effectiveness, then these resources are considered valuable. Valuable resources allow the company to exploit opportunities and neutralize threats (J. Barney, 1991). Although a company has valuable resources, the organization cannot attain a sustained competitive advantage if all firms within the industry have access to the same resources. For a valuable resource to contribute to sustained competitive advantage, the resource mix must enable a firm to implement a value-creating strategy that has to be rare and cannot be duplicated by other companies within the industry. The valuable and rare resources have to be imperfectly imitable. In other words, rival firms in the industry cannot develop the same resources due to unique historical conditions as the resource-generating organization advantages are socially complex (J. Barney, 1991). The final requirement is that for the company to maintain sustained competitive advantage, the firm's valuable rare and imperfectly imitable resources should be able to provide a competitive advantage that is strategically equivalent if the resources are used separately.

As discussed, prior research shows that an organization cannot achieve sustained competitive advantage. However, a firm can create a temporary competitive advantage by using the valuable, rare, imperfectly imitable, and sustainable resources as part of formal and informal strategic planning initiatives (J. Barney, 1991; Lieberman & Montgomery, 1998). Many organizations use information technology to build a competitive advantage by implementing the latest IT platforms to build efficiencies and increase productivity, which gives these organizations the first-mover advantage. Bharadwaj (2000), Mao et al. (2016), and Zhuang and Lederer (2006) studies identified information systems are used or incorporated into the firm's formal and informal strategic planning initiatives that give a company a competitive advantage, but it is temporary.

2.5 Firm Performance

Past research linking IT to competitive advantage has focused on the organization's IT resources, such as big data platforms, eCommerce, knowledge management, workforce management, and enterprise resource planning systems (Bharadwaj, 2000; Mao et al., 2016; Zhuang & Lederer, 2006). This research examines the investment in internal resources such as intelligent systems to enhance the competitive advantage and firm performance. The company performance is both measured by financial and efficiency indicators. Financial performance measures include return on assets (ROA), return on equity (ROE), return on investment (ROI), return on sales (ROS), sales growth, and market capitalization (Dehning & Stratopoulos, 2002; Helfat & Peteraf, 2003; Liang et al., 2010; Mao et al., 2016; Menachemi et al., 2006; Ravichandran & Lertwongsatien, 2005; Zhuang & Lederer, 2006). Financial performance measures are important to the organization as lenders and investors use these statistics to gauge the organization’s health regarding positive cash flow and profitability. Efficiency indicators are related to non-financial measures in an organization, such as productivity (Liang et al., 2010; Ravichandran & Lertwongsatien, 2005).

Measuring the success of an organization can be addressed by observing its sales and profitability. There is a strong correlation between the degrees of competitive advantage and a firm's financial performance (Alexandra Twin, n.d.; Dehning & Stratopoulos, 2002; Holdford, 2018; Zhuang & Lederer, 2006). This study explores the link between IT resources and capabilities with firm performance. Based on past empirical research, several studies have utilized RBV and DCF within IT to determine a firm's competitive advantage to measure company performance (Dehning & Stratopoulos, 2002; Powell & Dent-Micallef, 1997; Zhuang & Lederer, 2006). IT investments such as eCommerce and customer relationship management platforms have allowed the organization to increase revenue. Prior empirical studies have measured the competitive advantage of the firm by quantifying profits over total sales (Holdford, 2018; Shan et al., 2019; Zhuang & Lederer, 2006). IT increases the productivity of all employees and reduces the cost of products and services, which helps the organization increase profitability. Hence, this study will examine organization sales and profit growth as part of the analysis of the company’s performance.

2.6 Intelligent Systems

AI and ML have been around for decades, but organizations are slow to utilize these frameworks. With the introduction of Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS), such as Amazon Web Service (AWS), Microsoft Azure, and Google Cloud platforms, companies have been exploring the use of

AI and ML. In addition, as opensource organizations, such as Apache Software Foundation, developed a framework that allows for the distributed processing of massive data sets across a parallel stack of computers, which has enabled the proliferation of AI and ML (Dwivedi et al., 2019). Companies have invested in data platforms for years to mine customer information, and these firms have found novel solutions using these platforms by implementing AI and ML for data mining. AI and ML adoption has been expanding in banking, insurance, healthcare, social media, transportation, and logistics industries as these companies have been investing heavily in data platforms (Dwivedi et al., 2019; Fountaine et al., 2019).

AI is a subfield of computer information systems, and the concept of intelligent agents has been a key theme of AI. For many years researchers in academia and industry did not have a universally accepted definition for intelligent agents. Wooldridge and Jennings (1995) identified intelligent agents as computer systems with the following characteristics, (a) information attitudes which are belief and knowledge, and (b) pro-attitudes which are aspirations, goals, duty, dedication, and selection. The agent's information is information attitudes, and actions that guide the agent are pro-attitudes. At least one of the information and pro-attitudes should be present for an agent to be considered intelligent.

Many organizations have developed enterprise resource planning, decision support systems, intelligent agents, and knowledge management systems to generate a competitive advantage. Companies use intelligent agents on eCommerce sites for search using search engines, to make product recommendations by using recommendation engines, detect fraud with fraud detection engines, firms use knowledge management systems to support customers and employees help desk functions to minimize employee ramp uptime and customer support costs (Shirley Gregor & Izak Benbasat, 1999). Many of these systems use AI and ML algorithms to mimic human knowledge and explain to human users the knowledge contained in the systems. Systems that use AI and ML algorithms for storing knowledge and retrieving knowledge for explanation are classified as intelligent systems (Shirley Gregor & Izak Benbasat, 1999). Intelligent systems are an IT investment that the organizations implement to compete with other firms in the industry. Intelligent systems bring rapid technological changes within the organizations, which help these companies innovate and build a competitive advantage over the firm's rivals (Vocke et al., 2019b). This study defines intelligent systems as systems that enable AI and ML algorithms for storing and retrieving customer transaction knowledge used for explanation and prediction.

As discussed, intelligent systems are an internal resource within an organization, and intelligent systems are part of its IT investment, enabling AI and ML capabilities. Intelligent systems that help rapidly transform the competitive landscape against the firm's rivals can be measured by the organization's resources and capabilities. In this study, RBV is used as the theoretical and practical foundation to investigate the mediating effect of intelligent systems capabilities on the relationship between intelligent systems resources and firm performance at organizations in Canada and the United States of America (USA).

2.6.1 Intelligent Systems Organization Resources

As discussed previously, prior research has identified that IT infrastructure, IT human resources, and IT business resources contribute to IT capabilities which provide a competitive advantage to organizations (Bharadwaj, 2000; Gupta & George, 2016; Liang et al., 2010; Mao et al., 2016; Mata et al., 1995; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Zhuang & Lederer, 2006). For this research, the organization IT resource constructs that will be studied are: (a) intelligent systems infrastructure, (b) intelligent systems IT human resources, and (c) intelligent systems business resources.

2.6.1.1 Intelligent System Infrastructure

During the 1980s and early 1990s, IT was decentralized, with each division within an organization implementing IT resources to meet the divisional goals. Decentralized IT resources added to an organization's operating costs, and the competitive advantage gained through IT was eroding (Bharadwaj, 2000; Mata et al., 1995). With the Year 2000 (Y2K) initiatives, companies started centralizing IT departments to standardize and streamline their IT functions and processes. Centralized IT operations have reduced operating costs, and firms have gained a competitive advantage by leveraging enterprise resource planning, customer relationship management, eCommerce, knowledge management, and decision support platforms.

Due to the demand to centralize IT resources, technology vendors further enhanced IT offerings by introducing virtualization technologies, which enabled the cloud computing environments available today (Dwivedi et al., 2019; Pinto et al., 2017). Citrix and VMware took the lead in introducing virtualization technologies to organizations. Both Amazon and Microsoft expanded virtualization with Amazon Web Services and Microsoft HyperV technology which ultimately was incorporated into the Microsoft Azure Cloud IaaS platform. Amazon, Microsoft, Google, IBM, and Oracle have IaaS platforms and expanded the product offering to include Big Data as a Service (BDaaS) platforms.

As discussed, intelligent systems are IT resources. For this study, intelligent systems infrastructure is defined as technology infrastructure, including centralized on-premise and cloud-hosted platforms that can enable and execute AI and ML algorithms that contribute to intelligent systems capabilities and give the organization a competitive advantage. As per prior research, IT infrastructure resources can be broken down into the following five factors; (a) IT change management, (b) enterprise data integration, (c) IT environment, (d) IT performance, and (e) IT user interface (Bharadwaj, 2000; Dehning & Stratopoulos, 2002; Liang et al., 2010; Mata et al., 1995; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Rivard et al., 2006; Ulrich Lichtenthaler, 2019; Wade & Hulland, 2004; Zhuang & Lederer, 2006). This research study will be investigating the following intelligent system infrastructure factors: (a) intelligent systems environment and (b) intelligent systems performance.

2.6.1.1.1 Intelligent Systems Environment

As discussed previously, the organization must invest in and build IT environments or infrastructure for a firm to implement the intelligent systems infrastructure. The IT environment gives the firm a temporary competitive advantage over the organization's rivals as it is complex and expensive to duplicate, with immense implementation risks for the competing firms to match (Bharadwaj, 2000; Dehning & Stratopoulos, 2002; Gupta & George, 2016; Liang et al., 2010; Mata et al., 1995; Mikalef & Gupta, 2021; Ravichandran & Lertwongsatien, 2005; Ulrich Lichtenthaler, 2019; Zhuang & Lederer, 2006). This study defines an intelligent system environment as a technology infrastructure that includes centralized on-premise and cloud-hosted platforms to enable and execute AI and ML algorithms.

2.6.1.1.2 Intelligent Systems Performance

As companies invest in intelligent system environments, the firm must ensure the IT infrastructure meets the end-user performance expectations. For example, the network bandwidth to access on-premise and cloud server instances that host the applications should be fast and effective and not crash when AI and ML algorithms execute on the infrastructure. Although all companies can implement IT environments, companies that have attained a competitive advantage have implemented IT infrastructure that changes and increases the infrastructure performance as required by business and market changes (Bharadwaj, 2000; Liang et al., 2010; Mata et al., 1995; Powell & Dent-Micallef, 1997). For this research, intelligent systems performance is defined as the network, service, and device performance of intelligent system infrastructure.

2.6.1.2 Intelligent Systems IT Human Resources

As organizations build IT infrastructure resources, these firms have to build teams with internal or outsourced IT human resources to implement, maintain and manage this valuable investment that generates a competitive advantage. IT human resources include (a) technical skills and (b) managerial IT skills (Bharadwaj, 2000; Gupta & George, 2016; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005). IT technical skills include programming, system analysis, and design. Managerial IT skills include technology management, project management, and leadership skills.

The organization must develop an IT human resource strategy, where existing IT human resources will be trained on intelligent systems skills. In addition, companies will have to hire new IT resources with intelligent systems skills and experience to fill the job openings to implement intelligent systems technology to generate a competitive advantage (Bharadwaj, 2000; Mata et al., 1995). When companies started implementing eCommerce platforms during the dot-com boom, these organizations had to build eCommerce technology teams with project managers, business analysts, software engineers, and development and operations (DevOps) resources to implement and manage the eCommerce technology. Therefore, organizations will be required to build intelligent systems IT teams with intelligent systems technical skills and management skills.

For organizations to build intelligent systems technical skills and management skills, their senior executives will have to invest in intelligent systems IT human resources. Senior executives at retailers such as Toys R Us and Walmart committed to reducing the operating costs and increasing operational efficiencies by investing in best-of-the-breed inventory management systems by training and hiring IT resources with technical and management skills. Senior executives at Federal Express are committed to increasing customer satisfaction by investing in technology for customer support applications by training and hiring resources with technical and management skills to implement these solutions (Bharadwaj, 2000). Therefore**,** the organization will require senior executives to commit to investing and expanding technical and management skills to leverage intelligent systems resources and capabilities. For this research study, intelligent systems information technology (IT) human resources will combine intelligent systems technical skills and intelligent systems technical management skills.

2.6.1.3 Intelligent Systems Business Resources

The firm develops intangible resources as an organization invests in IT resources such as intelligent systems. The intangible resources allow the firm to increase product quality, improve customer service, increase market responsiveness, and improve efficiencies by integrating with suppliers and customers (Bharadwaj, 2000; Powell & Dent-Micallef, 1997; Zhuang & Lederer, 2006). Organizations have found IT to be an asset in achieving the following: (a) high levels of customer orientation by the ability to track and predict customer taste and preferences in rapidly changing market environments, (b) knowledge formalization, consolidation, and distribution across the organization, and (c) sharing resources and capabilities across the organization by creating organization synergy in sharing knowledge and information to respond to fast-changing market needs rapidly. Intelligent systems intangible resources are combined into intelligent systems business resources, an independent construct for this study. Prior studies have identified IT business resources to include the following five factors (a) benchmarking, (b) planning, (c) IT business relationship, (d) process redesign, and (e) technical vendor relationships (Bharadwaj, 2000; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Ray et al., 2004; Rivard et al., 2006; Wade & Hulland, 2004). For this research, intelligent systems business resources that will be studied include the following three factors; a) intelligent system planning, b) process redesign, and c) IT external relationships.

2.6.1.3.1 Intelligent Systems Planning

When an organization identifies a competitive advantage based on the firm's resources and capabilities, the organization will select a strategy and create a short-term and long-term plan to implement the selected strategy. Then the firm will review and update the plan as needed. Planning is key for a company to identify technology resources and capabilities to invest in, to create a competitive advantage (Liang et al., 2010; Rivard et al., 2006; Wade & Hulland, 2004). Therefore, for this research, intelligent system planning is defined as short-term and long-term planning activities to implement an intelligent systems strategy in the organization.

2.6.1.3.2 Process Redesign

Powell and Dent-Micallef (1997) defined benchmarking as methodical surveillance and duplication of competitive resources. When implementing new technology resources, a firm looks at the available technology used by its rivals in the same industry or technology used by companies in other industries to gain a competitive edge and then duplicate these technology resources. Benchmarking helps the organization identify areas of the business process to change through process redesign. Identifying and changing the business processes to meet market changes help organizations compete and build a competitive advantage (Powell & Dent-Micallef, 1997; Ray et al., 2004). As organizations implement intelligent systems, these companies must adjust the internal business processes and associated business resources to compete with other firms in the industry. In other words, business processes and resources must be changed to compete. For example, some studies have identified the changes to the business process as business process reengineering, and IT has a history that enables business process reengineering

(Powell & Dent-Micallef, 1997; Rivard et al., 2006). Zhuang and Lederer (2006) defined process redesign as the ability of the organization to change business processes to meet business and market changes. For this research, we will be using Zhuang and Lederer's definition of process redesign.

2.6.1.3.3 IT External Relationships

Prior research has found that the relationship between information technology and other business functions has been contentious and non-cooperative in many organizations (Mata et al., 1995). When there is cooperation and trust between information technology and business departments, this relationship becomes valuable in implementing IT solutions that help the company build a competitive advantage. For example, Wade and Hulland (2004) defined an IT business relationship as the process of incorporation and alignment between IT functions and other functions or departments in the company.

As the information technology department within the organization matures, these departments learn from the organization's manufacturing, sourcing, and merchandising teams and start to copy by forming strategic partnerships with IT equipment, service, and outsourcing vendors. These IT relationships can be valuable in implementing IT solutions that meet business teams' requirements. Wade and Hulland (2004) defined the technical vendor relationship as the firm's ability to manage linkages between the IT function and vendors. Zhuang and Lederer (2006) classified the IT vendor relationship as a partner relationship. Their study also identified IT-business relationships and technology vendor relationships as key relationships maintained by IT departments to deliver IT solutions that help the company build a competitive advantage. This research will define IT

External Relationships as the IT team's business and vendor relationships that align and link IT functions with business and vendor teams.

2.6.2 Intelligent Systems Capabilities

As discussed, organization capabilities include management, marketing, financial, and technical capabilities. Organization resources are building blocks for organization capabilities, and IT capabilities are part of the overall technical capabilities (Bharadwaj, 2000; Gupta & George, 2016; Liang et al., 2010; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005). Information Technology capabilities are developed when an organization invests in IT infrastructure, IT human resources, and IT intangible or business resources. Intelligent systems are part of an organization's internal IT resources, and intelligent systems infrastructure, intelligent system IT human resources, and intelligent systems business resources are combined to form an immobile and heterogonies intelligent systems capabilities that contribute to a firm's competitive advantage.

Wamba et al. (2017) study identified the following second-order constructs for IT capabilities, (a) infrastructure flexibility, (b) IT management capabilities, and (c) personnel experience capabilities. Infrastructure flexibility includes the following latent constructs IT connectivity, IT compatibility, and IT modularity dimensions. IT management capabilities include the following latent constructs: IT planning, investment, coordination, and control. Personnel experience capabilities include the following latent constructs IT technical knowledge, IT technology management capability, IT business knowledge, and IT relational knowledge. Chasalow and Baker (2014) identified the following second-order constructs for IT capabilities at organizations, which are (a) organization processes, (b) IT assets, and (c) firm history. Organization processes include the following latent constructs sensing, learning, coordination, and integrating dimensions. IT assets include the following latent constructs IT Infrastructure and Information repository dimensions. Firm history includes the following latent constructs IT dynamic capability and information dynamic capabilities dimensions. For this research, the organizational capabilities construct will be intelligent systems capabilities. This research study defines intelligent systems capabilities as competence to provide intelligent business insight using intelligent systems infrastructure, personnel, and management capabilities to transform the business into a competitive force. The dimensions of interest for this study will be 1) intelligent systems infrastructure capabilities, 2) intelligent systems personnel capabilities, and 3) intelligent systems technology management capabilities.

2.6.2.1 Intelligent Systems Infrastructure Capabilities

Prior studies have defined IT infrastructure capabilities as technology-driven capabilities that optimize the business process for efficiencies (Chasalow & White Baker, 2014; Lin & Wu, 2014; Santoro et al., 2021; Wamba et al., 2017). As an organization builds IT infrastructure capabilities, the company builds immobile and heterogonies IT capabilities that contribute to a firm's competitive advantage. This study defines intelligent systems infrastructure capabilities as AI and ML-driven capabilities that optimize the business process for efficiencies.

2.6.2.2 Intelligent Systems Personnel Capabilities

Past research has defined IT personnel capabilities as the information technology staff's technical skills and knowledge to undertake and complete assigned tasks (Shan et al., 2019; Wamba et al., 2017). Information technology personnel capabilities help the organization stay ahead of its competitors by building advanced technology capabilities that create a competitive advantage which helps increase firm performance. This research defines intelligent systems personnel capabilities as information technology staff's big data, AI, and ML skills and knowledge to undertake and complete assigned tasks to transform the business into a competitive force.

2.6.2.3 Intelligent Systems Management Capabilities

Prior research has identified IT management capabilities as the IT department's ability to handle procedures in a structured manner to manage IT resources in harmony with business needs and priorities (Wamba et al., 2017). IT management capabilities help the organization build immobile and heterogonies IT capabilities that will contribute to a firm's competitive advantage by helping it prioritize and leverage IT resources to meet its business priorities by increasing firm performances. For this research study, we define intelligent systems management capabilities as the IT department's ability to handle procedures in a structured manner to manage intelligent systems resources in harmony with business needs and priorities.

3. RESEARCH MODEL AND HYPOTHESIS

3.1 Research Model

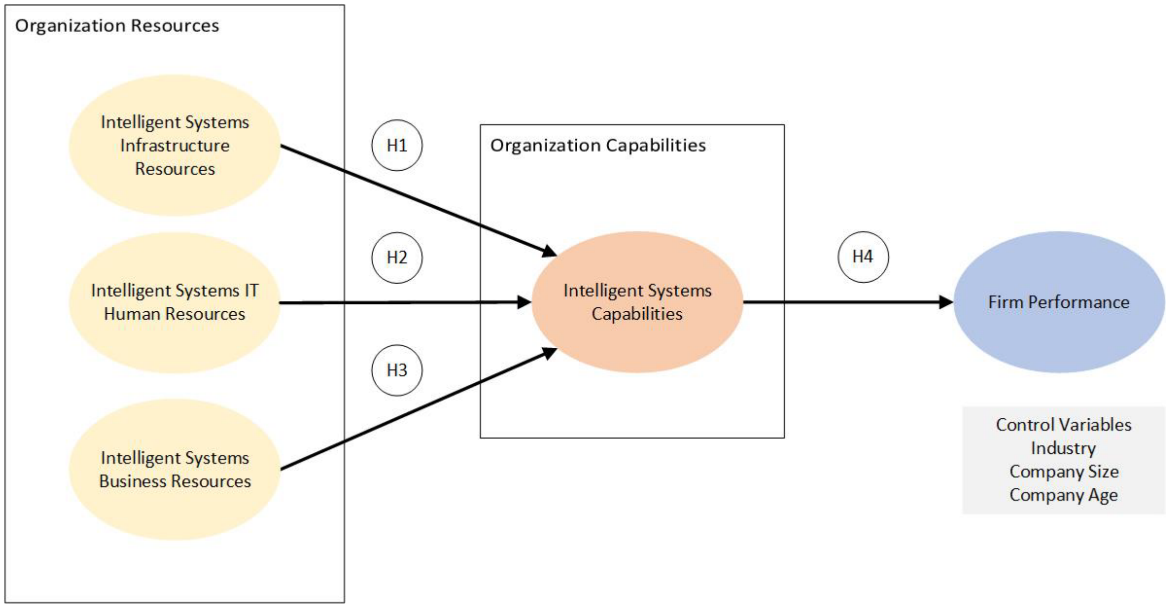

Figure 2 Key Constructs and their relationship to this research study

Figure *2* above depicts the research model with independent, mediating, and dependent constructs based on the RBV, which explains the firm's investment in internal resources such as intelligent systems and firm performance. Table 1 below provides definitions for the proposed research model constructs. In this research model, the dependent variable is firm performance, and the independent variables are intelligent systems infrastructure (intelligent systems environment and performances), intelligent systems IT human resource (intelligent system technical skills and management skills), and intelligent systems business resources (intelligent systems planning, process redesign and IT external relationships). The firm's intelligent systems capabilities mediate the relationships between intelligent systems resources (intelligent systems infrastructure, IT human resources, and business resources) and firm performance. The control variables for this study will be industry, company size, and company age.

Table 1 *Definitions of Constructs from RBV Theory*

Construct	**Definition**
Intelligent Systems Infrastructure Resources (ISIR)	Technology infrastructure includes centralized on-premise and cloud-hosted platforms that can enable and execute AI and ML algorithms, including intelligent systems environment and performance sub-factors that contribute to intelligent systems capabilities.
Intelligent Systems IT Human Resources (ISITHR)	Technical and management skills that contributed to intelligent systems capabilities.
Intelligent Systems Business Resources (ISBR)	Complementary and intangible business resources that contributed to intelligent systems capabilities, which include intelligent systems planning, process redesign and IT external relationships sub factors.
Intelligent Systems Capabilities	All intelligent systems resources combined to form immobile and heterogonies capabilities that contribute to a firm's competitive advantage. These include intelligent systems infrastructure, personnel and management capabilities sub-factors.
Firm Performance	Financial performances to measure competitive advantage as denoted by firm sales growth and profitability.

3.2 Hypothesis Justification

3.2.1 Intelligent Systems Infrastructure Hypothesis

In the current environment, IT infrastructure is like commodities, which can be purchased and implemented by any organization. When firms implement new IT infrastructure, these companies receive a temporary competitive advantage by allowing the firm to be the first mover in the industry (J. Barney, 1991; Bharadwaj, 2000; Grant, 1991; Powell & Dent-Micallef, 1997). Investment in IT is risky and expensive to copy and implement. Competitors can try to duplicate and implement IT infrastructure. However, the rivals might be unable to erode the firm's competitive advantage as the competing organization will not have the same IT capabilities (K. Kim et al., 2017; Mithas & Rust, 2016; Saunders & Brynjolfsson, 2016). Investment in IT infrastructure benefits the firm by enhancing an organization's IT capabilities by increasing its performance. Intelligent systems are an internal IT resource, and implementing intelligent systems infrastructure enhances the firm's intelligent systems capabilities, giving the firm a competitive advantage and increasing its growth.

An intelligent systems environment is a technology infrastructure that includes centralized on-premise and cloud-hosted platforms to enable and execute AI and ML algorithms. There is empirical research that has found that implementing an IT environment can give a firm a temporary competitive advantage as a first mover, and the duplication of organization capabilities can be complex, expensive, and risky for the firm's competitors (Akter et al., 2016; Bharadwaj, 2000; Byrd et al., 2008; Gupta & George, 2016; Mata et al., 1995; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Ulrich Lichtenthaler, 2019; Wade & Hulland, 2004; Wamba et al., 2017; Zhuang & Lederer, 2006). For example, Walmart has been able to withstand competitors such as Sears and, more recently, Amazon due to sophisticated IT infrastructure environment investments that have allowed Walmart to continue adding innovative business processes. Sears, Amazon, and other retailers have implemented the same IT environments and matched some of the IT capabilities of Walmart. Nevertheless, the competition has not matched the overall IT environment capabilities built by Walmart. As intelligent systems are IT resources, a sophisticated, intelligent systems environment will give a firm a temporary competitive advantage over its rivals by allowing it to implement superior intelligent systems capabilities, which can increase firm performance.

For this research, intelligent systems infrastructure performance is defined as the network, service, and device performance of intelligent system infrastructure. When firms have a robust IT infrastructure that operates without crashing and auto-scale to meet business user demands on the infrastructure, this creates a scalable resource that can enhance the organizational IT capabilities (Bharadwaj, 2000; Mata et al., 1995; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Ulrich Lichtenthaler, 2019; Wade & Hulland, 2004; Zhuang & Lederer, 2006). For example, Amazon, Microsoft, Salesforce, and Shopify as leading software as a service (SaaS) vendors, have invested millions of dollars in implementing scalable platforms. These platforms provide high-speed networks and auto-scaling instances that provide superior performance to meet their customers' 99.999% up times and milliseconds application response requirements. As identified earlier, intelligent systems are an IT resource. Therefore, by investing in intelligent systems performance, these companies can enable high-speed and auto-scaling capabilities, which will give a firm a competitive advantage over its rivals. The capabilities allow the firm to complete advance customer and market predictive analytics using intelligent system capabilities that meet user demand without crashing to grow the business. Therefore, the following hypothesis is proposed:

- ***Hypothesis 1 (H1):*** *Intelligent systems infrastructure resources have a positive effect on the firm's intelligent systems capabilities.*

3.2.2 Intelligent Systems IT Human Resources Hypothesis

Although an individual organization's IT resources are complex to implement, a firm can create a competitive advantage by effectively and efficiently combining all the intelligent systems resources in the firm to create an overall intelligent systems capability which is hard to imitate by the firm's competitor (J. Barney, 1991; Bharadwaj, 2000; Grant, 1991; Gupta & George, 2016; Liang et al., 2010; Mata et al., 1995; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997). For example, when combined with intelligent systems IT human resources, an organization's flexible, intelligent systems infrastructure becomes a deadly capability, enhancing the organization by efficiently responding to changing customer demand due to varying market conditions.

As discussed before, IT human resource skills that include technical and management skills can be unique to an organization and hard to duplicate by competitors. Organizations that have a track record of attracting top talent from universities and an organization's culture that allows its employees to thrive by taking risks by allowing the employees to experiment and implement new technology will enhance the firm's competitive position (Akter et al., 2016; Bharadwaj, 2000; Gupta & George, 2016; K. Kim et al., 2017; Malhotra, 2001; Mao et al., 2016; Mikalef & Gupta, 2021; Mithas & Rust, 2016; Powell & Dent-Micallef, 1997; Wamba et al., 2017). Organizations can build intelligent systems IT human resources skills that will help develop intelligent systems capabilities that their competitors cannot duplicate, giving the company a competitive advantage. A commitment by the organization's senior executives is a critical requirement to attract top talented resources. For example, when Canadian Tire corporation implemented the big data platform to leverage artificial intelligence and machine learning algorithms, the organization started to train and hire information technology human resources with the following: (a) technical skills: data scientists, data architects, data analysts, data engineers, big data development operations engineers and (b) technical management skills: big data project managers, big data development managers, and senior data science executives. Therefore, the following hypothesis is proposed:

- ***Hypothesis 2 (H2):*** *Intelligent systems IT human resources have a positive effect on the firm's intelligent systems capabilities.*

3.2.3 Intelligent Systems Business Resources

Intelligent systems intangible resources or intelligent systems business resources are hard to duplicate by competitors. Even if competitors can duplicate these business resources, competitors might not be able to profit as these business resources are immobile and heterogeneous to the organization (Bharadwaj, 2000; Gupta & George, 2016; Malhotra, 2001; Mao et al., 2016; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997).

For this research study, intelligent systems planning is defined as short-term and long-term planning activities to implement an intelligent systems strategy in the organization. As companies invest in IT, the organization must identify the technology resources and capabilities to provide a competitive advantage to meet its strategic business objectives and goals. The organization must plan and identify the projects that meet future priorities and objectives. For example, Rogers Communications (Rogers), Ontario Lottery, and LoyaltyOne out of Toronto, Ontario, Canada, have strategic planning sessions for sales, marketing, merchandising, and technology every third quarter of the financial year. Based on the strategic priorities and goals, the technology road map for the following year is planned, and estimated investments are calculated; then, projects are moved to the budgeting phase for capital allocation. As per prior research, this process of identifying technology resource projects to invest in will strengthen the technical capabilities of the organization (Barney, 1991; Bharadwaj, 2000; Grant, 1991; Liang et al., 2010; Powell & Dent - Micallef, 1997; Ray et al., 2004; Rivard et al., 2006; Wade & Hulland, 2004; Zhuang & Lederer, 2006). Intelligent systems are an IT investment that will be part of its strategic planning process. The organization can develop the intelligent systems roadmap for capital funding requests for the projects to implement intelligent systems functionality and resources to help the organization create exceptional, intelligent systems capabilities. Intelligent systems planning will be complex for competitors to duplicate as the intelligent systems planning process will be unique to the organization.

As stated before, process redesign is defined as the ability of the organization to change business processes to meet business changes (Zhuang & Lederer, 2006). As the organization invests in IT resources to build technology capabilities, the firm must change its business processes. For example, organizations implemented eCommerce sites as an additional channel for sales growth during the eCommerce boom. After implementing the eCommerce platforms, these organizations had to change and retool their business processes for eCommerce to succeed. Hence, the business process changes gave these companies a competitive advantage over their rivals (Zhuang & Lederer, 2006). With the investment in intelligent systems, the firm will have to change the current business processes to implement intelligent systems. After implementation, the insights provided by the AI and ML algorithms will help modify the existing business processes and build formidable capabilities. By incorporating business process reengineering, the firm can create powerful, intelligent system capabilities that are heterogeneous and immobile. Therefore these capabilities will be hard to replicate by its rivals due to the complexity and costs of changing the business processes will not justify the duplication (Powell & Dent-Micallef, 1997; Zhuang & Lederer, 2006).

As per past research, the relationship between IT and business is defined as cooperation and alignment between IT functions and other functional departments (Wade & Hulland, 2004). As an organization builds up the information technology footprint, the technology and business teams have to start building trust and cooperating to achieve the organization's strategic goals and objectives. In addition, technical teams will have to align with other business functions to create project teams that contribute to organization success by working on IT roadmaps (Powell & Dent-Micallef, 1997; Rivard et al., 2006; Wade & Hulland, 2004; Zhuang & Lederer, 2006). This collaboration will contribute by creating superior IT capabilities, and the alignment with other business functions will create technology capabilities that are hard to duplicate by competitors.

Technical vendor relationships are defined as the firm's ability to manage linkages between the IT function and vendors (Wade & Hulland, 2004). As companies invest in IT resources, they form strategic partnerships with IT hardware, software, services, and outsourcing partners. In doing so, these technical vendors become part of the organization's extended teams that help organizations create and align technology capabilities that are heterogeneous and immobile. Competitors will find these capabilities hard to copy as building technical vendor trust and relationships take longer to establish through trial and error (Liang et al., 2010; Mata et al., 1995; Powell & Dent-Micallef, 1997; Wade & Hulland, 2004). For example, Greater Toronto Airport Authority (GTAA) which manages Pearson International Airport has strategic IT partnerships with third-party vendors for technology services. When projects are initiated at GTAA, all technical vendors that manage an impacted IT application sit as stakeholders and part of the project team. These strategic partnerships created by GTAA with the technology vendors have helped GTAA reduce costs while servicing 40 million passengers and be named the best large airport in North America three years in a row from 2017 to 2019. As discussed, intelligent systems are part of an organization's technology investment. Therefore, the IT department must align IT functions with other business functions and form strategic partnerships with intelligent systems hardware, software, and technical service vendors. These partnerships will help build valuable, intelligent systems capabilities that are heterogeneous and immobile, hard to duplicate by the firm's rivals. Therefore, the following hypothesis is proposed:

Hypothesis 3 (H3): *Intelligent systems business resources have a positive effect on the firm's intelligent systems capabilities.*

3.2.4 Intelligent Systems Capabilities

Prior empirical studies have shown that organizations use IT to enhance firm performance (Akter et al., 2016; Bohanec et al., 2017, 2017; Cruz-Dominguez & Santos-Mayorga, 2016; Dwivedi et al., 2019; Fountaine et al., 2019; Gupta & George, 2016; Martínez et al., 2018; Mikalef & Gupta, 2021; Sun et al., 2008; Wamba et al., 2017). Companies can leverage intelligent systems to enhance their marketing capabilities by using analytics to add new product features and introduce or enhance new services. Furthermore, companies can implement recommendation engines and search engines to help generate revenues from multiple channels to increase cash flows. For example, Amazon started as an online book retailer competing with Barns and Noble. However, the technology resources investment by Amazon has given the firm many IT capabilities, one of which is shared cloud computing capabilities. Amazon packaged the cloud computing capabilities as Amazon Web Services and branched into direct competition with IBM, Microsoft, and Oracle. Companies can use intelligent systems to enhance sales by predicting future growth potential for existing and new products and services (Dwivedi et al., 2019; Ulrich Lichtenthaler, 2019; Vocke et al., 2019b).

This study defined intelligent systems infrastructure capabilities, such as AI and ML-driven capabilities that optimize business processes for efficiencies. As per prior research, an organization's investment in AI and ML capabilities help the firm create a temporary competitive advantage that helps companies optimize business process and increase sales and profitability (Akter et al., 2016; Gupta & George, 2016; Mikalef & Gupta, 2021; Wamba et al., 2017). For example, Amazon, Canadian Tire, Rogers Communications, and Walmart have invested in AI and ML-driven search engines, recommendation engines, fraud engines, supply chain management, and information security. These companies have used intelligent systems capabilities to optimize eCommerce and warehouse management to increase sales and reduce financial fraud.

This research study defines intelligent systems personnel capabilities as IT staff's big data, AI/ML skills, and knowledge to undertake and complete assigned tasks to transform the business into a competitive force. Past studies have shown that as an organization invests in intelligent systems, the organization will develop unique intelligent system personnel capabilities that will be hard to duplicate by its competitors (Akter et al., 2016; Gupta & George, 2016; Mikalef & Gupta, 2021; Wamba et al., 2017).

Ant Group, Google, and Uber have invested heavily in AI and ML platforms. The technical and business teams at these organizations have developed unique intelligent systems personnel capabilities which have been hard to duplicate by the competitors. These intelligent systems personnel capabilities have enabled these companies to increase sales and profits more than their rivals.

As discussed previously, we define intelligent systems management capabilities as the IT department's ability to handle procedures in a structured manner to manage AI and ML resources in harmony with business needs and priorities. Prior research has shown that as organizations invest in intelligent systems, these organizations will develop unique intelligent system management capabilities that will be hard to duplicate by rivals (Akter et al., 2016; Gupta & George, 2016; Mikalef & Gupta, 2021; Wamba et al., 2017). For example, Amazon, Facebook, Tesla, and Twitter have invested heavily in AI and ML platforms. The management teams at these organizations have developed unique intelligent systems management capabilities which have been hard to duplicate by their competitors. These intelligent systems management capabilities have enabled these companies to increase sales and profits more than their rivals and be admired by investment analysts. Therefore, the following hypothesis is proposed:

- ***Hypothesis 4 (H4):*** *Intelligent systems capabilities positively mediate the relationship between intelligent systems resources and the firm performance.*

4. METHODOLOGY

4.1 Unit of Analysis and Observation

In social science research unit of analysis includes individuals, groups, organizations, countries, resources, and objects the research is studying (Babbie, 2015). This study is to understand if the investment in intelligent systems that generates a competitive advantage affects firm performance at organizations in Canada and the USA. Intelligent systems are a type of company's internal resources that is part of IT investment that combines the features and capabilities of several big data applications and utilities within a single solution that enables the organization to execute AI and ML algorithms for analytics (Techopedia, n.d.). This study measures the mediating effect of intelligent systems capabilities on intelligent systems resource's relationship to an organization's performance. Therefore, the unit of analysis of this study is resources. Since the study is looking at firms leveraging intelligent systems capabilities to increase the competitive advantage, the unit of observation of this study is the organization.

4.2 Population of Interest

This research is focused on companies in Canada and the USA that invest heavily in intelligent systems platforms to stay competitive and ward off threats from competitors such as Amazon and Walmart. The research participants were from C-Level to line managers of the organizations.

4.3 Research Procedure and Design

This research used the scientific method of research inquiry using quantitative analysis. Quantitative analysis is used for the following, (a) look at indicating a failure to reject a hypothesis and not prove or disprove the hypotheses, (b) test the theory and then refine, discard or formulate new theories based on the evidence at hand, (c) use data, evidence and rationale to shape the knowledge, (d) try to prove the theories using variables that have causal relationships using quantitative analysis and (e) objective is to examine that methods used do not introduce biases (Creswell, 2013). This research used an online survey that was administered via Qualtrics. Therefore, this research incorporated quantitative and practical online survey research for collecting, organizing, and analyzing data (Babbie, 2015).

The research study has identified significant trends and gaps through a literature review (Vandenberg, 2006), and the literature review was used as empirical observation for theory verification (Creswell, 2006). As part of the quantitative analysis, non-experiment design methods such as surveys can be used to collect data. The study used a questionnaire survey data to identify if investment in internal resources, such as intelligent systems (based on AI and ML), generates a competitive advantage for the firm. This research prepared ordinal scales for construct measurements. The Likert scale is a popular method used for ordinal data in social science research (Babbie, 2015; Bhattacherjee, 2012). Therefore, this study implemented the Likert summative scaling method.

4.4 Measures

Powell and Dent-Micallef (1997) published their scholarly paper on identifying the linkages between IT and firm performance. Zhuang and Lederer (2006) modified Powell and Dent-Micallef's survey measurement scales to study the RBV of eCommerce implementation. Studies completed by Gupta and George (2016), Mikalef and Gupta (2021), Wamba et al. (2017), and Zhuang and Lederer (2006) have published survey measurement scales with Cronbach alpha of 0.70 and higher. This research study adapted and modified Gupta and George, Mikalef and Gupta, Wamba et al., and Zhuang and Lederer survey measurement items.

4.4.1 Content Validity

The instrument can be assumed valid when construct scale items have been developed from a literature review and pool of questions are from prior empirical research (Straub, 1989). When research scientists design new concepts, construct proliferation or redundancy can appear when the new constructs are built using existing constructs. Shaffer et al. (2016) and Rönkkö and Cho (2022) identified that construct proliferation and redundancy could cause issues with discriminant validity. Prior researchers have recommended doing the following during concept development based on a literature review (a) survey the empirical literature to identify the previous definitions of constructs, (b) interview subject matter experts, colleagues, and practitioners, (c) use focus groups and direct observation, (d) use of case studies, and (e) compare the constructs with its negative pole and examine the literature for the current implementation of the constructs (Podsakoff et al., 2003, 2016; Shaffer et al., 2016). This research study followed the same approaches recommended by past researchers by conducting extensive research on published peer-reviewed journal articles on RBV, information technology, intelligent systems, and firm performance spanning over 40 years. Constructs and related factors were extracted or defined based on a thorough literature review, and measures were selected and modified to fit the research scope.

4.4.2 Demographic information

This study collected demographic information, including participants' job function, department, industry, age range, gender, and the number of years with the organization, to minimize any possibility of determining the identity of any of the survey participants. The job function was a multiple-choice selection with c-level to line management and text input to capture other titles. Department was a multiple-choice selection with Accounting and Finance, Customer Support, Data Science and Analytics, eCommerce, Sales and Marketing, Technology, and text input to capture other departments. The industry was a multiple-choice selection the participants were able to choose. The age range was a multiple-choice selection with under 25, 25-45, 45-65, and over 65. Gender was a multiple-choice selection for males or females. Text input was used to capture the number of years worked at the organization.

4.4.3 Intelligent Systems Infrastructure

As previously discussed, intelligent systems infrastructure is defined as technology infrastructure, including centralized on-premise and cloud-hosted platforms that can enable and execute AI and ML algorithms that contribute to intelligent systems capabilities, which gives the organization a competitive advantage. Intelligent system infrastructure was measured using the following two factors a) intelligent systems environment and b) intelligent systems performances.

4.4.3.1 Intelligent systems environment

An intelligent system environment is a technology infrastructure that includes centralized on-premise and cloud-hosted platforms, which can enable and execute AI and ML algorithms. Mikalef and Gupta (2021) measured AI and ML technology with eight survey items. This study has adapted Mikalef and Gupta survey items to measure the intelligent systems environment. The adapted intelligent system environment measures consist of eight survey items designed to measure the executive's perception of the intelligent system environment's impact on intelligent systems capabilities. In addition, the intelligent system environment scale items were evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.3.2 Intelligent Systems Performance

Intelligent systems performance is defined as the intelligent system infrastructure's network, service, and device performance. Zhuang and Lederer (2006) measured network performance with three survey items. This research study adopted Zhuang and Lederer survey items to measure intelligent systems performance. The modified survey measurement scales for Intelligent system performance consist of five items designed to measure executives' perception of the impact of intelligent system performance on intelligent systems capabilities. Intelligent system performance scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.4 Intelligent Systems IT Human Resources

As noted, intelligent systems information technology (IT) human resources will combine the following two factors, intelligent systems technical skills and intelligent systems management skills.

4.4.4.1 Intelligent Systems Technical Skills

Intelligent systems technical skills are technical skills that contribute to intelligent system capabilities. Gupta and George (2016) measured technical skills with six survey items. This study has adopted Gupta and George survey items to measure intelligent systems technical skills. Intelligent system technical skills consist of six survey items designed to measure executives' perception of the intelligent system technical skills impact on intelligent systems capabilities. Intelligent system technical skills scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.4.2 Intelligent Systems Management Skills

Intelligent system technical management skills are management skills that contribute to intelligent system capabilities. Gupta and George (2016) measured management skills with six survey items. This research adopted Gupta and George's survey items to measure intelligent systems management skills. The modified intelligent system management skills consist of nine survey items designed to measure executives' perception of the intelligent system management skills' impact on intelligent systems capabilities. Therefore, Intelligent system management skills scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.5 Intelligent Systems Business Resources

This study defines intelligent systems business resources as complementary and intangible business resources that contribute to intelligent systems' capabilities. Intelligent systems business resources will include the following three factors; (a) intelligent system planning, (b) process redesign, and (c) IT external relationships.

4.4.5.1 Intelligent System Planning

This study defines intelligent system planning as short-term and long-term planning activities to implement intelligent systems strategy in the organization. Zhuang and Lederer (2006) measured eCommerce planning with three survey items. This study adopted Zhuang and Lederer's survey items to measure Intelligent system planning, consisting of six survey items designed to measure executives' perception of the intelligent system planning on intelligent systems capabilities. Intelligent system planning scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.5.2 Process Redesign

In this research study, process redesign is defined as the ability of the organization to change business processes to meet business and market changes (Zhuang & Lederer, 2006). Zhuang and Lederer (2006) measured process redesign and benchmarking with six survey items. This study adopted Zhuang and Lederer's survey items to measure process redesign, consisting of eight items designed to measure executives' perception of process redesign on intelligent systems capabilities. Process redesign scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.5.3 IT External Relationships

For this research, IT external relationships are defined as internal and external relationships that align and link IT functions with business and vendor teams. Zhuang and Lederer (2006) measured partner and IT business relationships with six survey items. This study adopted Zhuang and Lederer's survey items to measure external IT relationships. Nine survey items were designed to measure executives' perception of the IT relationships with business and vendor teams' impact on intelligent systems capabilities. IT external relationships scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.6 Intelligent Systems Capabilities

For this study, intelligent systems capabilities are defined as competence to provide intelligent business insight using intelligent systems infrastructure, personnel, and management capabilities to transform the business into a competitive force. Wamba et al. (2017) introduced research scales to study big data analytics capabilities' relationship to firm performance. This study adopted Wamba et al. study survey measurement scales. Intelligent systems capabilities consist of forty-six survey items designed to measure executives' perception of the intelligent systems capabilities' contribution to firm performance. Intelligent systems capabilities scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.4.7 Firm Performance

This research defines firm performance as financial performance to measure competitive advantage. Powell and Dent-Micallef (1997) published their scholarly paper on identifying the linkages between IT and firm performance. Zhuang and Lederer (2006) modified Powell and Dent-Micallef's survey measurement scales to study the RBV of eCommerce implementation. This research study adapted and modified Zhuang and Lederer's survey measurement scales. The firm performance scale items consist of five survey items designed to measure executives' perception of the impact of the intelligent system on financial performance. Firm performance was designed as a subjective measure of financial performance which consists of five questions about the firm's overall revenue growth and profitability since the implementation of intelligent systems (Powell & Dent-Micallef, 1997; Zhuang & Lederer, 2006). Firm performance scale items will be evaluated using Likert response gages ranging from one (Strongly Disagree) to five (Strongly Agree).

4.5 Informed Pilot

This research study conducted an informed pilot with faculty members from FIU Chapman Graduate School Information Systems and Business Analytics department and selected members from FIU DBA cohort 2 class. Furthermore, three industry subject matter experts (SMEs) with a doctor of philosophy in AI were consulted. This research study proposal was nominated and was selected for the Engaged Management Scholarship (EMS) 2021 Doctoral Consortium. Therefore, additional feedback was received from two prominent external faculty members from Pepperdine University Grasiadio Business School and Georgia State University Robinson College of Business. In addition to the external faculty members, six other DBA students from various US and global universities took part in the EMS 2021 Doctoral Consortium breakout sessions. The research proposal and survey instrument were emailed to the informed pilot study participants in advance. In addition, the research proposal abstract, PowerPoint presentation, and video presentation recording were uploaded and shared with the Doctoral Consortium breakout session participants four weeks before the meeting.

The external faculty members recommended changing the dissertation title to accurately portray the research study’s primary intent: to study executives’ perception of investment in intelligent systems and the effect on firm performance. The title recommendation was incorporated into the study. FIU faculty suggested further readings to add hypotheses between intelligent systems infrastructure resources and the direct effect on firm performance. This recommendation was incorporated into the revised main study hypothesis. Industry SMEs recommended including executive commitment construct to moderate intelligent systems resources relationship to intelligent systems capabilities. This recommendation was not incorporated after speaking with the dissertation chair. Based on the feedback from the informed pilot group and external faculty, the survey instrument was modified, and the formal pilot study survey questionnaire is in Appendix 2. Informed pilot members recommended using a convenient sample of former colleagues who have worked with the researcher to complete one pilot study. This recommendation was given as the population of interest is specialized and to reduce burning out too many research participants before conducting the main study. Therefore, the methodology section was updated per the informed pilot group recommendations.

5. DATA ANALYSIS & RESULTS

5.1 Formal Pilot

5.1.1 Data Collection

5.1.1.1 Procedure

This research study conducted a formal pilot by reaching out to industry practitioners who have previously worked with the researcher at various client companies. These participants were selected to validate the measurement instrument, as the pilot study can be used as a testing ground before the surveys are administered to the main study participants (Straub, 1989). In addition, the research participants were senior information technology leaders and managers of their organizations.

5.1.1.2 Dataset Preparation

In order to complete the statistical analysis of the dataset, the pilot study data had to be cleaned and prepared using the below steps:

1. Variable names were deleted in the instrument, and kept only the unique identifier number given to each question.
2. Numeric variables that require decimal were coded.
3. Variable values with missing values were coded with -99.

5.1.2 Data Analysis

Pilot study data collection spanned four weeks with an email sent out to 35 industry practitioners, inviting them to participate in the survey. The survey instrument published for the formal pilot is included in Appendix 2. Reminder emails were sent out to participants weekly during the first two weeks, and during the last two weeks, the reminder emails were sent twice a week.

5.1.2.1 Sample Size and Response Rate

The pilot study used an online survey that asked respondents to provide their perceptions concerning company investment in intelligent systems and organization performance. A non-probability sampling technique was used, also known as a convenience sample. This study reached out to industry practitioners who have previously worked with the researcher at various client companies. Invitation email was sent out to 35 industry practitioners, and a total of 35 surveys were completed, resulting in a response rate of 100%.

Table 2 Pilot Study Sample Characteristics (N=35)

Baseline characteristics	**Pilot Sample**	
	N	***%***
Company Industries		
Education	1	2.9
Finance and Insurance	10	28.6
Health/social care	1	2.9
Information	5	14.3
Real estate, Renting and Leasing	1	2.9
Retail	6	17.1
Services	2	5.7
State and Local Government	3	8.5
Other *(consulting and telecommunications)*	6	17.1
Company Location		
Canada	27	77.1
United States of America	7	20.0
Other *(multinational)*	1	2.9
Number of Employees		
Under 100 employees	4	11.4
Between 100 to 999 employees	3	8.6
Between 1000 to 4999 employees	6	17.1
Between 5000 to 10,000 employees	6	17.1
Over 10,000 employees	16	45.8
Company Revenues		
Under $100 million in revenue	7	20.0
Between $100 million to $999 million in revenue	4	11.4
Between $1 billion to $4.9 billion in revenue	6	17.1
Between $5 billion to $10 billion in revenue	8	22.9
Over $10 billion in revenues	10	28.6
Participant Job Title		
C-Level	5	14.3
Upper Management	4	11.4
Middle Management	7	20.0
Line Management	9	25.7
Other *(technical consultant, engineer, developer, solution architect)*	10	28.6
Department		

Baseline characteristics	**Pilot Sample**	
	N	***%***
eCommerce	2	5.7
Technology	31	88.6
Other *(consulting and product management)*	2	5.7
Participant Age		
25 to 34 years	3	8.5
35 to 44 years	9	25.7
45 to 65 years	22	62.9
Over 65 years	1	2.9
Participant Gender		
Male	33	94.3
Female	2	5.7

As depicted in Table 2 above, the formal pilot study consists of *N*=35 participants, of which 33 (94.3%) were men and 2 (5.7%) were women. The formal study participants were located in Canada 27 (77.1%), the United States 7 (20%), and other *(multinational)* 1 (2.9%). The respondents primarily worked in technology 31 (88.6%), eCommerce 2 (5.7%), and other *(consulting and product management)* 2 (5.7%). Participants job titles included c-level 5 (14.3%), upper management 4 (11.4%), middle management 7 (20%), line management 9 (25.7%), and Other *(technical consultant, engineer, developer and solution architect)* 10 (28.6%).

5.1.2.2 Construct Validity Analysis

Exploratory factor analysis (EFA) is used in scientific research in social science to determine the underlying factors to retain for the latent variable of interest. Widely used mathematical and psychometric criteria for EFA are the Kisaser-Guttman criterion, parallel analysis, and minimum average partial method (Dinno, 2009; Garrido et al., 2013). Many statistical packages use the eigenvalue greater than one and scree test to identify variables that significantly load on factors. Past research has identified Horn's parallel analysis (PA), which has emerged as one of the most accurate when determining the number of factors. For example, Garrido et al. (2013) study identified that PA with Pearson Correlations (PCOR) had performed better than other methods and recommended other researchers to use this method. In their published papers, Hayton (2004) and Dinno (2009) showed a step-by-step guide to using parallel analysis to generate average eigenvalues using SPSS and Stata. The actual and PA eigenvalues must be generated when using PA in research. A comparison of both eigenvalues is completed. It is recommended to retain only the factors greater than the PA average eigenvalues (Dinno, 2009; Garrido et al., 2013). This research study used PA to determine the number of factors to retain.

The sample size of the responses collected from the formal pilot was too small to complete a factor analysis using second-order constructs (Chong & Jun, 2005; Dohoo et al., 1997; Farrar & Glauber, 1967; Fornell & Larcker, 1981; Rönkkö & Cho, 2022). Therefore, separate factor analysis was completed for each of the constructs. Factor analysis (FA) using the principal component extraction method with direct oblimin rotation was performed on all the instrument items for each construct in the formal pilot study data (n=35) valid cases. The Kaiser-Meyer-Olkin measure of sampling adequacy is a statistical value used to decide whether or not the sample is sufficient for performing factor analysis (An Gie Yong & Sean Pearce, 2013; Costello & Osborne, n.d.; Garrido et al., 2013). The latent variable factors had Kaiser-Meyer-Olkin measure of sampling adequacy greater than .500, confirming the sample size was adequate for the factor analysis. Bartlett's test of sphericity is the second measure of sampling adequacy, which tests for the overall significance of all correlations among all items on the measuring instrument (An Gie Yong & Sean Pearce, 2013; Garrido et al., 2013). Bartlett's test of sphericity for all factors was significant, which supported the hypothesis that all correlations tested simultaneously were statistically different from zero.

Some first-order latent variables had multiple factors with eigenvalues greater than 1.00. Therefore, PA for each of the first-order constructs was completed and analyzed. However, the study only retained factors greater than the PA average eigenvalues. Hence, all the first-order latent variables based on the parallel analysis had a one-factor model for each construct in the research.

5.1.2.3 Construct Reliability Analysis

Table 3 Pilot Data Descriptive Statistics with Reliability (N=35)

Second Order Construct	**First Order Construct**	**Item #**	**Mean**	**Std. Deviation**	**α**
Intelligent Systems Infrastructure (ISI)	Intelligent Systems Infrastructure Environment (ISI-ENV)	ISI-ENV_1	3.94	1.06	0.879
		ISI-ENV_2	3.80	1.11	
		ISI-ENV_3	3.91	1.12	
		ISI-ENV_4	3.17	1.07	
		ISI-ENV_5	3.17	1.10	
		ISI-ENV_6	3.54	1.17	
		ISI-ENV_7	3.54	1.29	
		ISI-ENV_8	4.00	0.84	
	Intelligent Systems Infrastructure Performance (ISI-PERF)	ISI-PERF_1	4.06	0.802	0.914
		ISI-PERF_2	3.89	0.796	
		ISI-PERF_3	3.4	1.063	
		ISI-PERF_4	3.57	0.979	
		ISI-PERF_5	3.57	0.85	
Intelligent Systems IT Human Resources (ISITHR)	Intelligent Systems IT Human Resources Technical Skills (ISITHR-TS)	ISITHR-TS_1	2.97	0.92	0.880
		ISITHR-TS_2	3.37	1.00	
		ISITHR-TS_3	3.26	0.98	
		ISITHR-TS_4	3.37	0.94	
		ISITHR-TS_5	3.26	1.04	
		ISITHR-TS_6	3.54	0.89	
		ISITHR-MS_1	4.14	0.81	0.912

Second Order Construct	First Order Construct	Item #	Mean	Std. Deviation	α
	Intelligent Systems IT Human Resources Management Skills (ISITHR-MS)	ISITHR-MS_2	3.49	0.98	
		ISITHR-MS_3	3.37	1.00	
		ISITHR-MS_4	3.91	0.98	
		ISITHR-MS_5	3.54	0.98	
		ISITHR-MS_6	3.46	1.07	
		ISITHR-MS_7	3.60	1.06	
		ISITHR-MS_8	3.60	1.01	
		ISITHR-MS_9	3.54	1.04	
Intelligent Systems Business Resources (ISBR)	Intelligent Systems Business Resources-IT External Relationship (ISBR-ITER)	ISBR-ITER_1	3.86	0.88	0.921
		ISBR-ITER_2	4.00	0.64	
		ISBR-ITER_3	3.86	0.85	
		ISBR-ITER_4	3.69	0.76	
		ISBR-ITER_5	3.63	0.77	
		ISBR-ITER_6	4.06	0.77	
		ISBR-ITER_7	3.89	0.90	
		ISBR-ITER_8	3.80	1.05	
		ISBR-ITER_9	3.54	0.98	
	Intelligent Systems Business Resources-Process (ISBR-PR)	ISBR-PR_1	3.23	1.24	0.912
		ISBR-PR_2	3.29	1.07	
		ISBR-PR_3	3.57	0.88	
		ISBR-PR_4	3.40	0.85	
		ISBR-PR_5	3.20	0.90	
		ISBR-PR_6	3.80	0.83	
		ISBR-PR_7	3.49	0.89	
		ISBR-PR_8	3.40	0.88	
	Intelligent Systems Business Resources - Planning (ISBR-PLN)	ISBR-PLN_1	4.11	0.93	0.887
		ISBR-PLN_2	3.74	1.04	
		ISBR-PLN_3	3.71	0.96	
		ISBR-PLN_4	3.97	0.79	
		ISBR-PLN_5	3.74	0.89	
		ISBR-PLN_6	3.51	0.95	
		ISBR-PLN_7	3.40	1.06	
		ISBR-PLN_8	3.37	1.11	
Intelligent Systems Capabilities	Intelligent Systems Capabilities-Infrastructure Capabilities	ISC-IC_1	3.09	0.95	0.909
		ISC-IC_2	3.17	1.01	
		ISC-IC_3	3.26	0.95	
		ISC-IC_4	3.17	1.07	
		ISC-IC_5	3.14	0.97	
		ISC-IC_6	3.00	0.87	
		ISC-IC_7	3.20	0.96	
		ISC-IC_8	3.03	0.86	
		ISC-IC_9	3.03	1.01	
		ISC-IC_10	3.31	0.96	

Second Order Construct	First Order Construct	Item #	Mean	Std. Deviation	α
	Intelligent Systems Capabilities-Personnel Capabilities (ISC-PC)	ISC-PC_1	3.31	0.96	0.970
		ISC-PC_2	3.37	0.91	
		ISC-PC_3	3.20	0.87	
		ISC-PC_4	3.37	0.97	
		ISC-PC_5	3.20	0.93	
		ISC-PC_6	3.37	0.88	
		ISC-PC_7	3.34	0.84	
		ISC-PC_8	3.43	0.85	
		ISC-PC_9	3.34	0.80	
		ISC-PC_10	3.54	0.74	
		ISC-PC_11	3.34	0.77	
		ISC-PC_12	3.37	0.88	
		ISC-PC_13	3.40	0.81	
		ISC-PC_14	3.49	0.78	
		ISC-PC_15	3.20	0.87	
		ISC-PC_16	3.14	0.91	
	Intelligent Systems Capabilities-Management Capabilities (ISC-MC)	ISC-MC_1	3.43	0.88	0.968
		ISC-MC_2	3.20	0.93	
		ISC-MC_3	3.11	0.87	
		ISC-MC_4	3.17	0.79	
		ISC-MC_5	3.17	0.89	
		ISC-MC_6	3.37	0.88	
		ISC-MC_7	3.26	0.85	
		ISC-MC_8	3.34	0.94	
		ISC-MC_9	3.43	0.78	
		ISC-MC_10	3.57	0.85	
		ISC-MC_11	3.49	0.85	
		ISC-MC_12	3.23	0.88	
		ISC-MC_13	3.11	0.90	
		ISC-MC_14	3.17	0.89	
		ISC-MC_15	3.40	0.85	
		ISC-MC_16	3.43	0.85	
		ISC-MC_17	3.46	0.78	
		ISC-MC_18	3.31	0.96	
		ISC-MC_19	3.43	0.88	
		ISC-MC_20	3.37	0.88	
-	Firm Performance (FPERF)	FPERF_1	3.80	0.90	0.968
		FPERF_2	3.74	0.89	
		FPERF_3	3.57	0.92	
		FPERF_4	3.69	0.93	
		FPERF_5	3.63	0.88	

Intelligent Systems Infrastructure Resources Reliability Analysis

As discussed before, the intelligent systems infrastructure second-order construct includes intelligent systems infrastructure environment and intelligent systems infrastructure performances latent variables. Table 3 above depicts pilot data descriptive statics with reliability. The intelligent systems infrastructure performance with a Cronbach's alphas = .914 and intelligent systems infrastructure environment with a Cronbach's alphas = .879 shows high reliabilities.

Intelligent Systems IT Human Resources Reliability Analysis

As discussed, intelligent systems IT human resources second-order construct has latent variables technical and management skills. Table 3 above depicts pilot data descriptive statics with reliability. The intelligent systems technical skills with Cronbach's alphas = .880 and intelligent systems management skills with Cronbach's alphas = .912, which had high reliabilities.

Intelligent Systems Business Resources Reliability Analysis

As identified before, intelligent systems business resources second-order construct has IT external relationships, process redesign, and planning latent variables. Table 3 above depicts pilot data descriptive statics with reliability. The intelligent systems process redesign with Cronbach's alphas = .912, intelligent systems IT external relationship with Cronbach's alphas = .921, and intelligent systems planning with Cronbach's alphas = .887 with high reliabilities.

Intelligent Systems Infrastructure Capabilities Reliability Analysis

The intelligent systems infrastructure capabilities with Cronbach's alphas = .909 had high reliability.

Intelligent Systems Personnel Capabilities Reliability Analysis

The intelligent systems personnel capabilities with Cronbach's alphas = .970 had high reliability

Intelligent Systems Management Capabilities Reliability Analysis

The intelligent systems management capabilities with Cronbach's alphas = .968, which had high reliability

Firm Performances Reliability Analysis

The firm performance Cronbach's alphas = .968, which had high reliability.

5.1.2.4 Discriminant Validity Analysis

Campbell and Fiske (1959) introduced the concept of discriminant validity with their research paper on evaluating or testing scientific research validity. Their article introduced the psychology and social science research communities to use the multitrait-multimethod (MTTM) matrices to identify discriminant validity. The discriminant validity test is to test the concepts or measurements that are not related are unrelated (Lim & Ployhart, 2006; Rönkkö & Cho, 2022; Shaffer et al., 2016). In other words, the discriminant validity test checks if unrelated latent variables or measurements are not highly correlated. In some cases, a high correlation of independent concepts or measurements with theoretically different measurements introduces multicollinearity. Multicollinearity violates or causes issues with discriminant validity. Correlation less than 0.70 can suggest that discriminant validity likely exists between two scales and that results greater than 0.70 indicate that the latent constructs overlap considerably. Therefore, these concepts measure the same thing causing issues with discriminant validity. For example, Hair et al. (2016) and Hair et al. (2017) identified and documented guidelines for researchers to complete the discriminant validity assessment and these steps are:

1) verify the outer loadings of the latent construct is greater than the cross-loadings of other constructs,
2) use the Fornell and Larker criterion, which compares the square root of average variance extracted (AVE) values with the other constructs,
3) and assess the heterotrait-monotrait (HTMT) ratio of the correlations

5.1.2.4.1 Cross-loading Analysis

The first step in assessing discriminant validity is to verify that the outer loading of the latent construct is greater than the cross-loadings of other constructs and that the cross-loading of other constructs should be near zero (Asparouhov et al., 2015; Hair, Hollingsworth, et al., 2017; Rönkkö & Cho, 2022). The pilot study data cross-loading analysis indicated that intelligent systems capabilities first-order constructs (intelligent systems infrastructure capabilities, intelligent systems management capabilities, and intelligent systems personnel capabilities) were cross-loading above 0.70 on intelligent systems resources (intelligent systems infrastructure resources, intelligent systems IT human resources and intelligent systems business resources) first-order constructs. Furthermore, intelligent systems capabilities constructs were cross-loading on each other above 0.70. This analysis indicated intelligent systems capabilities first-order constructs scale items are measuring the same thing, or the scale items are similar to intelligent systems resources first-order latent constructs measurement items. Therefore, all the cross-loading items greater than 0.70 were deleted from the data set.

5.1.2.4.2 Fornell-Larker Criteria Analysis

Fornell and Larker (1981) criteria were used in the second step to establish if the AVE is larger than the squared correlation with other latent constructs. The squaring correlation of 0.70 indicates that the other constructs explain 49% of each latent construct variance. Therefore, loading of the other latent constructs should be less than 0.70 (Fornell & Larcker, 1981; Hair et al., 2016; Henseler et al., 2016; Rönkkö & Cho, 2022). The pilot study data analysis showed that intelligent systems capabilities first-order constructs (intelligent systems infrastructure capabilities, intelligent systems management capabilities, and intelligent systems personnel capabilities) Fornell and Larker criterion (the AVE square root loading) was above 0.70 on intelligent systems resources (intelligent systems infrastructure resources, intelligent systems IT human resources and intelligent systems business resources) first-order constructs. Therefore, the pilot study data showed a violation of discriminant validity.

5.1.2.4.3 HTMT Ratio Analysis

Henseler et al. (2016) published that cross-loading fails to identify discriminant validity when latent constructs are perfectly correlated. Fornell and Larker criteria perform poorly when indicator loadings of the constructs differ only slightly. Hence the study proposed the use of HTMT to identify discriminant validity issues. The HTMT threshold greater than 0.85 indicates discriminant validity issues (Hair, Hollingsworth, et al., 2017; Rönkkö & Cho, 2022). HTMT ratio analysis on the pilot dataset indicated that intelligent systems management and personnel capabilities were loading close to 0.85 on intelligent systems infrastructure capabilities. These loadings were reported even after all cross-loading items equal to or higher than 0.70 were deleted. The pilot study dataset results indicated that intelligent systems capabilities first-order constructs (intelligent systems infrastructure capabilities, intelligent systems personnel capabilities, and intelligent systems management capabilities) show high correlation or scale items contributing to discriminant validity issues.

5.1.2.4.4 Addressing Discriminant Validity Issues

Prior research has identified, construct redundancy, model misspecification, similar construct scale items, and small sample size have contributed to discriminant validity violations. For example, Rönkkö and Cho (2022), in their published research article, identified that (a) construct proliferation or redundancy, (b) measurement model misspecification, and (c) sample issues cause discriminant validity issues. Shaffer et al. (2016) published paper identified that (a) when constructs scale items or measures are too similar, (b) when there is a causal relationship between constructs, and (c) when there is empirical redundancy of constructs can lead to a violation in discriminant validly between constructs. Therefore, this research study continued with discriminant validity analysis to identify the root cause, and the findings are discussed next.

5.1.2.4.4.1 Construct Redundancy Analysis

Shaffer et al. (2016) and Rönkkö and Cho (2022) identified that construct proliferation and redundancy have caused discriminant validity issues in organizational research. Construct proliferation and redundancy happens when constructs are extended from existing literature and constructs cannot be distinguished or the construct is not inimitable. Podsakoff et al. (2016) and Shaffer et al. (2016) provided guidelines for creating better concept definitions by reviewing past empirical research, interviewing subject matter experts, and using case studies. This study extensively researched past peer-reviewed journal articles on AI, RBV, IT, intelligent systems, and firm performance spanning over 40 years. The research study constructs were developed based on RBV theory. Therefore, construct proliferation and redundancy can be ruled out as the cause of issues with discriminant validity.

5.1.2.4.4.2 Model Misspecification Analysis

Model misspecification violations are found in research when the model the researcher designed using regression analysis is in error. Model misspecification introduces coefficients and errors that produce biased parameter estimations. Hu and Bentler (1998), Jarvis et al. (2003), and MacKenzie et al. (2005) analyzed journal articles published in marketing and organization research journals, and their studies identified that 29% of the articles had model misspecification issues which may cause Type I and Type II errors of conclusions in hypothesis testing. Most documented model misspecifications have been issues related to formative constructs being modeled incorrectly as reflective constructs. Hence, the research study model was validated against the RBV and DCF literature to identify the model misspecification issues.

Past journal articles have all modeled both first-order latent constructs for organizational resources and organizational capabilities as reflective (Akter et al., 2016; Liang et al., 2010; Malhotra, 2001; Mao et al., 2016; Powell & Dent-Micallef, 1997; Wamba et al., 2017; Zhuang & Lederer, 2006). Hierarchical models are common in empirical marketing, organizational, and information technology studies as research concepts are multidimensional constructs. RBV constructs are multidimensional constructs, and the same is true for DCF constructs (Akter et al., 2016; Liang et al., 2010; Malhotra, 2001; Mao et al., 2016; Powell & Dent-Micallef, 1997; Wamba et al., 2017;

Zhuang & Lederer, 2006). Both reflective and formative construct combinations can be part of the hierarchical model when modeling hierarchical multidimensional constructs. RBV and DCF prior research studies have modeled the second-order composite latent constructs as formative, with first-order latent constructs being reflective (Akter et al., 2016; Liang et al., 2010; Malhotra, 2001; Mao et al., 2016; Powell & Dent-Micallef, 1997; Wamba et al., 2017; Zhuang & Lederer, 2006). The original research model in Figure 2 above uses a hierarchical model with formative second-order composite latent constructs and reflective first-order latent constructs. As per the model misspecification analysis, the original model is without model misspecification issues.

5.1.2.4.4.3 Sample Size Analysis

The pilot dataset was based on (N=35) sample size, which resulted in few observations for many independent variables. Chong and Jun (2005), Dohoo et al. (1997), Farrar and Glauber (1967), Fornell and Larcker (1981), , and Rönkkö and Cho (2022) identified that multicollinearity, confounding, and interaction problems in research can be attributed to small sample size. Small sample sizes can introduce bias into a research study and inflate the results, which will lead to incorrect hypothesis justifications. In order to validate if discriminant validity is due to sampling size, additional dataset collection is recommended. For example, Fornell and Larcker (1981), Dohoo et al.(1997), and Rönkkö and Cho (2022) recommended collecting additional datasets to complete the discriminant validity analysis prior to hypothesis testing to rule out sample size as the cause. Therefore, this research included intelligent systems capabilities scale items (intelligent systems infrastructure capabilities, intelligent systems personnel capabilities, and intelligent systems management capabilities) as part of the main study survey to verify whether the sample size was the cause of discriminant validity violations.

5.1.2.4.4.4 Similar Constructs Scale Items and Measures Analysis

Dynamic capability theory is built on RBV theory, which states that organizational resources build organizational capabilities. As per past research on RBV, IT infrastructure resources, IT human resources, and IT business resources form information technology resources that contribute to building IT infrastructure capabilities, IT personnel capabilities, and IT management capabilities which form IT capabilities (Akter et al., 2016; Gupta & George, 2016; Mikalef & Gupta, 2021; Wamba et al., 2017; Zhuang & Lederer, 2006).

This applied research study adopted preexisting scales from Gupta and George (2016), Mikalef and Gupta (2021), Zhuang and Lederer (2006) for intelligent systems resources first-order constructs and Wamba et al. (2017) for intelligent systems capabilities first-order constructs. Prior research has identified that theoretically distinct concepts that are hard to distinguish might have scale items with similar content (Chong & Jun, 2005; Dohoo et al., 1997; Farrar & Glauber, 1967; Fornell & Larcker, 1981; Rönkkö & Cho, 2022). Although inimitable, unique construct scale items might have similar scale items and would contribute to multicollinearity and discriminant validity issues. Gupta and George (2016) and Mikalef and Gupta (2021) defined first-order information technology resources constructs and scales to measure big data analysis and artificial intelligence. However, these studies utilized higher-order models, which used the latent variable scores of the first-order constructs to form the second-order corresponding variables. These two studies did not create separate scales for IT capabilities. Zhuang and Lederer (2006) created information technology resources to measure eCommerce infrastructure, IT human, and business resources. However, this study did not create separate measures for eCommerce capabilities. This research study used Wamba et al. (2017) scale items for intelligent systems capabilities first-order constructs. Wamba et al. (2017) used a higher-order model similar to Gupta and George's and Mikalef and Gupta's studies, which used the latent variable score first-order constructs to form the second-order corresponding variables. Wamba et al. did not create separate scale measurements for information technology resources.

As per the literature review, this research study is the first known study to combine the Gupta and George (2016), Mikalef and Gupta (2021), Zhuang and Lederer (2006) and Wamba et al. (2017) survey scale items for a theoretical study. As per the pilot study dataset, Fornell-Larcker criteria and HTMT ratio analysis resulted in violations of discriminant validity. As per the discriminate validity issue analysis, intelligent systems resources first-order latent constructs and intelligent system capabilities first-order constructs scale items are similar. When responding, the participants would have found distinguishing between the scale items difficult, and similar scale items may have contributed to the covariance across variables.

This research study identified that construct redundancy and model misspecification do not contribute to discriminant validity violations. Samples size and similar scale items have been identified as probable causes of the issues with discriminant validity. As previously discussed, to test that sample size is causing the discriminant validation issues, the main study survey included intelligent systems capabilities first-order construct measurement items (Chong & Jun, 2005; Dohoo et al., 1997; Farrar &

Glauber, 1967; Fornell & Larcker, 1981; Rönkkö & Cho, 2022). As a second step, an analysis will be conducted to validate that similar scale items or measures are causing the discriminant validity issues. Once the similar scale items or measures are confirmed as the cause of the discriminant validity issues, intelligent systems capabilities first-order constructs will be deleted from the study, and the model will be altered to complete the main study data analysis (Chong & Jun, 2005; Dohoo et al., 1997; Farrar & Glauber, 1967; Fornell & Larcker, 1981; Rönkkö & Cho, 2022).

As per the advice from the dissertation committee chair, intelligent systems capabilities first-order constructs were deleted. Moreover, discriminant validity assessment was completed with dependent variable firm performance and the independent variables intelligent systems infrastructure (intelligent systems environment and performances), intelligent systems IT human resource (intelligent system technical skills and management skills) and intelligent systems business resources (intelligent systems planning, process redesign and IT external relationships) on the pilot study dataset. As per the analysis, there were no discriminant validity issues found. Therefore, as shown in Figure 4 below, the research study proposed a revised model for the main study.

5.1.2.5 Revised Main Study Model

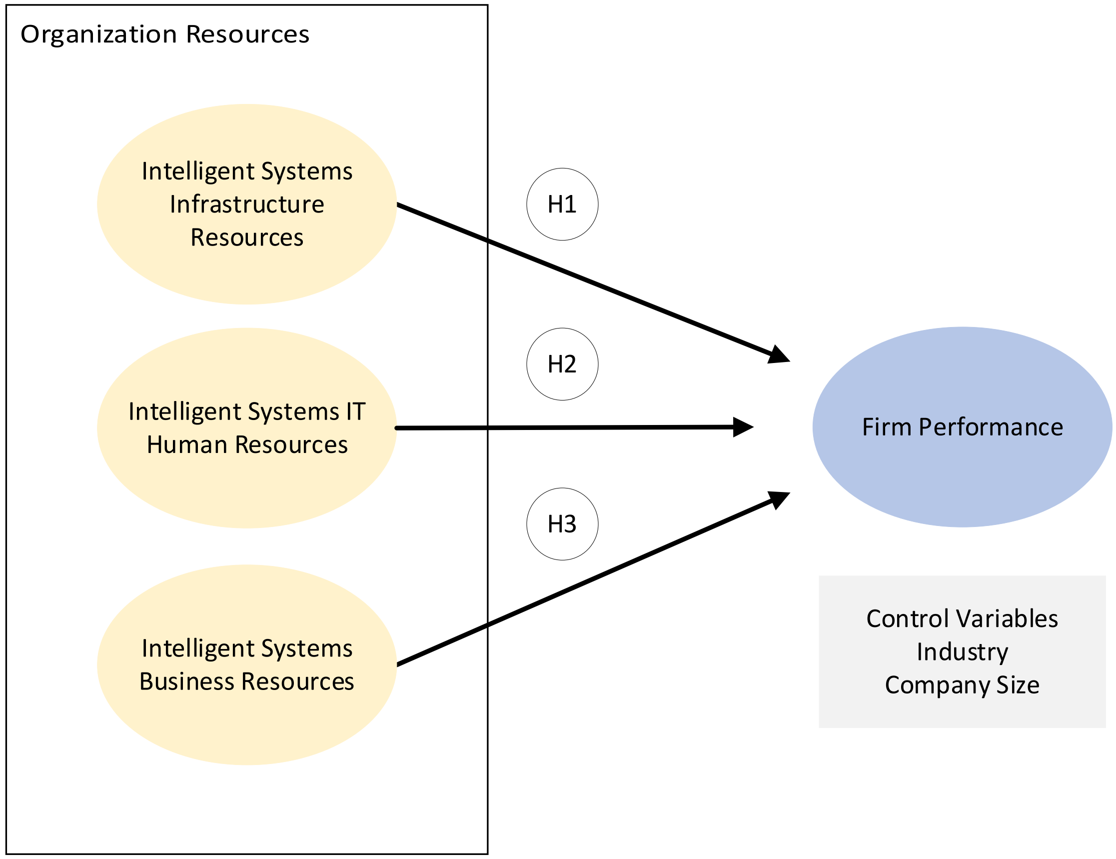

Figure 3 Revised Main Study Model

Figure 3 above depicts the revised research model for the main study based on the pilot study analysis. The revised model with independent and dependent constructs is based on the RBV, which explains the firm's investment in internal resources such as intelligent systems and firm performance of the organization. In this research model, the dependent construct is firm performance, and the independent constructs are intelligent systems infrastructure (intelligent systems environment and performances), intelligent systems IT human resource (intelligent system technical skills and management skills), and intelligent systems business resources (intelligent systems planning, process redesign, and IT external relationships). The control variables for this study are industry and company size.

5.1.2.6 Restating Main Study Hypothesis Justification

5.1.2.6.1 Intelligent System Resource and Firm Performance Hypothesis

Prior research studies have found the link between IT resources and firm performance. For example, Powell and Dent-Micallef (1997) found that IT alone does not produce sustainable performance advantages. Their study identified that firms had gained performance advantages by using IT to leverage intangible complementary human and business resources such as flexible culture, strategic planning, IT integration, and supplier relationships to increase firm performance. As discussed before, IT infrastructure, human resources, and business resources allow companies to gain a temporary competitive advantage over rivals and increase organization performance by increasing revenue and profitability. For example, Zhuang and Lederer (2006) identified that eCommerce infrastructure resources, IT human resources, and eCommerce intangible or business resources increase eCommerce performance and provide a competitive advantage that drives firm performance. Recent studies have identified that big data and AI platforms increase firm performance. For example, Gupta and George (2016) and Mikalef and Gupta (2021) studies identified that big data and AI infrastructure, IT human resources, and business resources provide a competitive advantage by building big data and AI capabilities. These IT capabilities contribute to firm performance. With these observations, this research study proposes to validate the intelligent systems resources effect on firm performance. Therefore, this research study propositions the following hypothesizes:

- ***Hypothesis 1 (H1):*** *Intelligent systems infrastructure resources has a positive effect on firm performance.*
- ***Hypothesis 2 (H2):*** *Intelligent systems IT human resources has a positive effect on firm performance.*
- ***Hypothesis 3 (H3):*** *Intelligent systems business resources has a positive effect on firm performance.*

5.2 Main Study

5.2.1 Data Collection

5.2.1.1 Procedure

The main study was conducted at organizations in Canada and the USA. For the main study total of 2000 participants were sent emails with invitations to participate in the research. The invitation email which was sent out is documented in Appendix 3. Of the 2000 participants, 1600 technology managers, directors, and senior executives were sent a targeted email campaign using LinkedIn Campaign Manager. In addition, another 400 participants were from the researcher's contact database of managers working in IT on eCommerce and data analytics department projects at organizations in Canada and the USA. The 400 participants were sent emails through Google Mass Email. The research study used an online survey that was administered via Qualtrics. Although surveys are an effective and efficient medium to reach stakeholders to collect data, low response rates can contribute to small sample size and introduce nonresponse bias (Rogelberg & Stanton, 2007). Following steps were taken to reduce nonresponse bias; (a) initial emails were sent out inviting the participants with the link to the survey, (b) the first follow up email was sent one week after the initial email with the link to the survey, (c) additional follow up emails were sent the next two weeks, (d) for surveys which were not completed within 4 weeks reminder emails were sent out twice a week for the next four weeks and (e) the LinkedIn campaign was configured to send invites to 200 unique participants each week during the eight weeks.

5.2.1.2 Dataset Preparation

To complete the statistical analysis of the main study dataset, the main study data had to be cleaned and prepared. The following steps were completed:

1. Variable names were deleted in the instrument and kept only the unique identifier number given to each question.
2. Numeric variables that require decimal were coded.
3. Variable values with missing values were coded with -99.

5.2.2 Data Analysis

5.2.2.1 Missing Data Analysis

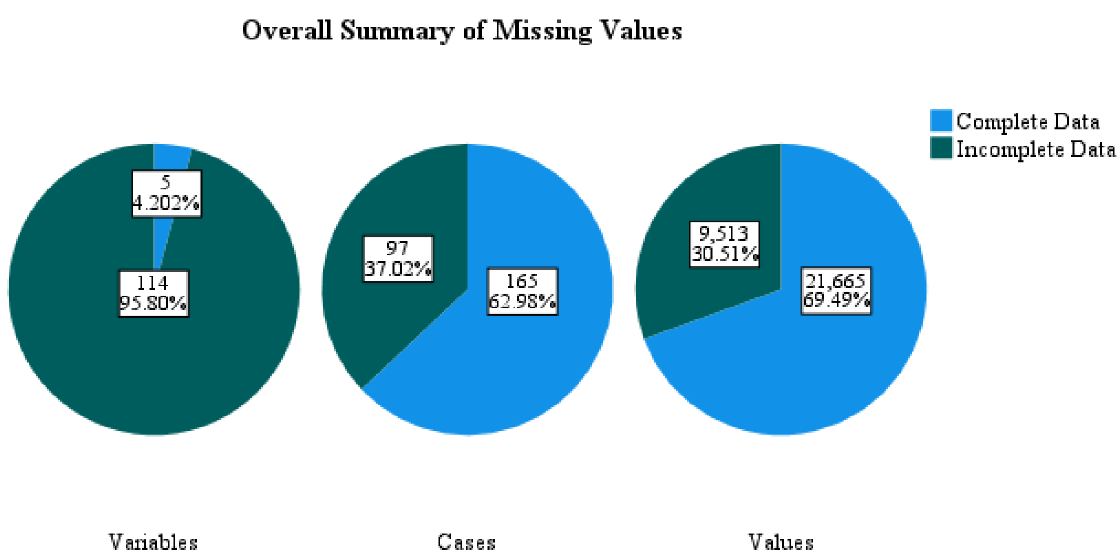

Figure 4 Main Study Overall Summary of Missing Values

Missing data in a research study is a common occurrence, and 15% to 20% of all research studies have missing data (Dong & Peng, 2013; Schlomer et al., 2010). Missing data can impact the statistical inference by introducing bias to the numerical analysis. There are two types of missing data, (a) unit-level non-response and (b) item-level non-response (Dong & Peng, 2013). Unit level non-response happens when the participants refuse to participate in the study or decline to take the survey. Item level non-response happens when participants do not follow through by answering all the questions. Therefore, there is incomplete information collected. A 5% or less missing rate does not introduce bias, but a 10% or more missing rate will introduce bias into the statistical analysis (Dong & Peng, 2013; Schlomer et al., 2010). Figure 4 above summarizes this research study's listwise percentage of missing cases.

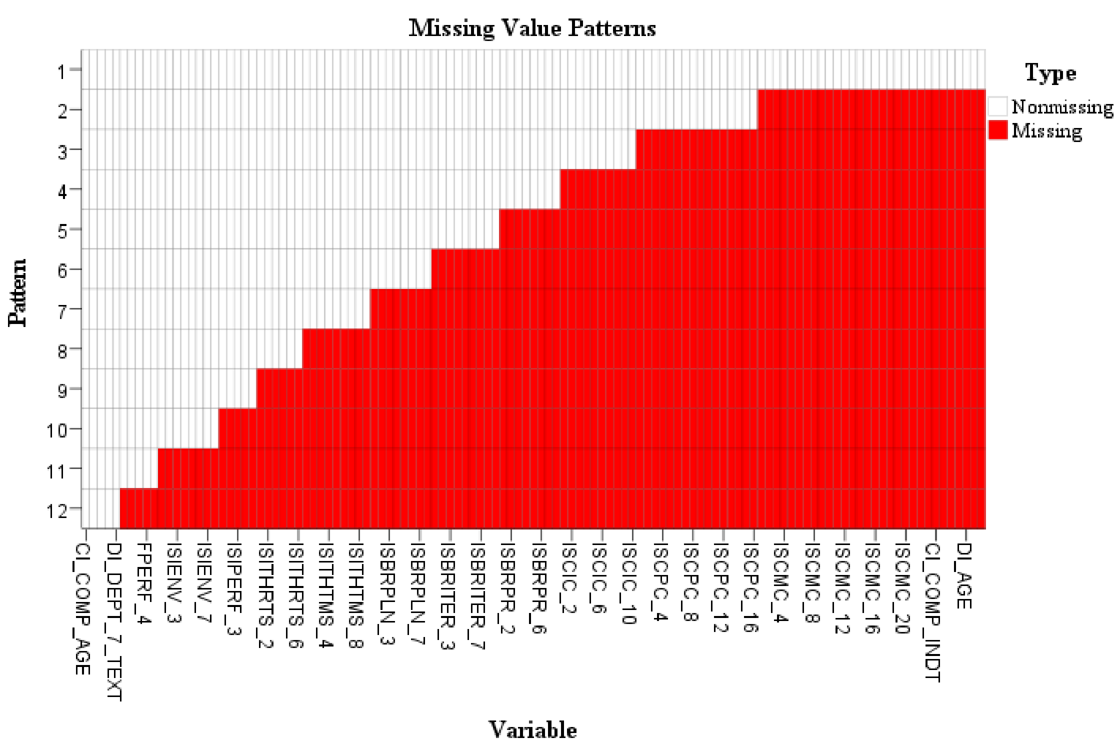

Figure 5 Main Study Missing Value Pattern

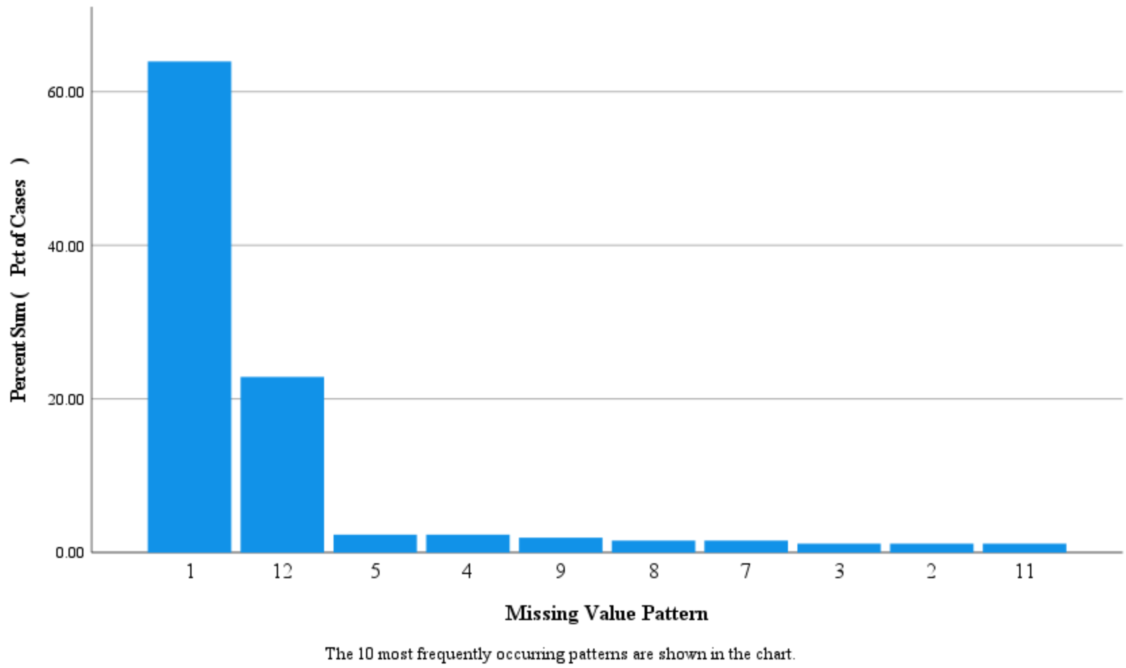

Figure 6 Main Study Missing Pattern Frequency Graph

Multiple imputation analysis was completed on the main study dataset. Figure 4 above shows the missing variables, cases, and values. The pie chart to the left shows that 95.8% of the variables have missing data, the middle pie chart shows that 37% of cases have missing data, and the pie chart to the right shows that 30.5% of values have incomplete data. Figure 5 above shows the missing value patterns, with each row in the graph showing the missing data patterns. The first row displays the pattern which does not have any missing data, and the twelfth row shows that there are more missing values in pattern 12. The organization of the missing red lines appears on the lower right. Hence there is monotonicity. The missing values pattern depicts the data as missing, not at random (MNAR). MNAR definition states there is a relationship between the value of the missing variable and why it is missing (Dong & Peng, 2013; Schlomer et al., 2010). In other words, data are missing not at random when the missing values are connected to the variable itself, even after regulating for other variables. For example, variables with missing cases in the main study dataset can be attributed to lack of time to complete or survey fatigue. Therefore, most missing cases are due to incomplete surveys or survey fatigue participants. Hence the fields are left null on purpose by the participants. Figure 6 above is the pattern frequencies graph, which shows that the first pattern is the most common and has no missing data across all the variables. The rest of the patterns have missing variables across all the variables.

The MNAR introduces bias to the dataset, and the missing data must be added through an imputation method. Stochastic imputation methods such as (a) stochastic regression, (b) expectation maximization (EM), (c) multiple imputations (MI), and (d) full information maximum likelihood (FIML) can be used to generate missing values for variables (Dong & Peng, 2013; Schlomer et al., 2010). Stochastic imputation methods are effective when the sample size is large, and with a small sample size adding missing data can be difficult (Nassiri et al., 2018). When a research study has a small sample size, the missing data will be imputed through median substitution, a non-stochastic imputation method (Dong & Peng, 2013; Schlomer et al., 2010). When the missing values' percentage exceeds 15%, then stochastic imputation or median substitution methods cannot be used. Therefore, as per past research, the missing value records have to be deleted from the study as the imputation methods can introduce bias to the research study dataset (Dong & Peng, 2013; Schlomer et al., 2010). The main study had more than 15% missing. Hence the dataset was prepared by deleting all the missing records from the dataset.

5.2.2.2 Response Rate and Participant Characteristics

Out of 2000 participants, only 165 surveys were fully completed by respondents. Resulting in a response rate of 8.25%. Although a response rate of 8.25% can be viewed as low, there is prior research that has found the studies targeting information technology c-level, upper management, middle, and line management has response rate between 7% to 20% range (Gerow et al., 2015; Preston et al., 2006; Wonseok Oh & Alain Pinsonneault, 2007). The main study response rate falls well within the 7%-20% expected range based on an 8.25% response rate. Out of the 348 participants who clicked on the survey link, only 165 completed the survey. Therefore, the corporation rate is 47.4%.

Table 4 Main Study Sample Characteristics (N=165)

Baseline characteristics	**Main Sample** *N*	*%*
Intelligent Systems Length of Use		
Less than 3 years	28	17.0
4-6 years	46	27.9
7-9 years	23	13.9
10 years or more	68	41.2
Industries		
Construction	1	0.6
Education	3	1.8
Federal Government	3	1.8
Finance and Insurance	32	19.4
Health/social care	6	3.6
Information	17	10.3
Manufacturing	7	4.2
Real estate, Renting and Leasing	8	4.9
Retail	19	11.5
Services	24	14.6
State and Local Government	2	1.2
Utilities	3	1.9

Baseline characteristics	**Main Sample**	
	N	**%**
Other *(computer gaming, consumer goods, defense, entertainment, energy, professional sports technology, telecommunication, and transportation)*	40	24.2
Location		
Canada	78	47.3
United States of America	76	46.0
Other *(multinationals operating in Canada and USA)*	11	6.7
Number of Employees		
Under 100 employees	14	8.5
Between 100 to 999 employees	13	7.9
Between 1000 to 4999 employees	27	16.4
Between 5000 to 10,000 employees	22	13.3
Over 10,000 employees	89	53.9
Company Revenues		
Under $100 million in revenue	27	16.4
Between $100 million to $999 million in revenue	20	12.1
Between $1 billion to $4.9 billion in revenue	22	13.3
Between $5 billion to $10 billion in revenue	22	13.3
Over $10 billion in revenues	74	44.9
Participant Job Title		
C-Level	12	7.3
Upper Management	58	35.2
Middle Management	62	37.6
Line Management	15	9.0
Other *(technical consultant, engineer, developer, solution architect)*	18	10.9
Department		
Accounting and Finance	6	3.6
Customer Support	5	3.0
Data Science and Analytics	11	6.7
eCommerce	27	16.4
Sales and Marketing	12	7.3
Technology	93	56.3
Other *(business development, human resources, legal, product management, supply chain, strategy and transformation)*	11	6.7

Baseline characteristics	Main Sample	
	N	***%***
Participant Age		
25 to 34 years	18	10.9
35 to 44 years	62	37.6
45 to 65 years	84	50.9
Over 65 years	1	0.6
Participant Gender		
Male	137	83.0
Female	28	17.0

Table 4 above, the main study consists of *N*=165 participants, of which 137 (83%) were men and 28 (17%) were women. The main study participants located in Canada were 78 (47.3%), the United States of America with 76 (46.0%), and other *(multinational)* 11 (6.7%). The respondents primarily worked in accounting and finance 6 (3.6%), customer support 5 (3.0%), data science and analytics 11 (6.7%), eCommerce 27 (16.4%), sales and marketing 12 (7.3%), technology 93 (56.3%), and other *(business development, human resources, legal, product management, supply chain, strategy and transformation)* 11 (6.7%). Participants job titles included c-level 12 (7.33%), upper management 58 (35.2%), middle management 62 (37.6%), line management 15 (9.0%) and Other *(technical consultant, engineer, developer, solution architect)* 18 (10.9%).

5.2.2.3 Original Model Discriminant Validity Testing

As discussed, the main study included the intelligent systems capabilities first-order constructs (intelligent systems infrastructure capabilities, intelligent systems management capabilities, and intelligent systems personnel capabilities) scale items in the survey and was tested for discriminant validity issues. Intelligent systems capabilities first-order construct Fornell and Larker criterion and HTMT ratio analysis indicated discriminant validity violations similar to the pilot study findings. The participant size (N=165) indicated this was not due to sample size, but the analysis confirmed that similar scale items or measures cause the discriminant validity issues. Therefore, intelligent systems capabilities first-order scale item records were deleted from the main study dataset. As shown in Figure 3 above, the revised study model and the revised hypothesis documented in section 5.1.2.6 above were used for the main study analysis.

5.2.2.4 Common Method Bias

The research study has to measure what the study set out to assess successfully, and the study has to draw the correct deductions from the data collected. Construct validity is a prerequisite to developing and accurately testing organization theories in empirical research (Doty & Glick, 1998; Podsakoff et al., 2003). Common method variance introduces biases to the relationship between two variables. When variance is introduced by the measurement method rather than the variables' true relationships, this confounds the proper relationship between the variable by either inflating or deflating the observed relationship by introducing Type I and Type II errors (Doty & Glick, 1998; Jarvis et al., 2003; MacKenzie et al., 2005; Podsakoff et al., 2003). For example, there is evidence that using key informant response can introduce common method bias, as he/she can introduce bias based on the position or unique knowledge within the organization. Correspondingly common method bias can be introduced based on the context of the question asked and how the interview phrases the questions. Therefore, to reduce common method bias, this study used an online survey hosted on Qualtrics for the main study. The main study included multiple participants in different job functions from Canada and the USA.

5.2.2.4.1 Original Research Model Common Method Bias

Harman's one-factor test was used to evaluate the amount of bias inherent in the items. Harman single factor test unrotated first factor should be less than 0.5 (Podsakoff et al., 2003). The main study dataset principal component factor analysis was performed on the original model for an unrotated single factor. The unrotated single factor cumulative was 0.521, which is more than 0.5. Therefore, common method variance on the original research model is a problem for structured equation modeling (SEM).

5.2.2.4.2 Revised Research Model Common Method Bias

The principal component factor analysis of the main study dataset was performed on the revised research model for an unrotated single factor. The unrotated single factor cumulative was 0.494, which is less than 0.5. Therefore, common method variance on the revised research model is not a problem for SEM. Common method bias analysis further corroborated that the revised main study model is the best model to complete the analysis.

5.2.2.5 Nonresponse Bias

Organization surveys effectively and efficiently assess participants' perceptions and attitudes for organization research. Low response rates can skew the results due to the small sample size, undermining the credibility and generalizability of the survey by introducing nonresponse bias (Rogelberg & Stanton, 2007). A non-response bias test is to identify if participants are any different from those in the non-response group. As per Rogelberg and Stanton (2007), "wave analysis" can test for nonresponse bias in research by comparing responses from early and late respondents. It has been proposed to add a variable called wave with early = 0 and late = 1, then compare it with key demographic variables to identify the late respondent's interest in the survey. The rationale for this test is that if the late responders differ from early responders, it is primarily due to nonresponse bias (Rogelberg & Stanton, 2007).

The main study (*N*=165) dataset was divided into two groups according to the wave analysis. The first group of respondents took the survey during the first four weeks (early respondents), and the second group took the survey during the last four weeks (late respondents). A variable marked wave was populated with early = 0 and late = 1. The two groups' demographic variables, company industry, department, and age, were compared to identify the late respondent's interest in the survey.

The early participants (N=74) were associated with industry M=12.28(SD=4.98). The late group participants (N=91) were associated with industry M=13.57(SD=5.10). In order to test the hypothesis that early and later respondents were not statistically significant, an independent samples t-test was performed. The t-test results are documented in Appendix 5 – Main Study Nonresponse Results (T-Test). The assumption of homogeneity of variances was tested and satisfied via Levene's F test, $F(163)=0.12$, $p=0.734$. The independent sample t-test was not statistically significant, $t(163)=-1.630$, $p=0.105$. The independent sample t-test analysis on industry indicated no significant difference between early and later responders.

The early participants (N=74) were associated with department M=5.30(SD=1.59). The late group participants (N=91) were associated with department M=5.05(SD=1.33). In order to test the hypothesis that early and later respondents were not statistically significant, an independent samples t-test was performed. The t-test results are documented in Appendix 5 – Main Study Nonresponse Results (T-Test). The assumption of homogeneity of variances was tested and satisfied via Levene's F test, F(163)=0.19, p=0.661. The independent sample t-test was not statistically significant, t(163)=1.07, p=0.287. The independent sample t-test analysis on the department indicated no significant difference between early and later responders.

The early participants (N=74) were associated with age *M*=3.49(*SD*=.65). By comparison, the late group (N=91) was associated with age *M*=3.35(*SD*=.72). In order to test the hypothesis that early and later respondents were not statistically significant, an independent samples *t-test* was performed. The *t*-test results are documented in Appendix 5 – Main Study Nonresponse Results (T-Test). The assumption of homogeneity of variances was tested and satisfied via Levene's *F* test, *F*(163)=1.57, *p*=0.211. The independent sample *t-test* was not statistically significant, *t*(163)=1.25, *p*=0.213. The independent sample t-test analysis on age indicated no significant difference between early and later responders.

5.2.2.6 Validation of Instruments

There has been an increased use of unobserved variables in IT research to measure knowledge management and IT concepts. For example, Cepeda-Carrion et al. (2018), Chin (2010), Hair et al. (2017) (2019), Henseler et al. (2014) (2016), Ringle et al.(2012), and Wetzels et al. (2009) studies identified that in IT research there is an increased use of unobserved variables. The unobserved variables are classified as latent variables, which cannot be directly observed and have to be inferred from other directly observed variables in scientific research (Cepeda-Carrion et al., 2018; Hair et al., 2016;

Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009). There are numerous data analysis techniques to measure unobserved variables, and one of these techniques is structural equation modeling (SEM). SEM is a second-generation statistical technique used for empirical research, which is used for testing and estimating causal relationships using a mix of statical data and qualitative causal assumptions. SEM is a method that connects multi-item scales into constructs and defines relationships between constructs (Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2014, 2016). SEM is important in social science research as many variables are latent variables, and latent variables cannot be defined easily. Covariance-based SEM (CB-SEM) and partial least square structured equation model (PLS-SEM) are two SEM analysis methods. CB-SEM is based on common variance, were as PLS-SEM is based on total variance (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009).

Researchers who use the common factor model should use CB-SEM, and research using composites should use PLS-SEM. PLS-SEM is increasingly used in information technology research for data analysis. For example, Cepeda-Carrion et al. (2018), Chin (2010), Hair et al. (2017) (2019), Henseler et al. (2014) (2016), Ringle et al.(2012), and Wetzels et al. (2009) identified that PLS-SEM as an effective analysis method in IT research. CB-SEM and PLS-SEM are both used in hierarchical model analysis. There has been an increased application of PLS-SEM in marketing, organizational, and IT research for higher-order model analysis. For example, Wetzels et al. (2009) research showed that PLS-SEM path modeling could be used for higher-order construct models in marketing.

As per past empirical research, PLS-SEM is preferred over CB-SEM when research includes uninterrupted moderators, prediction with latent variable scores due to indeterminacy, and higher-order constructs with only two first-order constructs (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009).

This research study model is grounded on theoretical research centered on RBV, which has latent variables that define IT concepts that are composites. As per prior empirical studies, PLS-SEM can analyze hierarchical construct models (Wetzels et al., 2009). This research has higher-order latent variables built on manifest variables of the underlying first-order latent constructs. The hierarchical research model has an outer model (measurement model) and an inner model (structured model). Prior research proposes PLS-SEM path analysis and first-order latent variable scores as manifest variables for higher-order latent variables (Wetzels et al., 2009). Recent studies have shown that PLS-SEM is suited for IT research due to the following: (a) as PLS-SEM generates no bias with composites, (b) the PLS-SEM procedures model utilizes a separate set of regressions, (c) the intricacy of the model is not a concern with PLS-SEM, and (d) PLS-SEM appropriately determines latent score variables (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009). Therefore, this research paper used PLS-SEM, and SmartPLS software was used for the data analysis.

5.2.2.6.1 Measurement Model Assessment

5.2.2.6.1.1 Reliability Assessment

Confirmatory factor analysis (CFA) was conducted to identify the relationship structure between the variables and the respondents. Construct validity is the degree to which the variables measure the construct it is supposed to measure. There are two subtypes of construct validity; convergent validity and discriminant validity (Cook & Campbell, 1979; Peter, 1981; Straub, 1989). When completing the PLS-SEM measurement model assessment, the research must assess indicator reliability, convergent validity, and internal consistency reliability.

Indicator reliability is measured with the size of the outer loading, and high outer loadings indicate the associated items consolidate on one factor. Loadings of all indicators must be statistically significant. A common rule of thumb is that the outer loadings should be greater than or equal to 0.708, or the communality of an item should be at least 50% (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009).

Convergent validity tests whether the measurement items that are designed to measure the construct, loads on the same construct (Peter, 1981; Straub, 1989). To estimate convergent validity, the research should use outer loading and average variance extracted (AVE). The objective is to have an AVE greater than 0.50 (Bagozzi & Yi, 1988; Cepeda-Carrion et al., 2018; Fornell & Larcker, 1981; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012)

Internal consistency reliability is measured using scale reliabilities calculated from each construct's retained items. Criteria for internal consistency are calculated using Cronbach's alpha. Cronbach's alpha is sensitive to the number of items in the factor and usually lowballs the internal consistency reliability. Therefore, the researcher has to consider composite reliability. Both Cronbach's alpha and composite reliability vary between 0 and 1, with values higher than 0.70 are considered acceptable (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009).

Table 5 Measurement Model for First-Order Constructs

Constructs	**Items**	**Loadings[a]**	**AVE[b]**	**CR[c]**	**Alpha[d]**	**Rho_A[e]**
IS Environment	ISIENV_2	0.827	0.668	0.889	0.834	0.836
	ISIENV_3	0.873				
	ISIENV_7	0.780				
	ISIENV_8	0.786				
IS Performance	ISIPERF_3	0.780	0.794	0.920	0.869	0.912
	ISIPERF_4	0.952				
	ISIPERF_5	0.931				
IS Technical Skills	ISITHRTS_1	0.908	0.880	0.957	0.932	0.942
	ISITHRTS_2	0.953				
	ISITHRTS_3	0.953				
IS Management Skills	ISITHRMS_1	0.821	0.696	0.920	0.891	0.896
	ISITHRMS_4	0.782				
	ISITHRMS_5	0.867				
	ISITHRMS_8	0.867				
	ISITHRMS_9	0.832				
IS Planning	ISBRPLN_5	0.917	0.902	0.965	0.945	0.949
	ISBRPLN_7	0.967				
	ISBRPLN_8	0.965				
IT External Relationships	ISBRITER_1	0.803	0.673	0.925	0.901	0.902
	ISBRITER_2	0.839				
	ISBRITER_3	0.856				
	ISBRITER_4	0.870				
	ISBRITER_5	0.837				
	ISBRITER_7	0.706				
	ISBRPR_1	0.940	0.817	0.930	0.887	0.886

Constructs	Items	Loadings[a]	AVE[b]	CR[c]	Alpha[d]	Rho_A[e]
IS Process	ISBRPR_2	0.917				
Design	ISBRPR_6	0.851				
Firm	FPERF_1	0.903	0.802	0.953	0.938	0.945
Performance	FPERF_2	0.923				
	FPERF_3	0.825				
	FPERF_4	0.894				
	FPERF_5	0.931				

a. All items loadings < 0.5 were deleted
b. AVE = Average Variance Extracted
c. CR = Composite Reliability
d. Alpha = Cronbach's Alpha
e. Rho_A= Joreskog rho_A reliability indices for each construct

Table 5 above depicts the measurement model assessment for the first-order constructs. Indicator items loading below 0.50 were removed, and all item loadings greater than 0.50 indicates indicator reliability. The average variance extracted (AVE) for latent constructs was greater than 0.50 showing convergent reliability. All latent constructs had composite reliability (CR) greater than 0.70 indicating internal consistency. Cronbach's alpha and Rho_A were greater than 0.70 showing indicator reliability.

5.2.2.6.1.2 Discriminant Validity

The discriminant validity tests check that the measurement items are designed to measure only the construct related and not any other (Peter, 1981; Straub, 1989). PLS-SEM discriminant validity assessment includes cross-loading analysis, Fornell and Larcker criteria analysis and HTMT ratio analysis (Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2014, 2016). As discussed before, a correlation less than 0.70 can suggest that discriminant validity likely exists between two scales, and results greater than 0.70 indicate that the latent constructs overlap greatly. Therefore, the concepts are measuring the same thing causing issues with discriminant validity. As the first step, Fornell and Larker (1981) criteria were used to establish if the square root of the AVE is larger than the squared correlation with any other latent constructs. As depicted in Table 6 below, the loading of the other latent constructs was less than the square root of the construct AVE. The HTMT Ratio assessment was completed as a second step, and the HTMT ratio should be less than 0.85 (Hair, Hollingsworth, et al., 2017; Rönkkö & Cho, 2022). This study's thresholds for HTMT (Table 15 below) were less than 0.85. Fornell and Larcker criteria and HTMT ratio analysis indicated strong discriminant validity in the main study dataset for the revised model.

5.2.2.7 Hypothesis Testing

Once the research has confirmed that the variable measures are reliable, hypothesis testing can be completed by assessing the structured model. The structured model assessment includes evaluating the structural model for collinearity issues, measuring the significance and relevance of the structural model relationships, and calculating the level of R Square (Cepeda-Carrion et al., 2018; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2009, 2014, 2016; Ringle et al., 2012; Wetzels et al., 2009). As a next step, the estimates were obtained for the structural model relationship, representing the hypothesized relationships among the constructs by looking at the path coefficients. Path coefficient values range from -1 and +1. The values close to +1 present a strong positive relationship, values close to -1 present a strong negative relationship, and values close to 0 have a weak relationship (Chin, 2010; Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2014). The PLS-SEM is a non-parametric test. The PLS-SEM

Table 6 Intercorrelations of the Latent Variables for First-Order Construct[†]

Constructs	AVE	CR	Alpha	1	2	3	4	5	6	7	8
1. Firm Performance	0.802	0.953	0.938	0.896							
2. IS Environment	0.668	0.889	0.834	0.631	0.818						
3. IS Management Skills	0.696	0.920	0.891	0.697	0.595	0.834					
4. IS Performance	0.794	0.920	0.869	0.559	0.679	0.501	0.891				
5. IS Planning	0.902	0.965	0.945	0.675	0.595	0.692	0.715	0.950			
6. IS Process Redesign	0.817	0.930	0.887	0.565	0.490	0.628	0.529	0.610	0.904		
7. IS Technical Skills	0.880	0.957	0.932	0.613	0.610	0.707	0.748	0.735	0.548	0.938	
8. IT External Relationships	0.673	0.925	0.901	0.536	0.589	0.600	0.672	0.643	0.654	0.686	0.820

[†] Square root of the AVE on the diagonal

Table 7 Path Coefficient Results[a]

	Hypotheses	Model 1 Result	Significance	Model 2 Result	Significance
H1	Intelligent systems infrastructure resources have a positive effect on firm performance	Supported	t = 2.219*	Supported	t = 2.534*
H2	Intelligent systems IT human resources has a positive effect on firm performance	Supported	t = 2.462*	Supported	t = 2.201*
H3	Intelligent systems business resources have a positive effect on firm performance	Not Supported	t = 1.881	Not Supported	t = 1.857
	Control Variable Test				
	Company Size Significance			Not Supported	t = 0.926
	Industry Significance			Not Supported	t = 1.178

a. Note: *p < 0.05

bootstrapping is used to analyze statistical significance (Chin, 1998). Therefore, it is recommended to use BCa bootstrap confidence intervals for significance testing (Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2014). Complete bootstrapping was run on the main study dataset with sub samples of 5000, the test type was two-tailed, and the significance level was 0.05. Research model's predictive values are measured by the coefficient of determination or R^2 value, which ranges from 0 to 1, with R^2 values of 0.25, 0.50, or 0.75 are denoted as weak, moderate, and substantial (Hair et al., 2016; Hair, Hollingsworth, et al., 2017; Hair et al., 2019; Henseler et al., 2014). The R^2 value for the main study research model was 0.6, or 60% of the variance in firm performance is explained by the main study research model.

5.2.2.7.1 Hypothesis 1 Testing

As discussed before, the research study propositioned that **Hypothesis 1 (H1):** intelligent systems infrastructure resources have a positive effect on the firm performance. As depicted in Table 7 above, this hypothesis was supported in both model 1 and model 2. Model 2 includes control variables. As per the research study path coefficient analysis intelligent systems infrastructure resources has a significant positive effect on firm performance in model 1 ($\beta = 0.191$, $t = 2.219$, $p<0.05$) and model 2 ($\beta = 0.214$, $t = 2.534$, $p<0.05$). Variations in firm performance can be attributed to companies investing in intelligent systems resources such as intelligent system infrastructure, which aligns with the existing empirical literature on RBV. Past theoretical RBV research has shown that IT infrastructure resources positively affect firm performances. For example, (Bharadwaj, 2000), Ravichandran and Lertwongsatien (2005), Zhuang and Lederer (2006), and Mikalef and Gupta (2021) drew on the RBV theory to examine how IT resources affect firm performance. These research studies provided strong evidence that variations in firm performance can be explained by the extent to which IT is used to support and enhance a firm's core competencies by investing in IT infrastructure. Intelligent system infrastructure is the foundation for building the intelligent systems within the organization. The data collected in this research study further validates that investing in intelligent system infrastructure positively impacts firm performance.

5.2.2.7.2 Hypothesis 2 Testing

As discussed, this research study made the presupposition that **Hypothesis 2 (H2):** intelligent systems IT human resources have a positive effect on the firm performance. As depicted in Table 7 above, this hypothesis was supported in both model 1 and model 2. Model 2 includes control variables. As per the research study path coefficient analysis intelligent systems IT human resources has a significant positive effect on firm performance model 1($\beta = 0.361$, $t = 2.462$, $p < 0.05$) and model 2 ($\beta = 0.357$, $t = 2.201$, $p < 0.05$). (Bharadwaj, 2000), Ravichandran and Lertwongsatien (2005), Zhuang and Lederer (2006), and Mikalef and Gupta (2021) study drew on the RBV theory to examine how IT resources affect firm performance, and IT human resources have been identified as a key resource which positively affects firm performance. These prior research studies provided strong evidence that increases in firm performance can be explained by companies investing in developing or hiring the information technology human resources to build information technology capabilities. Intelligent system IT human resources are key contributors to implementing intelligent systems within the organization. The data collected in this research study further empirically validated that investment in intelligent system IT human resources positively impacts firm performance.

5.2.2.7.3 Hypothesis 3 Testing

As discussed before, this research postulated **Hypothesis 3 (H3):** intelligent systems business resources have a positive effect on the firm performance. As depicted in Table 7 above, this hypothesis was not supported in both model 1 and model 2 (which include control variables). As per the research study path coefficient analysis intelligent systems business resources has no significant positive effect on firm performance model 1 ($\beta = 0.290$, $t = 1.881$, $p > 0.05$) and model 2 ($\beta = 0.289$, $t = 1.857$, $p > 0.05$). (Bharadwaj, 2000), Ravichandran and Lertwongsatien (2005), Zhuang and Lederer (2006), and Mikalef and Gupta (2021) study drew on RBV to examine how IT resources affect firm performance, and IT business resources have been identified as a contributor to affect firm performance positively. IT planning, process redesign, and IT external relationships were considered IT business resources in this study. However, as many organizations use project management, software development lifecycle, six sigma, and vendor management methodologies to improve information technology business resources, their competitors will start copying and implementing them as rivals can easily duplicate these resources. As per prior theoretical studies, resources that competitors can easily copy will erode the competitive advantage provided by these business resources, and the positive effect on firm performance will diminish (J. Barney, 1991; J. B. Barney & Arikan, 2017; Grant, 1991; Lieberman & Montgomery, 1998). This research provides empirical evidence that this study's selected intelligent system business resources constructs do not impact firm performance.

5.2.2.7.4 Control Variable Testing

This research study used two control variables, company size based on revenues (mid-market and large) and industry (non-technology and technology). As depicted in Table 7 above company size ($\beta = -0.052$, $t = 0.926$, $p > 0.05$) and industry ($\beta = -.057$, $t = 1.178$, $p > 0.05$) were not significant.

5.2.2.8 Post Hoc (Multi Group) Analysis

As depicted in Table 7 above, model 2 analysis considered two control variables company size and industry. Although the control variables showed no significance, H1 and H2 were supported. The H1 *t* value increased from 2.219 (model 1) to 2.534 (model 2), and the H2 *t* value decreased from 2.462 (model 1) to 2.201 (model 2). This research completed a multigroup analysis of company size and industry as a next step.

5.2.2.8.1 Industry Multigroup Analysis

As a first step, a multigroup analysis was completed on the industry using SmartPLS with group A non-technology companies and group B technology companies. High technology companies are classified as companies in industries that adopt and use technology for competitive advantage or to reduce costs (Braja & Gemzik-Salwach, 2019). Companies in finance and insurance, information, telecommunication, and technology industries adopt technology at a rapid pace (Braja & Gemzik-Salwach, 2019; Fountaine et al., 2019; Pinto et al., 2017). For example, JP Morgan in banking, Amazon and Microsoft in technology, and AT&T and Rogers Communication in telecommunication adopt technology to create a competitive advantage and reduce costs. Therefore, companies in the high technology industries in the main study dataset, including finance and insurance, information, telecommunication, and technology

Table 8 Industry Multi-Group Analysis Results[a]

	PLS MGA		Non-Technology		Technology	
Hypothesis	**Result**	**Significance**	**Result**	**Significance**	**Result**	**Significance**
H1[b]	Not Supported	β = -0.067	Not Supported	β = 0.165, t = 0.920	Supported	β = 0.229, t = 2.380*
H2[c]	Not Supported	β = -0.278	Not Supported	β = 0.099, t = 0.769	Supported	β = 0.349, t = 1.991*
H3[d]	Not Supported	β = 0.302	Supported	β = 0.603, t = 2.913**	Not Supported	β = 0.315, t = 1.318

a. Note: *p<0.05; **p<0.01
b. H1 = Intelligent systems infrastructure resources have a positive effect on the firm performance.
c. H2 = Intelligent systems IT human resources has a positive effect on the firm performance.
d. H3 = Intelligent systems business resources has a positive effect on the firm performance.

Table 9 Company Size Multi Group Analysis Results[a]

	PLS MGA		Mid Size		Large Size	
Hypothesis	**Result**	**Significance**	**Result**	**Significance**	**Result**	**Significance**
H1[b]	Not Supported	β = 0.091	Supported	β = 0.335, t = 2.654**	Supported	β = 0.285, t = 2.803**
H2[c]	Not Supported	β = 0.302	Supported	β = 0.380, t = 2.044*	Not Supported	β = 0.191, t = 1.374
H3[d]	Not Supported	β =- 0.315	Not Supported	β = 0.228, t = 0.339	Supported	β = 0.407, t = 2.804**

a. Note: *p<0.05; **p<0.01
b. H1 = Intelligent systems infrastructure resources have a positive effect on the firm performance.
c. H2 = Intelligent systems IT human resources has a positive effect on the firm performance.
d. H3 = Intelligent systems business resources has a positive effect on the firm performance.

industries, were classified as companies in the technology industry. All other companies were classified as the non-technology industry. The industry group dummy variable was introduced in the main study data set with non-technology = 0 and technology = 1.

As presented in Table 8 above, the multigroup analysis PLS results indicated no difference between non-technology and technology groups in the main study data set as H1(β = -0.067, $p > 0.05$), H2 (β = -0.278, $p > 0.05$), and H3 (β = 0.302, $p > 0.05$) were not significant. Complete bootstrapping was run on the main study dataset with sub samples of 500, the test type was two-tailed, and the significance level was 0.05 for the group analysis. As per prior research, a sub-sample of 500 can be used for bootstrapping (Hair et al., 2016).

Detail analysis of the bootstrapping results indicate that at group level non technology companies H1 (β = 0.165, t = 0.920, $p > 0.05$) and H2 (β = 0.099, t = 0.769, $p > 0.05$) were not supported but H3 (β = 0.603, t = 2.913, $p < 0.01$) was supported. Non-technology companies are laggards in adopting technology. Non-technology companies implement IT systems after the first movers have implemented the latest IT systems, and there is a proven track record of cost savings or revenue generation (Bharadwaj, 2000; Lieberman & Montgomery, 1998; Pinto et al., 2017). Non-technology companies focus on planning, process improvement, and building relationships rather than investing in the latest technology (Kingsley & Malecki, 2004). For example, Home Hardware and Toys R Us Canada have been able to keep revenues and profits stable by improving vendor relationships, process redesign, and planning compared to high technology companies in the retail sector that invests and implements the latest technology. The main study results provide evidence that non-technology industry companies attribute intelligent system business resources to increase firm performance over intelligent systems infrastructure resources or IT human resources.

For technology companies H1 ($\beta = 0.229$, $t = 2.380$, $p < 0.05$) and H2 (0.349, $t = 1.991$, $p < 0.05$) were supported but H3 ($\beta = 0.315$, $t = 1.318$, $p > 0.05$) was not supported. As discussed before, high technology companies invest in information technology at a rapid pace and use technology for innovation, then use these innovations as a competitive advantage to increase organization revenue and profitability. High technology companies invest in technology to leverage the first-mover advantage over their rivals, thus giving the organization a competitive advantage (Bharadwaj, 2000; Lieberman & Montgomery, 1998; Pinto et al., 2017). For example, Tesla has used technology to innovate and to build a brand, while becoming the most valuable car company by increasing revenue and profitability. The main study results provide analytical evidence that companies in the technology industry attributed intelligent systems infrastructure resources and IT human resources to increase firm performance over intelligent system business resources.

5.2.2.8.2 Company Size Multigroup Analysis

As a second step, multigroup analysis was completed on company size using SmartPLS with group A mid-size companies and group B large companies. Mid-size companies were identified based on company revenues between $10 million to $1 billion, and large-size companies were identified as companies with over $1 billion in revenue (Roberts, 2009). The main study dataset included the company size dummy variable with mid-size = 0 and large size = 1.

As depicted in Table 9 above multigroup analysis PLS results indicated there is no difference between mid-size and large size company groups in the main study data set as H1 ($\beta = 0.091$, $p > 0.05$), H2 ($\beta = 0.302$, $p > 0.05$), H3 ($\beta =- 0.315$, $p > 0.05$) were all not significant. Same as the industry multigroup analysis, a complete bootstrapping was completed on the main study dataset for company size with sub samples of 500. The test type was two-tailed, and the significance level was 0.05 for the multigroup analysis.

Detail analysis of the bootstrapping results indicate that at group level mid-size companies H1($\beta = 0.335$, $t = 2.654$, $p < 0.01$) and H2 ($\beta = 0.380$, $t = 2.044$, $p < 0.05$) were supported but H3 ($\beta = 0.228$, $t = 0.339$, $p > 0.05$) was not supported. Medium-size companies maintain an entrepreneurial culture, and as per similarity-attraction theory, these companies attract employees who thrive in an entrepreneurial environment (Carroll, 1993; Devendorf & Highhouse, 2008; Glen, 2006; Kickul, 2001). Cash-infused startups overnight became midsize companies due to venture capital investment, and established midsize companies strive to compete with established larger companies by investing in technology to innovate (Davenport, 2006; Davenport et al., 2010; Pinto et al., 2017). For example, LoyaltyOne, Facebook, and Uber invested heavily in technology and attracted employees from established companies looking for an entrepreneurial environment to dethrone established rivals. The main study results provide empirical evidence that midsize companies attributed intelligent systems infrastructure resources and IT human resources to increase firm performance over intelligent system business resources.

For large size companies H1 ($\beta = 0.285$, $t = 2.803$, $p < 0.01$) and H3 ($\beta = 0.407$, $t = 2.804$, $p < 0.01$) were supported but H2($\beta = 0.191$, $t = 1.374$, $p > 0.05$) was not supported. As discussed before, large-size companies have over $1 billion in revenues, and with high revenues, these companies tend to employ tens of thousands of employees. Therefore, large companies emphasize planning and process redesign to improve efficiency by adopting standard operating procedures to manage these large organizations (Carroll, 1993; Kickul, 2001). In order to implement and monitor the standard operating procedures, these organizations invest heavily in IT to increase worker productivity (Carroll, 1993; Davenport et al., 2010; Glen, 2006; Lieberman & Montgomery, 1998; Pinto et al., 2017; Roberts, 2009). For example, GE and Motorola invested heavily in IT systems to introduce six sigma process improvement and implemented project management methodology to improve operational efficiencies and delivery. The main study results provide statistical evidence that large companies attributed intelligent systems infrastructure and business resources as driver of firm performance over intelligent systems IT human resources.

6. DISCUSSION

Intelligent systems based on AI and ML have been touted as the next innovation in IT by the traditional media, and vendors have been promoting AI and ML as the next industrial revolution. Many technology vendors have incorporated AI and ML into their existing product lineup. For example, Salesforce has revamped Salesforce CRM by including Salesforce Einstein, and SAP has incorporated AI and ML into their enterprise resource planning (ERP) platform. Startups and established companies that have distributed a press release mentioning AI and ML have increased the share price and market capitalization without any growth in revenue or profitability. Furthermore, these companies have attracted millions of dollars in venture funding and attained unicorn status (Columbus, 2019b; Mathews, 2022). All this hype around intelligent systems, companies that have implemented big data platforms and intelligent systems applications with AI and ML are finding it hard to realize enterprise benefit or value from their intelligent systems investment. Intelligent systems research is still in its infancy. There are empirical IT articles that focus only on the base technology aspects of AI and ML. Only a few academic researchers look at intelligent systems' contribution to firm performance (Dwivedi et al., 2019).

6.1 Theoretical Implications

This study attempts to understand if investment in internal resources such as big data platforms to leverage intelligent systems (based on AI and ML algorithms) provides a competitive advantage for organizations that impact firm performance. This research used RBV, traditionally used in IT empirical research, to understand the contribution of IT to enterprise value (J. B. Barney & Arikan, 2017). Industry and practitioner publications advocate using intelligent systems to generate organizational value. However, few theoretical research studies have justified the investment in intelligence systems that drive enterprise value. Using a theoretical view helps information technology academics and experts better understand the value of intelligent systems investment and its relationship to firm performance.

This research findings have identified three important contributions to the literature on intelligent systems' impact on enterprise value. First, this research built on the existing theoretical framework of RBV literature, which spanned over four decades, and identified two primary technical resource constructs and one non-technical resource construct relevant to organizational setting when studying intelligent systems investment that contributes to enterprise value. This study identified constructs and built a model to test the intelligent systems investments impact on organization performances. RBV theory has identified that IT infrastructure, IT human resources, and IT technology business resources provides a competitive advantage for organizations (Bharadwaj, 2000; Gupta & George, 2016; Liang et al., 2010; Mao et al., 2016; Mata et al., 1995; Mikalef & Gupta, 2021; Powell & Dent-Micallef, 1997; Ravichandran & Lertwongsatien, 2005; Zhuang & Lederer, 2006). In this research model, the intelligent systems infrastructure has two factors intelligent systems environment and performances. Intelligent systems IT human resources, which has two sub-factors intelligent system technical skills and management skills. The intelligent systems business resources, which has three sub-constructs, intelligent systems planning, process redesign and IT external relationships. The study then validated the model using survey data from 165 participants, including c-level executives, technology managers, and IT professionals. The study findings empirically validated and supported that intelligent system infrastructure resources and intelligent systems IT human resources significantly impact firm performance.

Past theoretical research has found that business resources contribute to firm performance. For example, Gupta and George's (2016) research on big data intangible resources (data-driven culture and organization learning) contribute to firm performance. Mikalef and Gupta's (2021) research on artificial intelligence business resources (organization change capacity and risk proclivity) contribute to organizational performance. However, this study has identified that intelligent systems business resources, including IT planning, process redesign, and IT external relationships, do not contribute to firm performance. Barney (1991) and Grant (1991) identified that to have a sustained competitive advantage, the resource heterogeneity and immobility requirement has to be met, and Liberman and Montgomery (1998) identified that companies have a competitive advantage as the first mover. However, the competitive advantage will erode when rivals start to copy the organizational resources. This study hypothesized that intelligent systems business resource contributes to firm performance. However, the empirical findings from this research contribute to the literature by confirming that competitive advantage diminishes when competitors copy organization resources. Furthermore, the said resources do not contribute to firm performance. Therefore, this study provides evidence that not all business resources contribute to building a competitive advantage nor provide an impact on firm performance.

Second, the study contributes to existing theoretical literature by providing empirical evidence that intelligent systems resource constructs contribute to firm performances based on the industry and company size. Hair et al. (2016) (2017) and Ringle (2012) recommended multigroup analysis to be used in research to identify unobserved heterogeneity by partitioning the data into groups and identifying significant differences among the groups. This study contributes to the existing literature by providing the following empirical evidence, (a) firms in the technology industry, midsize companies, and large organizations see value in investing in intelligent system infrastructure resources as it impacts firm performance, (b) technology industry organizations and midsize companies see value in investing in intelligent systems IT human resources as it impacts organization performance, and (c) firms in the non-technology industry and large organization see value in investing in intelligent system business resources as it impacts firm performance.

Finally, the research study contributes to the existing literature on RBV by completing the study in two countries, mainly Canada and the USA. Past research has found that companies adopt technology based on the country, organization, and management culture (Hofstede, 1994; Schneider et al., 2013). This study argues that regardless of the firm's country, the intelligent systems infrastructure, IT human resources, and business resources would have the same impact on firm performance. For example, Mikalef and Gupta (2021) completed the research with participants from the USA that provided support for artificial intelligence capabilities contributing to firm performances, and Wamba et al. (2017) completed the study with respondents from China that provided support for big data capabilities contributing to firm performances. In this research, the participants were located in Canada 78 (47.3%), the United States 76 (46.0%), and other *(multinational)* 11 (6.7%). The main study respondents from Canada and USA were statistically tied. Therefore, this study provides empirical evidence that intelligent systems infrastructure resources and intelligent systems IT human resources increase firm performance regardless of the country. Nevertheless, intelligent systems business resource constructs selected for the study do not impact firm performance.

6.2 Practical Implications

The research study was initiated to understand the executive perception of investing in intelligent systems and its effect on firm performance. The main idea of this study is to document and provide empirical evidence to help company managers', board of directors, and investors ascertain the enterprise value of investing in intelligence systems. As discussed, AI and ML have been promoted by popular press and vendors as the next industrial revolution. Companies such as Salesforce, SAP, Microsoft in technology, Ford, General Motors, Tesla in the automobile sector, Volvo sand Saab in trucking, and major shipbuilders invest in AI. These intelligent systems investments are made to help these companies gain a competitive advantage using AI-enabled platforms and products.

This research findings have identified three important contributions to the practitioner community on intelligent systems' impact on enterprise value. First, this research sheds light on which intelligent systems resources to prioritize to be invested by IT managers to enhance a firm's competitive advantage that can impact an organization's performance. Companies can invest limited monetary resources on building intelligent systems infrastructure resources and intelligent systems IT human resources. As per past literature, IT human resources are key to building IT resources and capabilities that will contribute to an organization's competitive advantage (J. Barney, 1991; J. B. Barney & Arikan, 2017; Grant, 1991; Ray et al., 2004). This study has shown empirical evidence that intelligent system IT human resources, mainly technical and technical management skills, contribute to firm performance. The managers who are responsible for implementing and supporting intelligent systems can use this study to convince the organization's senior executives and the board to invest in recruiting the top talent from the industry or allocating money to train their top-performing IT technical resources, technical management resources and non-technology functional resources on intelligent system skills. Furthermore, this research provides evidence that intelligent systems infrastructure resources enhance firm performance. The information technology managers can provide this study as evidence to sway the organization executives to provide the necessary funding to develop intelligent systems infrastructure resources and IT human resources to reap the benefits by building a competitive advantage that will increase revenue and profitability.

Second, this study helps practitioners be cautious when investing in intelligent systems business resources. As discussed before, financial performances can be measured by return on assets (ROA), return on equity (ROE), return on investment (ROI)), return on sales (ROS), sales growth, and market capitalization (Dehning & Stratopoulos, 2002; Helfat & Peteraf, 2003; Liang et al., 2010; Mao et al., 2016; Menachemi et al., 2006; Ravichandran & Lertwongsatien, 2005; Zhuang & Lederer, 2006). Information technology managers work with business teams to identify the technology road map to driver firm performance to be measured by said financial measurements. In their published theoretical research, Gupta and George (2016) and Mikalef and Gupta (2021) identified that big data and AI business resources enhance firm performances. However, this research identified that not all business resources increase a firm's revenue and profitability. Therefore, the firm's IT management team should properly assess and identify the intelligent systems business resources the organization should invest in before requesting or committing the firm's sparse financial resources.

Finally, this study helps the board of directors and investors discover the linkage between competitive advantage and investment in intelligent systems is the correct information technology investment decision to catapult organization growth. The board of directors monitor the organization on behalf of the shareholders by effectively controlling and distributing funds for capital-intensive projects such as IT (Hillman & Dalziel, 2003). The board members can use this theoretical research as an information source when providing the necessary capital to invest in intelligent systems resources that deliver enterprise value to the organization's shareholders. Shareholders and venture funds provide monetary investments that help companies invest in organization resources to enhance firm performance (Casciaro & Piskorski, 2005; Hillman et al., 2009; Hillman & Dalziel, 2003; Shu & Lewin, 2017). Individual shareholders, intuitional investors, and venture capital management teams can use this empirical study as a reference source when investing in established businesses or startups that try to attract funding for new intelligent systems initiatives.

6.3 Limitations and Future Research

As with all research, this study has its limitations. First, the main study model (Figure 3 above) used for the study is a reduced model from the original model (Figure 2 above). As previously discussed, the model misspecification analysis identified that the original model is without error. The original model discriminant validity test with the main study dataset confirmed that similar scale items or measures cause the discriminant validity issues. Future researchers should revise the intelligent systems capabilities scale items. In order to build new intelligent systems capabilities scale items, a qualitative research approach is proposed. The theoretical viewpoint frequently associated with qualitative researchers is phenomenology (Creswell, 2006; Creswell & Poth, 2017; Miles et al., 2019). The phenomenological researchers seek to comprehend connotation in proceedings and human interactions, and the context is important to interpreting data. This approach requires the researcher to focus on the endeavor to accomplish a sense of the meaning others give to their situations. (Creswell, 2006; Creswell & Poth, 2017; Miles et al., 2019). Case study analysis examines the phenomena within their context (Creswell & Poth, 2017; Eisenhardt, 1989; Yin, 1981). The case study analysis can be used in expletory research, enabling the researcher to gain initial insight into the phenomena. This method can be used in descriptive research by incorporating multiple cases to identify relationships between variables and in explanatory research to understand why the phenomena are happening (Baxter & Jack, 2008; Creswell, 2006; Miles et al., 2019). Case study research is an empirical study that examines a modern phenomenon within its real-life context that focuses on the organization, and multiple-case research can help capture the changes to organization capabilities with investment in intelligent systems resources (Creswell & Poth, 2017; Dube & Pare, 2003; Eisenhardt, 1989; Yin, 1981). Therefore, case studies will help future researchers create scale items for intelligent systems capabilities to properly test the original research model.

Second, this study examined the company size and industry groups as part of the post hoc (multigroup) analysis. However, the findings from the multigroup analysis did not provide any in-depth understanding of intelligent system adoption based on company size and industry. A quantitative study is proposed to explore the effects of company size and industry on the diffusion of intelligent systems innovation in organizations in Canada and the United States. There is prior research that has identified that diffusion of innovation (DOI), technology organization environment (TOE) framework and technology acceptance model (TAM) are the most widely used innovation adoption models for organizational level analysis (Hameed et al., 2012).

Ryan and Gross published the first theoretical study of the diffusion of innovations model in 1943. The study centered on hybrid seed corn diffusion in two communities of Iowa farmers (Ryan & Gross, 1950; Valente & Rogers, 1995). Everett Rogers expanded Ryan and Gross' work on the diffusion of innovations model by publishing a book with the same title in 1962. Rogers defined innovation as an idea, practice, or object perceived by an individual, group, or society as something new (Rogers, 2003; Valente & Rogers, 1995). The DOI is mainly used for the study of diffusion of innovation among individuals. For organizational research, DOI requires another framework to rationalize innovation adoption in organizations. The technology organization environment framework (TOE) is an academic model that justifies technology implementation in organizations and explains the method of adopting and implementing technological innovations, which are swayed by the technological context, organization context, and environment context (Tornatzky & Fleischer, 1990). Previous studies have combined TOE with the DOI framework to analyze information technology adoption at the organization level (Hameed et al., 2012; Martins et al., 2016). Therefore, future research should consider the diffusion of innovation (DOI) theory and technology organization environment (TOE) framework to identify the moderating effect of company size and industry on intelligent system adoption. Furthermore, this research study will enrich our understanding of intelligent systems utilization at the organization level.

Finally, this study was conducted with participants working in information technology departments at companies in North America (Canada and the USA). There is prior research that has identified when companies expand from the home country, these firms branch out to geographical, cultural, administrative, political, and economic similar countries (Ghemawat, 2001; Johanson & Mattsson, 2015; Johanson & Vahlne, 2009; W. C. Kim & Hwang, 1992). Canada and the USA are geographically, culturally, administrative, political, and economically similar countries. Furthermore, Canada and the USA are tightly integrated economically through the USMCA free trade agreement.

Organizations with their home base, geographical, cultural, administrative, political, or economic distant from companies in Canada and USA might have implemented and adopted intelligent systems differently. Potential new research on intelligent systems should incorporate surveying companies in Emerging markets, Europe and Asia with companies in North America. This research study will help us understand intelligent systems utilization and the capabilities developed to build a competitive advantage that enhances enterprise value based on the country setting.

7. CONCLUSION

This research was undertaken to study the effects of an investment in intelligent systems resources, both tangible and intangible, on an organization's revenue and profitability. In order to study if the resources enabled competitive advantage, this research used the RBV theory. RBV has gained distinction among academic scholars for understanding the investment in organization resources and its impact on firm performances. Companies invest in strategic resources to build a competitive advantage, and the reinvestment in these strategic investments by firms is to have a sustained competitive advantage. Barney (1991) and Grant (1991) defined sustain competitive advantage as when a firm implements an economic strategy that has not been employed by any of its current or future competitors at that moment in time. Therefore, competing firms are unable to duplicate the benefits of the said strategy.

Canada and USA have moved away from manufacturing and service base economies to knowledge base economies, where companies have to leverage data to build a competitive advantage. All external data points and the firm's internal data must be integrated into the organization's intelligent systems platform to run predictive analytics to gain a competitive advantage over its rivals. As a result, organizations cannot achieve sustained competitive advantage as a firm's rivals do not remain static entities. The said investments will only give the firm a first-mover advantage (Lieberman & Montgomery, 1998). Therefore, understanding the intelligent systems' tangible and intangible resources that contribute to competitive advantage is of utmost value to organizations.

To understand the impact of the intelligent system on firm performance, this study conducted extensive research on past peer-reviewed journal articles on RBV, IT, intelligent systems, and firm performance spanning over 40 years. Based on the literature review, the study identified tangible resources, intelligent systems infrastructure resources, intelligent systems IT human resources, and intangible intelligent systems business resources. This study then adopted scale items from existing research to prepare a survey and collected data to use statistical techniques to validate the RBV assumptions. Past research has identified that information technology business resources contribute to competitive advantage and impact firm performance (Gupta & George, 2016; Mikalef & Gupta, 2021; Wamba et al., 2017; Zhuang & Lederer, 2006). However, this study provides empirical evidence that not all business resources enhance firm performance. This academic research provides statistical evidence that tangible resources (intelligent system infrastructure and IT human resources) contribute to firm performance. However, further studies must be completed using intelligent systems, tangible and intangible resources, and intelligent systems capabilities. Academic researchers can use these findings to extend the model to understand intelligent systems' contribution to organizational performance. Finally, the practitioner community can use this study as a source of information to understand and support their decision to invest in intelligent system resources that directly impact firm performance and enterprise value.

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APPENDIX

Appendix 1 – Informed Pilot Survey Instrument

For the purpose of this research, we have adopted and modified Zhuang and Lederer (2006) survey measurement scales. All measurement items will be measured using a Likert response scale ranging from one (Strongly Disagree) to five (Strongly Agree).

Table 10 Informed Pilot Survey

Construct	Measurements
Intelligent Systems Infrastructure (ISI)	1. Our organization has implemented intelligent systems on Software as a Service Platform like Amazon, Azure, Google, Snowflake, etc... 2. Our organization's intelligent systems environment has been implemented with data zones such as raw data, trusted zones, reference zones, refined zones and analysis zones. 3. Source data ingesting into our organization's intelligent systems environment is within agreed service levels. 4. Our organization's intelligent systems allow us to load third-party data from external sources systems 5. Our organization's intelligent systems business intelligent reports execute within agreed service levels during peak usage hours. 6. Our organization's intelligent systems machine learning algorithms execution times are within agreed service levels during peak usage hours. 7. Our organization's intelligent systems artificial intelligence algorithms execution times are within agreed service levels during peak usage hours. 8. Our organization's intelligent systems applications exhibit high degree of reliability.
Intelligent Systems IT Human Resources (ISITHR)	1. Our intelligent systems technical teams have the best technical training to complete their tasks. 2. Our intelligent systems technical teams are trained on latest intelligent systems technologies. 3. Our intelligent systems technical teams are trained on latest intelligent systems best practices. 4. Our intelligent systems technical teams have skills to implement big data platforms.

Construct	Measurements
	5. Our intelligent systems technical teams have been trained to implement big data platforms. 6. Our intelligent systems management team has the experience to deliver all projects on time. 7. Our intelligent systems management team has the experience to deliver all projects on budget. 8. Our intelligent systems management team can put together project teams rapidly for project delivery. 9. Our intelligent systems management team is trained on the latest intelligent systems technologies. 10. Our intelligent systems management team is trained on the latest technology management strategies.
Intelligent Systems Business Resources (ISBR)	1. Our organization has a very open and trusting relationships with our technical vendors. 2. Our organization's technical vendors are proactively making recommendations on new features. 3. Our organization's technical vendors are committed to our intelligent systems success 4. Our organization's technical vendors are committed to our intelligent systems success 5. Our organization can rapidly redesign our business processes based on intelligent systems analytics to meet market changes. 6. Our organization can rapidly redesign our marketing/sales process based on intelligent systems analytics to meet market changes. 7. Our organization actively bring in intelligent systems consulting companies to audit and make recommendations to change our intelligent systems implementation based on the audit reports. 8. Our organization actively research the intelligent systems practices of companies in other industries. 9. Our organization's IT and business top executives' visions are aligned on how best intelligent systems will support the business. 10. Our organization has a clearly identified intelligent system project priorities. 11. Our organization has intelligent systems planning integrated with the overall organization business plan.
Intelligent Systems Capabilities	1. Our organization can predict customers buying patterns accurately 2. Our organization can predict new product/service demand accurately

Construct	Measurements
	3. Our organization can predict inventory depletion restocking rates accurately 4. Our organization can predict inventory restocking rates accurately 5. Our organization hold periodic meetings to inform employees about the latest innovations in intelligent systems 6. Our organization information technology management align intelligent system resources with business priorities 7. Our organization information technology management team actively seeks business teams' input for intelligent systems strategic road map 8. Our organization has the ability to capture customers information from all sources 9. Our organization extensively use machine learning algorithms for predictive analytics 10. Our organization extensively use artificial intelligence algorithms for predictive analytics 11. Our organization intelligence systems predictive analytics platforms are superior than nearest competitors 12. Our organization intelligence systems predictive analytics product features have been providing accurate marketing insights 13. Our organization intelligence systems predictive analytics product features have been providing accurate customer insights
Firm Performance	1. Our organization's yearly financial performance has exceeded the company's average prior 3 years performance. 2. Our organization has been more profitable than our competitors during the last 3 years 3. Our organization sales growth has exceeded the company's average prior 3 years sales growth. 4. Our organization profitability has exceeded the company's average prior 3 years profitability. 5. Our organization consistently outperformed EBITA (Earnings Before Interest, Taxes, Depreciation, and Amortization) estimates during the prior 3 years 6. Our organization consistently outperformed sales growth targets during the prior 3 years 7. Our organization consistently outperformed profit growth target during the prior 3 years 8. Our organization EBITA (Earnings Before Interest, Taxes, Depreciation, and Amortization) has exceeded analysts' predictions during the prior 3 years

Construct	Measurements
	9. Our organization sales growth has exceeded analysts' predictions during the prior the last 3 years 10. Our organization profitability has exceeded analysts' predictions during the prior 3 years

Appendix 2 – Pilot and Main Study Survey Instrument

This research adopted and modified Gupta & George (2016), Mikalef & Gupta (2021), Wamba et al. (2017), and Zhuang and Lederer (2006) survey measurement scales. All measurement items will be measured using a Likert response scale ranging from one (Strongly Disagree) to five (Strongly Agree).

Table 11 Pilot and Main Study Survey

Third Order Construct	Second Order Construct	Question #	Measurements	Source
Intelligent Systems Infrastructure (ISI)	Intelligent Systems Infrastructure Environment (ISI-ENV)	ISI-ENV_1	We have explored or adopted cloud-based services for processing data and performing AI and machine learning (eh., Amazon, Azure, Google, Snowflake, etc...)	Adapted from (Mikalef & Gupta, 2021)
		ISI-ENV_2	We have the necessary processing power to support AI applications (e.g., CPUs, GPUs).	
		ISI-ENV_3	We have invested in networking infrastructure (e.g., enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency).	
		ISI-ENV_4	We have explored or adopted parallel computing approaches for AI data processing.	
		ISI-ENV_5	We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g., Microsoft	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			Cognitive Services, Google Cloud Vision).	
		ISI-ENV_6	We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology	
		ISI-ENV_7	We have invested in data storage infrastructure that support multiple data zones for raw data, trusted zones, reference zones, refined zones and analysis zones.	
		ISI-ENV_8	We have explored or adopted in data streaming platforms that ensure loading data from all internal and external sources systems (e.g., ETL tools such as DataStage, MuleSoft, Talend, Kafka etc...)	
	Intelligent Systems Infrastructure Performance (ISI-PERF)	ISI-PERF_1	We have invested in scalable data storage infrastructure that is reliable.	Adapted from (Zhuang & Lederer, 2006)
		ISI-PERF_2	We have invested in data storage infrastructure that support source data ingesting within agreed service levels.	
		ISI-PERF_3	We have invested in business intelligent analytics platform that support execution of reports within agreed service levels during peak usage hours.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISI-PERF_4	We have invested in advanced cloud services to allow artificial intelligence and machine learning algorithms to execute within agreed service levels during peak usage hours.	
		ISI-PERF_5	We have invested in artificial intelligence and machine learning platforms that exhibit high degree of reliability.	
		ISI-PERF_6	We have invested in scalable artificial intelligence and machine learning predictive analytics infrastructure that is reliable	
Intelligent Systems IT Human Resources (ISITHR)	Intelligent Systems IT Human Resources Technical Skills (ISITHR-TS)	ISITHR-TS_1	Our big data technical teams have the best artificial intelligence and machine learning technical training to complete their tasks.	Adapted from (Gupta & George, 2016)
		ISITHR-TS_2	Our information technology technical teams are trained on latest Big Data technologies.	
		ISITHR-TS_3	Our information technology technical teams are trained on latest artificial intelligent and machine learning technologies.	
		ISITHR-TS_4	Our information technology technical teams have skills to implement Big Data platforms successfully.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISITHR-TS_5	Our information technology technical teams have skills to implement artificial intelligent and machine learning project successfully.	
		ISITHR-TS_6	Our organization hires big data technical teams that have work experience in implementing artificial intelligent and machine learning platforms.	
	Intelligent Systems IT Human Resources Management Skills (ISITHR-MS)	ISITHR-MS_1	Our information technology management team has the experience to deliver information technology projects on time.	
		ISITHR-MS_2	Our information technology management team has the experience to deliver Big Data projects on time.	
		ISITHR-MS_3	Our information technology management team has the experience to deliver artificial intelligent and machine learning projects on time.	
		ISITHR-MS_4	Our information technology managers understand and appreciate the business needs of other functional managers, suppliers, and customers.	
		ISITHR-MS_5	Our information technology managers are able to work with	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			functional managers, suppliers, and customers to determine opportunities that big data, AI and machine learning might bring to our business	
		ISITHR-MS_6	Our information technology managers are able to coordinate Big Data, AI and machine learning activities in ways that support other functional managers, suppliers, and customers	
		ISITHR-MS_7	Our information technology managers are able to anticipate the future business needs of functional managers, suppliers, and customers	
		ISITHR-MS_8	Our information technology managers have a good sense of where to apply big data, AI and machine learning.	
		ISITHR-MS_9	Our information technology management team is trained on the latest technology management strategies.	
Intelligent Systems Business Resources (ISBR)	Intelligent Systems Business Resources-IT External Relationships (ISBR-ITER)	ISBR-ITER_1	Our organization has a very open and trusting relationships with our technical vendors.	Adapted from (Zhuang & Lederer, 2006)
		ISBR-ITER_2	Our organization's technical vendors are proactively making recommendations on new features.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISBR-ITER_3	Our organization's technical vendors are committed to our information technology success	
		ISBR-ITER_4	Our organization's technical vendors are committed to our Big Data platform success	
		ISBR-ITER_5	Our organization's technical vendors are committed to our artificial intelligent and machine learning platform success	
		ISBR-ITER_6	Our organization's IT and business top executives' visions are aligned on information technology strategy.	
		ISBR-ITER_7	Our organization's IT executives actively seek business top executives' input and feedback on information technology strategy.	
		ISBR-ITER_8	Our organization's IT executives actively seek business top executives' input and feedback on Big Data strategy.	
		ISBR-ITER_9	Our organization's IT executives actively seek business top executives' input and feedback on AI and machine learning strategy.	
	Intelligent Systems Business Resources-	ISBR-PR_1	Our organization can rapidly redesign our business processes based on information	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
	Process (ISBR-PR)		technology analytics to meet market changes.	
		ISBR-PR_2	Our organization can rapidly redesign our marketing/sales process based on information technology analytics to meet market changes.	
		ISBR-PR_3	Our organization actively bring in information technology consulting companies to audit and make recommendations to change our information technology implementation based on the audit reports.	
		ISBR-PR_4	Our organization actively bring in Big Data consulting companies to audit and make recommendations to change our Big Data implementation based on industry standards.	
		ISBR-PR_5	Our organization actively bring in artificial intelligent and machine learning consulting companies to audit and make recommendations to change our artificial intelligent implementation based on industry standards.	
		ISBR-PR_6	Our organization actively research the information technology best practices of	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			companies in other industries	
		ISBR-PR_7	Our organization actively research the Big Data best practices of companies in other industries.	
		ISBR-PR_8	Our organization actively research the artificial intelligent and machine learning best practices of companies in other industries	
	Intelligent Systems Business Resources - Planning (ISBR-PLN)	ISBR-PLN_1	Our organization has a clearly identified information technology project priorities.	
		ISBR-PLN_2	Our organization has a clearly identified Big Data project priorities.	
		ISBR-PLN_3	Our organization has a clearly identified AI and machine learning project priorities.	
		ISBR-PLN_4	Our organization has information technology planning integrated with the overall organization business plan.	
		ISBR-PLN_5	Our organization has Big Data planning integrated with the overall organization business plan.	
		ISBR-PLN_6	Our organization has AI and machine learning technology planning integrated with the overall organization business plan.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISBR-PLN_7	Our organization have a long-term strategic plan for big data, AI and machine learning platforms.	
		ISBR-PLN_8	Our organization have a long-term strategic plan for AI and machine learning based predictive analytics platforms.	
Intelligent Systems Capabilities	Intelligent Systems Capabilities-Infrastructure Capabilities	ISC-IC_1	Compared to rivals within our industry, our organization has the foremost available AI and machine learning predictive analytics systems.	Adapted from (Wamba et al., 2017)
		ISC-IC_2	All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing AI and machine learning predictive analytics insights.	
		ISC-IC_3	Our organization utilizes open systems network mechanisms to boost AI and machine learning predictive analytics connectivity.	
		ISC-IC_4	There are no identifiable communications bottlenecks within our organization for sharing AI and machine learning predictive analytics insights.	
		ISC-IC_5	Software applications can be easily used across multiple AI and machine learning predictive analytics platforms.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISC-IC_6	Our user interfaces provide transparent access to all AI and machine learning platforms.	
		ISC-IC_7	Information is shared seamlessly across our organization, regardless of the location.	
		ISC-IC_8	Reusable software modules are widely used in AI and machine learning new system development.	
		ISC-IC_9	End users utilize object-oriented tools to create their own AI and machine learning applications.	
		ISC-IC_10	AI and machine learning predictive analytics personnel utilize object-oriented technologies to minimize the development time for new applications.	
	Intelligent Systems Capabilities-Personnel Capabilities (ISC-PC)	ISC-PC_1	Our AI and machine learning predictive analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.).	
		ISC-PC_2	Our AI and machine learning predictive analytics personnel are very capable in terms of managing project life cycles.	
		ISC-PC_3	Our AI and machine learning predictive	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			analytics personnel are very capable in the areas of data management and maintenance.	
		ISC-PC_4	Our AI and machine learning predictive analytics personnel are very capable in the areas of distributed computing.	
		ISC-PC_5	Our AI and machine learning predictive analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.).	
		ISC-PC_6	Our AI and machine learning predictive analytics personnel show superior understanding of technological trends.	
		ISC-PC_7	Our AI and machine learning predictive analytics personnel show superior ability to learn new technologies.	
		ISC-PC_8	Our AI and machine learning predictive analytics personnel are very knowledgeable about the critical factors for the success of our organization.	
		ISC-PC_9	Our AI and machine learning predictive analytics personnel are very knowledgeable about the role of business analytics as a means, not an end.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISC-PC_10	Our AI and machine learning predictive analytics personnel understand our organization’s policies and plans at a very high level.	
		ISC-PC_11	Our analytics personnel are very capable in interpreting business problems and developing appropriate solutions.	
		ISC-PC_12	Our AI and machine learning predictive analytics personnel are very knowledgeable about business functions.	
		ISC-PC_13	Our AI and machine learning predictive analytics personnel are very knowledgeable about the business environment.	
		ISC-PC_14	Our AI and machine learning predictive analytics personnel are very capable in terms of managing projects.	
		ISC-PC_15	Our AI and machine learning predictive analytics personnel are very capable in terms of executing work in a collective environment.	
		ISC-PC_16	Our AI and machine learning predictive analytics personnel are very capable in terms of teaching others.	
		ISC-PC_17	Our AI and machine learning predictive analytics personnel work	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			closely with customers and maintain productive user/client relationships.	
	Intelligent Systems Capabilities-Management capabilities (ISC-MC)	ISC-MC_1	We continuously examine innovative opportunities for the strategic use of AI and machine learning predictive analytics.	
		ISC-MC_2	We enforce adequate plans for the utilization of AI and machine learning predictive analytics.	
		ISC-MC_3	We perform AI and machine learning predictive analytics planning processes in systematic ways.	
		ISC-MC_4	We frequently adjust AI and machine learning predictive analytics plans to better adapt to changing conditions.	
		ISC-MC_5	When we make AI and machine learning predictive analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work.	
		ISC-MC_6	When we make AI and machine learning predictive analytics investment decisions, we project how much these options will help end users make quicker decisions.	
		ISC-MC_7	When we make AI and machine learning	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			predictive analytics investment decisions, we estimate whether they will consolidate or eliminate jobs.	
		ISC-MC_8	When we make AI and machine learning predictive analytics investment decisions, we estimate the cost of training that end users will need.	
		ISC-MC_9	When we make AI and machine learning predictive analytics investment decisions, we estimate the time managers will need to spend overseeing the change.	
		ISC-MC_10	In our organization, business analysts and line people meet regularly to discuss important issues.	
		ISC-MC_11	In our organization, AI and machine learning predictive analytics and line people from various departments regularly attend cross-functional meetings.	
		ISC-MC_12	In our organization, AI and machine learning predictive analytics and line people coordinate their efforts harmoniously.	
		ISC-MC_13	In our organization, information is widely shared between AI and machine learning	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
			predictive analytics and line people so that those who make decisions or perform jobs have access to all available know-how.	
		ISC-MC_14	In our organization, the responsibility for AI and machine learning predictive analytics development is clear.	
		ISC-MC_15	We are confident that AI and machine learning predictive analytics project proposals are properly appraised.	
		ISC-MC_16	We constantly monitor the performance of the AI and machine learning predictive analytics function.	
		ISC-MC_17	Our analytics department is clear about its performance criteria.	
			Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.	
		ISC-MC_18	Our company is better than competitors in reducing cost within a business process.	
		ISC-MC_19	Our company is better than competitors in bringing complex analytical methods to bear on a business process.	

Third Order Construct	Second Order Construct	Question #	Measurements	Source
		ISC-MC_20	Our company is better than competitors in bringing detailed information into a business process.	
Firm Performance (FPERF)	-	FPERF_1	Using AI and machine learning platforms improved customer retention during the last 3 years relative to competitors.	Adapted from (Wamba et al., 2017)
		FPERF_2	Using AI and machine learning platforms improved sales growth during the last 3 years relative to competitors.	
		FPERF_3	Using AI and machine learning platforms improved profitability during the last 3 years relative to competitors.	
		FPERF_4	Using AI and machine learning platforms improved return on investment (ROI) during the last 3 years relative to competitors.	
		FPERF_5	Using AI and machine learning platforms improved overall financial performance during the last 3 years relative to competitors.	

Appendix 3 – Invitation Letter

Dear ${m://FirstName},

Hope this email finds you well. I am completing the Ph.D. program at Florida International University, Chapman Graduate School of Business. I am in the third year of the Ph.D. program, and I am conducting my dissertation research, which is studying the organization's investment in artificial intelligence and machine learning platforms and its relationship to the firm's performance.

You have been identified as a subject matter expert within the information technology field, and I would like to invite you to participate in my dissertation research study. It will only take 10 minutes of your time. Please click on the link below to complete the survey or you can copy and paste the URL link into your browser address bar.

FOLLOW THIS LINK TO THE SURVEY:

${l://SurveyLink?d=Take the Survey}

Or copy and paste the URL below into your internet browser:

${l://SurveyURL}

Follow the link to opt out of future emails:

${l://OptOutLink?d=Click here to unsubscribe}

Please rest assured that this study is voluntary and your answers are completely anonymous and confidential. This means that no individual will be associated with the survey's results. You can stop the survey at any time. For any questions on the survey and any technical difficulties, please contact me at nwije001@fiu.edu.

Thank you in advance for your participation in this study. Please feel free to forward this research survey to your friends and colleagues.

Sincerely,

Noel Wijesinha

Doctor of Business Administration (DBA) - Candidate

Chapman Graduate School of Business

Florida International University

Phone: 416-985-6300

Email: nwije001@fiu.edu

FIU | Business

FLORIDA INTERNATIONAL UNIVERSITY

Appendix 4 – Reminder Letter

Dear ${m://FirstName},

As per the email sent a ${d://Date}, I am completing the Ph.D. program at Florida International University, Chapman Graduate School of Business. My dissertation research is studying the organization's investment in artificial intelligence and machine learning platforms and its relationship to the firm's performance. You have been identified as a subject matter expert within the information technology field, and I would like to invite you to participate in my dissertation research study. It will only take 10 minutes of your time. Please click on the link below to complete the survey or you can copy and paste the URL link into your browser address bar.

FOLLOW THIS LINK TO THE SURVEY:

${l://SurveyLink?d=Take the Survey}

Or copy and paste the URL below into your internet browser:

${l://SurveyURL}

Follow the link to opt out of future emails:

${l://OptOutLink?d=Click here to unsubscribe}

Please rest assured that this study is voluntary and your answers are completely anonymous and confidential. This means that no individual will be associated with the survey's results. You can stop the survey at any time. For any questions on the survey and any technical difficulties, please contact me at nwije001@fiu.edu.

Thank you in advance for your participation in this study. Please feel free to forward this research survey to your friends and colleagues.

Sincerely,

Noel Wijesinha

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Appendix 5 – Main Study Nonresponse Results (T-Test)

Table 12 T-Test Group Statistics

	Wave	N	Mean	Std. Deviation	Std. Error Mean
Industry	Early	74	12.28	4.984	.579
	Late	91	13.57	5.095	.534
Department	Early	74	5.30	1.585	.184
	Late	91	5.05	1.328	.139
Age	Early	74	3.49	.646	.075
	Late	91	3.35	.721	.076

Table 13 Independent Sample Test

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Industry	Equal variances assumed	.116	.734	-1.630	163	.105	-1.288	.790
	Equal variances not assumed			-1.634	157.525	.104	-1.288	.788
Department	Equal variances assumed	.193	.661	1.069	163	.287	.242	.227
	Equal variances not assumed			1.049	142.460	.296	.242	.231
Age	Equal variances assumed	1.574	.211	1.251	163	.213	.135	.108
	Equal variances not assumed			1.266	161.413	.207	.135	.107

Appendix 6 - Main Study Outer Loadings

Table 14 Main Study Outer Loadings

Items	Firm Perf.[a]	IS Infra. Env.[b]	IS Mgmt. Skills[c]	IS Infra. Perf.[d]	IS Plan.[e]	IS Proc. Red.[f]	IS Tech, Skills[g]	IT Ext. Relation.[h]
FPERF_1	**0.903**	0.595	0.651	0.555	0.640	0.533	0.623	0.541
FPERF_2	**0.923**	0.584	0.640	0.510	0.650	0.499	0.544	0.479
FPERF_3	**0.825**	0.429	0.550	0.412	0.480	0.370	0.510	0.406
FPERF_4	**0.894**	0.542	0.657	0.465	0.603	0.538	0.552	0.457
FPERF_5	**0.931**	0.651	0.615	0.547	0.631	0.568	0.518	0.508
ISBRITER_1	0.413	0.383	0.546	0.420	0.371	0.557	0.496	**0.803**
ISBRITER_2	0.402	0.521	0.495	0.560	0.538	0.543	0.557	**0.839**
ISBRITER_3	0.429	0.466	0.437	0.462	0.399	0.581	0.485	**0.856**
ISBRITER_4	0.453	0.481	0.388	0.638	0.580	0.449	0.636	**0.870**
ISBRITER_5	0.451	0.541	0.403	0.704	0.606	0.434	0.656	**0.837**
ISBRITER_7	0.474	0.491	0.665	0.499	0.635	0.640	0.524	**0.706**
ISBRPLN_5	0.601	0.515	0.624	0.670	**0.917**	0.512	0.702	0.573
ISBRPLN_7	0.666	0.601	0.671	0.676	**0.967**	0.604	0.686	0.618
ISBRPLN_8	0.654	0.575	0.675	0.693	**0.965**	0.616	0.708	0.638
ISBRPR_1	0.512	0.416	0.545	0.431	0.543	**0.940**	0.458	0.560
ISBRPR_2	0.498	0.362	0.511	0.395	0.487	**0.917**	0.463	0.544
ISBRPR_6	0.520	0.544	0.641	0.602	0.617	**0.851**	0.561	0.663
ISIENV_2	0.520	**0.827**	0.464	0.577	0.477	0.328	0.553	0.457
ISIENV_3	0.539	**0.873**	0.478	0.455	0.405	0.361	0.424	0.396
ISIENV_7	0.521	**0.780**	0.515	0.620	0.559	0.528	0.542	0.512
ISIENV_8	0.479	**0.786**	0.491	0.574	0.509	0.385	0.479	0.572
ISIPERF_3	0.368	0.423	0.315	**0.780**	0.557	0.369	0.530	0.523
ISIPERF_4	0.558	0.660	0.484	**0.952**	0.682	0.507	0.722	0.628
ISIPERF_5	0.539	0.690	0.510	**0.931**	0.665	0.519	0.723	0.639
ISITHRMS_1	0.513	0.417	**0.821**	0.266	0.447	0.474	0.458	0.454
ISITHRMS_4	0.566	0.442	**0.782**	0.326	0.402	0.395	0.504	0.426
ISITHRMS_5	0.633	0.587	**0.867**	0.511	0.669	0.571	0.665	0.522
ISITHRMS_8	0.634	0.573	**0.867**	0.511	0.709	0.590	0.706	0.557
ISITHRMS_9	0.544	0.437	**0.832**	0.444	0.627	0.578	0.585	0.534
ISITHRTS_1	0.506	0.492	0.633	0.635	0.632	0.492	**0.908**	0.591
ISITHRTS_2	0.592	0.580	0.673	0.697	0.705	0.447	**0.953**	0.634
ISITHRTS_3	0.619	0.634	0.681	0.765	0.725	0.598	**0.953**	0.698

a. Firm Perf. = Firm Performance
b. IS Infra. Env. = IS Infrastructure Environment
c. IS Mgmt. Skills = IS Management Skills
d. IS Infra. Perf. = IS Infrastructure Performance
e. IS Plan. = IS Planning
f. IS Proc. Red. = IS Process Redesign
g. IS Tech. Skills = IS Technical Skills
h. IT Ext. Relation. = IT External Relationships

Appendix 7 – Main Study HTMT Ratio Analysis

Table 15 HTMT Ratio Analysis for First-Order Constructs

Constructs	AVE	CR	Alpha	1	2	3	4	5	6	7	8
1. Firm Performance	0.802	0.953	0.938								
2. IS Environment	0.668	0.889	0.834	0.707							
3. IS Management Skills	0.696	0.920	0.891	0.757	0.684						
4. IS Performance	0.794	0.920	0.869	0.605	0.783	0.549					
5. IS Planning	0.902	0.965	0.945	0.712	0.671	0.745	0.787				
6. IS Process Redesign	0.817	0.930	0.887	0.614	0.568	0.702	0.593	0.663			
7. IS Technical Skills	0.880	0.957	0.932	0.653	0.689	0.767	0.818	0.782	0.600		
8. IT External Relationships	0.673	0.925	0.901	0.578	0.681	0.664	0.753	0.690	0.728	0.742	

VITA

NOEL R. WIJESINHA

EDUCATION

1998	BSc. Management Information Systems Winona State University Winona, MN, USA
1998-2001	Various Technology Consulting Roles Fortune 500 Companies in USA
2001	Master of Software Systems University of Saint Thomas St. Paul, MN, USA
2002-2009	Various Technology Management Roles Fortune 500 Companies in USA, Canada and Sri Lanka
2007-Current	President/CEO Sciteqsoft Inc Toronto, ON, Canada
2011-Current	Co-Founder and Board Member Ecoestetics Corp Toronto, ON, Canada
2013	Master of Business Administration Wayne State University Detroit, MI, USA
2022	Doctor of Business Administration (Candidate) Florida International University Miami, FL, USA

PUBLICATIONS & PRESENTATIONS

Butler, U., Idani, P., Rey, J., Wijesinha N., *The Impact of Virtual Networks on Small and Medium Businesses: Observations from the Emergent Market Perspective* (Research Proposal). Paper presented at AIB Latin America (AIB-LAC) 2021 Online Conference.

Wijesinha N. *Studying the Executive Perception of Investment in Intelligent Systems the Affect on Firm Performance* (Dissertation Proposal). Paper presented EMS 2021 Doctoral Consortium Conference, Miami, Florida.