Thesis

Master of Science in Management

The Influence of Technology on Organizational Performance:

The Mediating Effects of Organizational Learning

Matthew Chegus

University of Ottawa, Telfer School of Management

January, 2018

Supervised by:

Professor Swee Goh

Professor Catherine Elliott

© Matthew Chegus, Ottawa, Canada, 2018

Table of Contents

Abstract

Organizations depend upon ever greater levels of information technology (IT), such as big data and analytics, a trend which shows no sign of abating. However, not all organizations have benefited from such IT investments, resulting in mixed perceptions on the value of IT. Organizations must be knowledgeable in order to properly utilize IT tools and be able to apply that knowledge to create unique competencies in order to gain sustained advantage from IT investments. Organizational learning (OL) has been proposed as the mechanism to accomplish this task. Existing empirical research demonstrates that OL may indeed act as a mediator for the effect of IT on organizational outcomes. Yet, these studies are not consistent in their conceptualizations of the relationships involved, nor in their definitions and measurement of OL. Many use a descriptive measure of OL despite theory suggesting that a normative measure may be more appropriate. This study aims to address these concerns in a Canadian setting by using structural equation modelling (SEM) to compare the effectiveness of descriptive and normative measures of OL as mediating variables in knowledge-intensive organizations. Survey results support OL as a mediator between IT and organizational performance in addition to normative measures of OL outperforming descriptive measures. Implications for research and practice are discussed.

1. Introduction

Organizations of all kinds are relying more on data and information processing systems than ever before (Stata, 1989; Orlikowski, 2001; Calvard, 2016). Investments in the tools of information technology (IT) infrastructures have been assumed to provide enhanced decision-making capabilities, increased efficiency, and improved productivity (Tippins & Sohi, 2003; Bhatt & Grover, 2005). A prime example for modern organizations, though not the only example, is that of 'big data' and 'analytics.' These relatively new technologies have high expectations to enhance organizational outcomes and, consequently, are invested in heavily. However, such investments do not always lead to better organizational outcomes. For example, Gartner reports that over half of big data projects fail to deliver the anticipated return on investment (Gartner, 2015).

While big data or analytics may be a relevant modern example of technology for enhancing organizational performance, the issues encountered with their use in practice are not limited to these technologies. More generally, there are examples where technologies lead to more organizational problems such as 'analysis paralysis' whereby managers spend too much time and effort analyzing an issue before action is taken which may prevent a timely response to that issue. There are also examples of organizations which spend an inordinate amount of resources collecting, organizing, and storing information that is never used to inform decision making, resources that can arguably be better used elsewhere with a higher return on investment. Furthermore, there are examples whereby organizations collect information they are unable to understand, but regardless, they continue to use that information in their decision-making processes resulting in ill-informed decisions. "The imprudent integration of such IT systems may eventually lead to a less desirable competitive position within an industry" (Tippins & Sohi, 2003, p. 757). IT may then result in worse outcomes for the organization as the organization either does not fully utilize IT infrastructure or it becomes inundated with data it is unable to effectively process. As a result, IT can become as much an impediment as an enabler of organizational performance (Romme & Dillen, 1997; Tippins & Sohi, 2003; Calvard, 2016). These issues represent a salient challenge for modern organizations which are increasingly reliant on large scale IT systems for organizational decision making and performance.

The challenges of IT utilization will only become more important as organizations are expected to increase their reliance on and utilization of organizational data processing systems (Stata, 1989; Tippins & Sohi, 2003; Real et al., 2006; Calvard, 2016). While automated forms of data analysis, such as statistical analyses, are good low-level tools, they are often inadequate for managers to 'get the big picture.' The development of this broad understanding is required to make informed organizational decisions at the highest level. Low-level analysis does not always provide this insight where more human perspectives are needed to answer the question 'what does this mean?' However, human analysis becomes problematic when datasets are very large, such as with big data. Big data databases can easily become so large that it would take human analysts too long to interpret manually. These situations then require a combination of automated analysis and human insight which is a combination that is often difficult to develop in practice. For some organizations, this has already happened; for others, it may just be a matter of time. Such prognostication suggests that the issue of how to best utilize IT will go beyond the initial investments in technological infrastructure, beyond a simple enhancement of existing business processes, and will require entirely new ways of operating.

Research into the organizational use of IT observes that IT infrastructure itself is not sufficient for competitive advantage (Tippins & Sohi, 2003; Bhatt & Grover, 2005). IT infrastructure is too easily imitated by other organizations and an inability to properly utilize existing resources may only increase operational overhead costs (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006). Instead, existing research demonstrates that, when combined with organizational learning (OL), IT may be used to develop unique organizational capabilities which then enable enhanced organizational performance; organizations must know how, and be willing to use, these tools properly in the form of IT capabilities. Such suggests that OL may be a mediating variable between IT and organizational performance (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Kane & Alavi, 2007).

This study aims to examine OL as a potential mediating variable in the relationship between IT and organizational performance. To do so, I will first review existing literature to discuss the use of technology in the organization, the application of organizational technology in a competitive environment, the case for OL as the key knowledge process, and the intersection between technology and OL as a knowledge-based means of improving organizational performance. Next, I will utilize existing measures of organizational performance, technology, and learning to conduct a survey of Canadian knowledge-intensive firms on these issues followed by a structural equation modelling analysis (SEM) to test the survey data against the proposed research question and hypotheses. I then confer conclusions from the survey and SEM analysis followed by a discussion of where this research fits into existing literature as well as implications for future research and practice.

Building upon the theoretical and empirical work conducted to date, this study will attempt to replicate existing findings which show there is no direct relationship between technology and organizational performance and that OL demonstrates a mediating relationship between technology and organizational performance. This replication will empirically test these relationships for the first time in a Canadian setting using existing SEM methodologies and survey measurements of IT, OL, and organizational performance. I then propose a novel perspective on the measurement of OL in this context which suggests an alternative measure of OL may provide superior accuracy. This study will compare the explanatory ability of both the existing and proposed measures to investigate the research question 'do normative measures of OL provide more explanatory power in mediating the relationship between organizational technology and organizational performance than descriptive measures of OL?' Directly comparing descriptive and normative measures of OL in explaining organizational performance, this study will help illuminate an important dynamic in modern technophilic organizations as well as empirically evaluate two alternative measures of OL in this dynamic giving researchers and organizations alike an empirical foundation upon which to build better technologically capable organizations.

2. Literature Review

2.1. Technology in the Organization

2.1.1. Information Technology and Information Systems Perspective

Technology in the organization has traditionally been studied from two main perspectives, the information technology/information systems (IT/IS) perspective and the organizational studies perspective. The former has tended to be more concerned with development and application of specific IT tools while the latter tends to develop and test broad theoretical explanations for organizational behavior (Orlikowski, 2001). Examples of specific technologies employed in organizations mainly include areas such as communication technology, knowledge repositories, databases, and analytical and computational capabilities. Other examples of research on specific technologies include Orlikowski's (2001) investigation of telecommuting, Dodgson et al.'s (2013) case study of virtualization technology, Myreteg's (2015) study of the use of enterprise resource planning systems, and Calvard's (2016) insights into big data. Areas that have not traditionally used IT have also started to embrace its use (Stata, 1989; Tippins & Sohi, 2003; Real et al., 2006; Calvard, 2016). Modern examples include human resource management (HRM), customer relations management (CRM), enterprise resource planning (ERP), and social media integration. It is not only the quantity of informational products that is growing but also the variety of information itself (Calvard, 2016) as together, these tools cover a vast swath of different data types and ranges of information. Data repositories, in general, have become central to many existing business processes that rely on data transactions, reports, and analyses. Modern incarnations of data repositories often fall under the purview of knowledge management approaches. For example, tools that aid in information storage, organization, retrieval, and sharing (King, 2009) are often characterized as 'big data' databases which are able to store very large quantities and varieties of data with high velocities of data transfer (Calvard, 2016).

2.1.2. Organizational Studies Perspective

Organizational studies, on the other hand, contend that technology should be thought of from a broader, less concrete perspective. Myreteg (2015) cautions that the specific application of technology is overemphasized in IT/IS literature compared to other organizational outcomes: "There is a heavy dominance of studies concerning how to use the ERP system itself, rather than investigating how IT can support learning processes that could have operational, managerial, strategic or organizational benefits" (p. 125). Seeing the organization from the social constructivist view, Orlikowski (2001), allows us to see how technologies reflect human agency and so embody the choices of the organization. The author suggests that technologies can then be shifted by the user as they become integrated into the organization and their application directed to create the desired outcome. Other studies at the organizational level have focused on the interaction of technology and organizational strategy where “firm strategies and IT capabilities are so closely interrelated that they should be developed concurrently” (Tippins & Sohi, 2003, p. 747). Kane and Alavi (2007) discuss how technologies and learning can be influenced by organizational behavioral variables such as personal differences, organizational contexts, and environmental turbulence. For these reasons, Orlikowski (2001) claims that organizational studies research has had more influence on specific information technology studies than IT has had on organizational studies. However, while these two perspectives have often been separated, scholars have more recently begun to bridge the gap.

2.1.3. Combining IT/IS and Organizational Perspectives

It can be said from the intersection of these two areas of study that IT acts generally on the organization in two ways. First, IT is able to better leverage existing resources to expand the potential choices and breadth of action than would otherwise be possible. Second, the organization’s choice of which technologies to employ and how to employ them serves to reinforce the shared values of the organization as organizations must make choices based on the shared goals and priorities that result in artefacts which stand as examples of their shared vision. Management information systems (MIS), for example, have developed from a more technological perspective towards integrating more of the social context of people using technology (Sidorova et al., 2008). Together, technology should then be thought of as both social and physical (Orlikowski, 2001; Kane & Alavi, 2007) as technology both impacts the *potential* choices of organizations as well as embodies the *current* choices made by organizations (Stata, 1989; Orlikowski, 2001; Bapuji & Crossan, 2004). This implies that technology cannot be considered separately from the way that people behave within the organization, supporting the development in the MIS literature to investigate not just technology but also its use in practice. Technology and behavior must then also interact over time (Bueno et al., 2010; BolíVar-Ramos et al., 2012) as technology influences the behavior of organizations and behavior influences organizational technology.

The interaction of technological and organizational behavior over time highlights a limiting assumption of the types of studies that focus solely on the application of specific technologies for specific purposes. Such studies tend to assume that organizational processes will remain qualitatively the same pre and post-technological application, merely occurring at greater scope, scale, or rate and would thus represent what I have termed the 'linear model' of organizational technology. The linear model of technology in the organization sees technologies merely as means to an end. This perspective, while perhaps useful through limited frames of reference, fails to appreciate the abovementioned underlying interaction between people and the tools that they employ which can lead to large scale discrepancies between applied technologies and their anticipated outcomes over time.

A more integrated approach to studying technology in the organization may aid in understanding the role that technology plays in the organization and the relationship that people have with technology. These relationships result in an iterative interaction over time whereby behaviors affect choices in technology and choices in technology affect future behaviors (Real et al., 2006; Kane & Alavi, 2007). The effects of the previous iterations are therefore compounded by the subsequent iterations, resulting in behaviour that may deviate vastly from its initial conditions, and is discussed in more detail below. I have termed this the 'non-linear model' of organizational technology. The non-linear model is then defined as the application of technology to enhance organizational performance by qualitatively changing the organizational processes and is a result of the interaction between technology and behavior over time. Non-linear model of technology in the organization does not presuppose a specific technology for a specific purpose but rather deals with changes to how an organization operates on a more fundamental level and so describes how organizational outcomes may exceed simple enhancements to scope, scale, or rates of organizational processes and result in non-linear organizational outcomes.

This insight into the interaction between technology and its use in practice may be of particular importance for modern organizations which invest in greater levels of IT expecting that such investments in technology alone will lead to better organizational outcomes. Unfortunately, in light of these dynamics, there may be a large gap between the tools employed and the realized outcomes – a consequence not easily explained by the linear model of organizational technology.

2.2. Technology in a Competitive Environment

It is often suggested that IT has become so ubiquitous an investment that it is assumed to provide value, increase productivity, and competitiveness as a matter of course. However, investments in IT have not always resulted in the expected gains (Tippins & Sohi, 2003; Bhatt & Grover, 2005). An example comes in the form of big data. Here, it is argued that vast volumes of data are difficult for people to interpret and make sense of at these grand scales (Romme & Dillen, 1997) which may impede effective understanding and use of such information (Calvard, 2016) resulting in cherry-picking of data, and inability to identify patterns and make appropriate generalizations. Failure to properly comprehend the data being relied upon to make organizational decisions may distort intentions, discourage the use of technological aids, or worse, set the scene for poor organizational decision making based on misunderstanding and misplaced confidence in the decision-making processes. The simple existence of a big data infrastructure is not sufficient for enhanced organizational processes as the potential for improper use of technology may undermine competitive positions. Technologies, such as big data, then need additional context to provide a competitive advantage.

2.2.1. Resourced-based View (RBV)

Organizational strategy literature provides insight into how and why organizations may not be achieving the desired outcomes from the application of technology. From this perspective, the resourced-based view of the firm (RBV) helps to elucidate the theoretical mechanisms that may be applied to technology in a competitive setting (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006). A brief overview of RBV may start with Wernerfelt (1984) who describes how organizations may be examined through the product side or the resource side, both of which may be considered ‘two sides of the same coin.’ The traditional product side has little concern for how the product was created and seeks only to maximize its value through market positioning while the resource side deals with how the product was created from the resources available to the firm. Wernerfelt explains how most traditional economic tools have operated on the product side of the firm’s value creation. However, a resource-based view considers anything that could be thought of as a strength or weakness of a firm to be a resource that can be used to create or deny value for that firm.

Peteraf (1993) summarizes the four RBV conditions that are necessary for resources to be used to create sustained competitive advantage. The first condition relies on the assumption that resources are heterogeneous and so can be exploited through monopolistic rents by securing superior resources. The second deals with the ongoing, ex-post competition for superior resources whereby there must be forces which limit competition. Otherwise competing organizations may negate the advantage of superior resources by acquiring the same resources over time. Wernerfelt (1984) describes this condition as a ‘resource position barrier’ wherein a resource becomes less valuable for a subsequent competitor to use the same resource. The third of Peteraf’s conditions is that of imperfect resource mobility where resources can become specialized to a specific firm which makes them less valuable in other situations. And finally, the last condition is ex-ante limits to competition. In other words, there must have been some reason, ex-ante, why a successful firm was able to capitalize on a particular set of resources when other firms were not. Otherwise, competition for those resources would have immediately started to erode the value of those resources before they could be uniquely exploited by the firm.

2.2.2. RBV and Organizational Strategy

Teece, Pisano, and Shuen (1997) summarize these perspectives in the strategic management literature as two types: strategizing and economizing. The former suggests that organizations attempt to maximize organizational value with a relatively static value proposition which is merely positioned within the market for maximum effect through the competitive forces model and the strategic conflict model. The latter, however, is based on the notion that an organization is capable of creating value in which the strategic component does not simply involve market placement but also the *process* of value creation itself. The authors further describe how the perspective of value creation can be extended into the knowledge based view (KBV) and finally the dynamic capabilities view. Knowledge based view is an extension of RBV in that it is not a new theory but merely one that includes knowledge as a strategic resource necessary for an organization to create value. Knowledge, in this context, may be thought of as a complementary resource to other more tangible resources; physical IT resources are necessary but may not be sufficient to create value if an organization does not know what to do with those physical resources. The KBV thus helps to explain why organizational knowledge becomes critical in organizational value creation. Dynamic capabilities, on the other hand, discuss a 'capability' as the combination of both the physical resources and the knowledge of how to use them. Dynamic capabilities then represent an ability for an organization to create new capabilities, new combinations of physical resources and knowledge. The ability to create new capabilities would be beneficial whenever an organization encounters change in their environment, changes their own strategic direction, or adopts new capabilities for achieving their strategic goals within their environment such as the application of new technologies.

2.2.3. Competitive Resources and IT Underperformance

These various RBV perspectives suggest that the dissatisfaction with IT outcomes in the organization may be explained through two main avenues: not having the knowledge to fully exploit IT resources or cases where competitive advantage is nullified. Knowledge is a necessity for anyone to make use of any tool. As such, knowledge represents a necessity for any type of organization intending to deploy IT. However, this explanation does not satisfy all examples. Tippins and Sohi (2003) and Bhatt and Grover (2005) both identify research which demonstrates that the perceived benefit of IT resources in a competitive environment can fall short of financial investment for many organizations even if they already have the capacity to properly deploy such tools. In these examples, despite an organization having the necessary knowledge, the organization was still unable to capitalize on it as a competitive advantage. Consequently, over and above the first requirement of knowledge, there must also be a competition-specific explanation for IT's role in organizational performance.

The resource-based view of the firm can then be used to explain the use of IT as a competitive resource in an organization. Tippins and Sohi (2003) describe how IT itself may not generate a sustainable competitive advantage because it can be easily commoditized, imitated, or otherwise acquired thus precluding some of the necessary conditions for successful resource-based competition as described by Peteraf (1993). A commercially available computer system, for example, may be purchased by anyone with the requisite financial resources thus negating any relative advantage over a competitor through lack of ex-ante competition (its availability and value proposition are announced to the whole market at the same time), ex-post competition (it is in the best interests of the retailer of the computer system to sell as many units as possible), and high resource mobility. However, when IT is combined with unique organizational knowledge to create an IT capability, knowledge may not only *enhance* those resources (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006) but also provide a way to *specialize* those IT resources to that particular organization (Tippins & Sohi, 2003; Bhatt & Grover, 2005) granting it imperfect mobility and providing limits on ex-post competition due to co-specialization of resources (Tippins & Sohi, 2003). Creating an IT capability requires the organizational knowledge necessary to understand the possibilities that IT affords and the know-how to capitalize on those possibilities in practice. The requisite knowledge must be unique to the firm such that it endows the firm with an ability to identify important applications for IT resources before other organizations granting it the ex-ante limit to competition and completing the necessary requirements for sustained competitive advantage through IT resources.

The RBV perspective thus highlights the importance of knowledge in the application of IT in a competitive setting. Knowledge is necessary but not sufficient for competitive use of IT resources. Unique organizational knowledge is what enables the organization to fully utilize IT resources and it is what endows IT with all the properties of a competitive advantage. Just as technology may be thought of as both social and physical, RBV highlights that organizational knowledge is that which connects the physical IT infrastructure with its *use* in practice in the organization in a competitive setting. The mechanism for how organizations may be able to develop the necessary knowledge is then presented through the lens of organizational learning (Anand, Mans, & Glick, 1998; Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Kane & Alavi, 2007; Myreteg, 2015; Calvard, 2016) which will be discussed further below.

2.3. Organizational Learning

The basic premise of organizational learning is that organizations exist within an environment which provides the resources for the organization's continued survival. The environment that the organization occupies changes in the amount, type, and availability of resources over time. The rate of change may vary depending on the circumstance but change is always occurring. Organizational decisions must then align with that changing environment to enable the organization to better cultivate resources and perform more effectively within that environment (Fiol & Lyles, 1985; de Geus, 1988). However, without information about the environment and how it is changing, the effectiveness of any organizational decision may be no better than chance. So, the challenge for any organization seeking long term survival becomes being able to learn about the environment in order to make better decisions to achieve higher performance (Fiol & Lyles, 1985; Lant et al., 1992; Mills & Friesen, 1992; Schein, 1993; Nevis et al., 1995; Tsang, 1997; Goh, 1998; Goh, 2001; Easterby-Smith et al., 2004; Goh et al., 2012) where organizational knowledge is the output of a learning process. And since the environment is constantly changing, learning cannot be thought of as a onetime investment but must be enacted continuously. "The rate at which individuals and organizations learn may become the only sustainable competitive advantage, especially in knowledge-intensive industries." (Stata, 1989, p. 64).

2.3.1. The Convergence of Normative and Descriptive Perspectives

Early work on organizational learning often took one of two perspectives: the more practitioner oriented ‘learning organization’ versus the more descriptive ‘organizational learning’ (Argyris & Schon, 1996). The two perspectives differed in their assumptions of the nature of learning. The former took a normative approach towards learning, assuming that learning for learning’s sake was inherently good because it produced desirable organizational outcomes. Garvin (1993) and Goh (1998), define a learning organization as an organization which is skilled at creating, acquiring, and transferring knowledge, and at modifying its behavior to reflect new knowledge and insights.

Normative perspectives often originated from managerial practice experience, such as the perspectives of Argyris and Schon (1978), de Geus (1988), or Senge (1990), where practitioners saw the positive outcomes to learning such as continuous improvement, enhanced quality of life, employee development, and organizational culture (Argyris & Schon, 1996). Empirical work by Goh (1998) suggests that outcomes can be seen in the long run delivery of services, innovation, and quality; and most describe learning as a means to better organizational performance (Fiol & Lyles, 1985; Nevis et al., 1995; Tsang, 1997; Mills & Friesen, 1992; Goh, 2001). This stream of thinking leads fairly quickly to discussions around how learning can, has, and perhaps *should* take place, citing examples of successful learning organizations like Royal Dutch Shell (de Geus, 1988), British Petroleum (Mills & Friesen, 1992) or Analogue Devices (Stata, 1989).

More descriptive discussions arose around organizational learning almost simultaneously. These discussions took a more critical look at the *processes* by which organizations were said to learn. Some questions centered around whether organizations are in fact able to learn or merely adaptation (Fiol & Lyles, 1985), or if so, whether organizations can change effectively in turbulent environments (Lant et al., 1992) or also whether complex systems make attributing outcomes to learning processes difficult (Tsang, 1997). Descriptive approaches examined these concepts by defining OL as a process that can be broken down in different phases of information acquisition, information interpretation, information dissemination, and organizational memory (Nevis et al., 1995; Dibella et al., 1996; Goh & Richards, 1997).

Despite theoretical differences between the normative approaches and the descriptive approaches, strong support for organizational learning through both methods have emerged such as Lant et al.'s (1992) concept of environmental alignment through 'strategic change' or Bapuji and Crossan's (2004) account that OL can enhance survival and innovation. Also, Goh's work in 2001 attributes positive outcomes in performance based on empirical study and later work in Goh et al.'s (2012) meta-analysis provides statistical support that learning improves both financial as well as non-financial organizational performance. OL is now generally defined through both normative and descriptive perspectives as the process which enables organizations to acquire and transfer knowledge and utilize that knowledge to alter the behavior of the organization with the goal of improved performance (Garvin, 1993; Miller, 1996; Goh, 1998). For instance, Jiménez-Jiménez and Sanz-Valle (2011) define OL as "the process by which the firm develops new knowledge and insights from the common experiences of people in the organization, and has the potential to influence behaviors and improve the firm's capabilities." (p. 409). Argote and Miron-Spektor (2011) are even broader by defining OL as "a change in the organization's knowledge that occurs as a function of experience." (p. 1124). These more unifying definitions help to emphasize both how the capture and production of new knowledge occurs (exemplified through the descriptive approach), and its use in practice (exemplified by the normative approach), which results in organizational outcomes, serving to unite both OL perspectives. Furthermore, both approaches speak to the earlier RBV concepts of knowledge as a resource and OL as a means of cultivating that resource (Anand, Manz, & Glick, 1998).

2.3.2. The Divergence of Normative and Descriptive Measures

Despite the convergence of definitions of OL, the measurement of OL is still divided with some studies using descriptive measures and others using normative. Descriptive approaches try to analyze the structural antecedents of OL to identify which mechanisms and processes constitute OL (Tsang, 1997; Jiménez-Jiménez & Sanz-Valle, 2011). Descriptive approaches tend to utilize lower-level constructs that are more explicit and so easier to measure and quantify. For these reasons, descriptive approaches have most often been employed for quantitative research, including existing research on technology and OL (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Kane & Alavi, 2007). However, these sub-processes of learning merely represent the necessary structural antecedents for OL to take place. It is possible that each sub-process of learning may exist on its own, in isolation, and not positively contribute to the organization's overall ability to learn. Alternatively, all components may exist but in a somewhat dysfunctional manner whereby the components are at odds with one another perhaps due to organizational conflicts. Consequently, measuring the pre-conditions for learning alone may highlight what is necessary for learning to take place but may fail to identify learning outcomes in some situations.

Normative definitions of OL, conversely, measure the outcomes of OL such as improvements in quality, employee satisfaction, and organizational performance to name just a few (Goh, 1998; Goh, 2001). These outcomes of learning are higher-level than their respective descriptive measures and as such tend to convey a broader meaning often associated with organizational learning. However, these broader constructs are more abstract and so difficult to measure as they may be exhibited in different ways for different organizations. Thus, there is a theoretical asymmetry between the reductive descriptive method and the more synthetic normative method since the descriptive perspective analyzes only the components of a concept while the normative perspective analyzes the broader implications.

The context of this study emphasizes the broad scale organizational issues with using technology for enhanced organizational performance which would suggest a closer theoretical alignment with the normative perspective's emphasis on broader organizational outcomes. Additionally, the non-linear outcomes associated with qualitatively novel technological impacts that build over time are not explained very well by descriptive measures of OL which do not measure how the sub-processes interact. Indeed, OL has been argued to be more than the sum of its parts (Fiol & Lyles, 1985; Goh & Richards, 1997; Popper & Lipshitz, 1998; Crossan et al., 1999) which is a quality that would not be measured by examining the structural antecedents alone. Consequently, descriptive measures may maintain that an organization is exhibiting all the necessary building blocks of learning while failing to account for the results of learning over time. Normative approaches, which focus on the outcomes of learning, may then be of more use in explaining the effect of OL on the organization as normative outcomes would suggest not just the presence of the necessary structural antecedents but also their use in practice. Such asymmetry suggests the normative approach to measuring OL may have advantages in the context of this study as it seeks to capture the whole rather than the sum of its parts. Since the relationship between OL and technology may be impacted heavily by their dynamic interaction, normative measures may be particularly appropriate here.

2.4. The Intersection between IT and Organizational Learning

Organizational learning has traditionally been approached through a people-centric focus based on notions of individual learning and behavior, team and group learning, shared understanding and cultural learning, as well as more cognitive based learning (Bapuji & Crossan, 2004). However, more and more organizational processes are being conducted with the aid of increasingly complex technological systems (Stata, 1989; Orlikowski, 2001; Calvard, 2016). As a result, concepts of how organizational learning processes affect the organization should be expanded to account for technology. Two learning applications for technology are paramount: using technology as a learning aid and learning from the outcomes of choices in technology. The former may be included in investigations of IT/IS that augment the learning processes such as those that make up the descriptive definition of OL: informational acquisition, informational dissemination, informational interpretation, and organizational memory. For example, the knowledge management systems of King (2009) speaks to organizational memory, or the virtualization technology studied by Dodgson et al. (2013) augments communication, just as the enterprise resource planning systems of Myreteg (2015) may study informational acquisition or dissemination. However, learning from the outcomes of technological choices is scarcer in the literature.

A search for literature specifically on the intersection between organizational learning and technology was conducted to help shed light on the issue of learning from technological choices in the organization. The reviewed articles suggest that the relationship between OL and technology remains a tangential subject in academic literature with few addressing the issue directly: “There is, however, no integrated model of all of these systems in the literature, nor is there a model that focuses on the broad concept of technology.” (BolíVar-Ramos et al., 2012, p.

332). However, what does exist, proposes that technology and organizational learning are more related than common consideration might imply. A more detailed summary chart of searched articles and their contributions to research may be found in Appendix A.

2.4.1. Conceptual Research

The most pertinent research breaks into two main groups: conceptual research on technology in the organization and empirical research. Research like that of Orlikowski (2001), Myreteg's (2015), and Calvard (2016) take a broader look at the use of technology and its impacts for organizations. Orlikowski (2001) discusses the conceptual argument for why technology should not be considered separately from its use in practice as technology is an extension of our own choices and how we use technology reflects our values. Myreteg (2015) concludes their article by stating that in order to fully understand the use of technology in the organization we must understand technology's role in the process of learning. Calvard (2016) goes further by describing how organizations may learn from technology through an iterative process of sensemaking and organizational learning. These conceptual investigations aligned with earlier discussed notions that not only is there a relationship between IT and OL but that IT and OL may continuously interact with each other over time leading to large scale influences on the organization which is something even the more empirical articles acknowledge (BolíVar-Ramos et al., 2012).

2.4.2. Empirical Research

Empirical research on the use of technology in the organization takes the form of a computational model (Kane & Alavi, 2007), a case study (Dodgson et. al, 2013), and statistical analyses based on survey instruments (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Bueno et al., 2010; Schoenmakers & Duysters, 2010; Huang, 2011; Sanz-Valle et al., 2011; BolíVar-Ramos et al., 2012). Here, two studies measure a link between technological innovation and organizational learning (Huang, 2011; Sanz-Valle et al., 2011) or between OL and 'radical invention' in a technical organization (Schoenmakers & Duysters, 2010) which has similar conceptual alignments as the innovation articles. Five studies (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Bueno et al., 2010; BolíVar-Ramos et al., 2012) attempt to measure organizational technology, performance, and their relationships with OL where organizational performance is the main dependent variable in all articles consequently making them the focus of more attention for this study. However, not all studies conceptualize or test their models in similar ways. These five statistical analyses from existing literature can then be further examined to see if one, or multiple analyses, may be used by this thesis as a model to further build upon.

The models used in Tippins and Sohi (2003) and Bhatt and Grover (2005) both use relatively simple models containing only measures of IT, OL, and organizational performance. Tippins and Sohi (2003) test OL as a mediating variable while Bhatt and Grover (2005) test different facets of IT as mediating variables. Real et al. (2006) test OL as a mediating variable but also include a measure of technological distinctive competencies as an organizational outcome. However, Bueno et al. (2010), and BolíVar-Ramos et al. (2012) use more complicated models with many intervening variables. Bueno et al. (2010) include measures of technological slack, tacit knowledge, organizational learning, innovation, and organizational performance while BolíVar-Ramos et al. (2012) include "top management support," "technological skills," technological distinctive competencies, organizational learning, innovation, and performance.

The inclusion of more complex models raises a bit of a concern. It can be argued that knowledge, learning, innovation, skills, and competencies are all knowledge-related variables.

Knowledge (tacit or explicit), skills, and competencies are manifestations of knowledge, while learning is the process which creates knowledge, and innovation is a process that uses knowledge as an input. As such, all these included variables have a related construct which is a direct violation of a fundamental assumption of the SEM analysis used by these papers which requires all variables to be independent. Utilization of variables with overlapping constructs may preclude discriminant validity of these measures as their effects may show systematic correlation as a result of the model specification alone and would then be more prone to showing statistically significant relationships. Thus, the more complicated models are less desirable compared to the simpler models which will reduce the likelihood of overlapping effects making simpler models more statistically robust. As a result, the main quantitative articles that will be used as models for this study's analysis will include Tippins and Sohi (2003), Bhatt and Grover (2005), and Real et al. (2006).

All three remaining empirical studies (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006) agree that IT only aids performance in combination with OL activities which supports the abovementioned conceptual investigations that also predict a relationship between IT and OL. While Tippins and Sohi (2003) and Real et al. (2006) find that IT influences OL, Bhatt and Grover (2005) provide evidence that IT capabilities are manifestations of learning. An example of the former, Tippins and Sohi (2003) describe how IT infrastructure is likely to enhance OL processes by providing faster and more effective means of sharing and acting on information within the organization. For this reason, not only are IT and OL considered necessary to work together on their effect on organizational performance, but more specifically, OL may be considered a mediating variable for IT's relationship on performance. In contrast, Bhatt and Grover's (2005) statistical model has OL influencing IT which in turn influences organizational performance. This follows from the theoretical insight from RBV that suggests knowledge is necessary *before* IT can become a competitive advantage. In fact, all three statistical studies describe a partial mediating relationship between IT and OL in some manner.

2.4.3. Synthesizing the Empirical Literature

The research papers identified by this literature search have thus demonstrated links between technology and learning and describe how the combination may overcome the previously discussed dissatisfaction in IT investments. Indeed, when empirically testing whether IT or OL affects firm performance, Tippins and Sohi (2003), Bhatt and Grover (2005), Real et al. (2006), and Kane and Alavi (2007) all show that IT only aids performance in combination with OL activities. Together, these studies have demonstrated that while IT itself may be easily imitated, using IT capabilities to develop unique competencies in combination with learning activities affords unique competitive advantages (Nevis et al., 1995; Pemberton et al., 2001; Tippins & Sohi, 2003; Real et al., 2006).

The above studies, however, do not agree on all aspects. The measurement of IT is one example. Bhatt and Grover (2005) measure IT using survey questions along three main themes. ‘IT infrastructure’ questions relate to the extent to which technology is broadly applicable in the organization and not limited to a single purpose, ‘IT business expertise’ questions reflect the level of business knowledge of those tasked with IT management, and ‘IT relationship infrastructure’ seeks questions that speak to how well IT and business managers ‘get along’ when setting organizational strategy. These measures do not seem to match with the insights afforded by existing research on IT in an organizational setting that necessitates a reflection of the tools of IT as well as its use in practice. There is also no argument presented for why IT infrastructure is more effective as a broadly applicable set of tools rather than many specific tools. One might suggest that such things are subjective and that it is reasonable to expect a mixture of both in most organizations. Additionally, the knowledge of IT managers about business priorities may aid in the selection of IT tools but fails to appreciate that such relations may be bi-directional, representing both physical IT tools and business uses. Perhaps the bi-directionality of technology and its use are attempted to be captured in the third category but this speaks more to knowledge sharing and collaboration, an OL attribute, than it does the use of technology in practice. As such, Bhatt and Grover's (2005) study does not measure organizational technology and its use in practice adequately and so should not be used to source measures of organizational technology for this study.

Real et al. (2006) also use three categories of survey questions to measure IT: technology that enables knowledge capture, technology that enables knowledge sharing and collaboration, and technology that enables the exploitation of knowledge for business use. These categories do align with the collective notions of technology and its use in practice in the organization better than Bhatt and Grover (2005) as they speak to the use of IT in knowledge activities and in application to business problems. However, they do not speak to the technologies themselves, the physical assets, nor how technology may be selected. Without measuring the presence or extent of physical IT, Real et al. (2006) also do not present an appropriate measure of IT for the context of this study. Tippins and Sohi (2003) instead measure IT explicitly as an organizational competency which requires both its physical presence, and knowledge of its use in practice. The authors break IT competency down into measures of IT knowledge, IT operations, and IT objects which reflects not only the physical tools of IT but also how to use them and their application to the business problems at hand. This combination of a measure of physical IT assets as well as its use in practice aligns with perspectives from the literature search that highlight the importance of these two aspects of technology in this setting. Consequently, Tippins and Sohi's (2003) measure of organizational IT is the most appropriate for this study moving forward.

A final critique of existing studies at the intersection between IT and OL is in the measurement of OL. Of the four studies that specifically address the intersection between IT and OL quantitatively, Kane and Alavi (2007) use a computational method which generates a model of OL but does not test it empirically. The remaining three, Tippins and Sohi (2003), Bhatt and Grover (2005), and Real et al. (2006) all measure organizational learning using descriptive measures which may inaccurately represent OL. As discussed earlier, descriptive measures only account for the structural antecedents of learning and do not account for their interaction in use or their organizational outcomes. As such, descriptive components of learning may be necessary but not sufficient to measure the outcomes of learning. For example, if one part of an organization is responsible for information acquisition and another responsible for information interpretation, descriptive measures might score these aspects highly. However, if these two areas of the organization fail to communicate and collaborate well together, then very little learning may be taking place at the organizational level despite the relatively high scores on the respective descriptive measures.

I propose that normative methods of measuring OL would instead be a more robust measure to capture the relationship between IT, OL, and organizational performance in this context because they focus around the organizational outcomes of, rather than structural antecedents of, learning. For example, an organization that needs to experiment with a process to find its optimal parameters would require not only going through the descriptive learning processes but that they all work synergistically for the organization. Successful experimentation within an organization would require the informational processes of acquisition (observation), interpretation (analysis and theorization), dissemination (communicating results), and memory (storing the results for later use) for it to be successful. Not only must all the sub-processes exist, but they must also be working well together for the organization to successfully learn using experimentation. Normative measures of OL then naturally encompass all the structural antecedents of learning meaning that an organization would only score highly for learning using normative measures if both the structural antecedents are present and functioning together which is a scenario that descriptive measures alone fail to adequately account for. This represents an opportunity for further investigation. By using normative measures of OL, a more comprehensive understanding of the interrelationship between IT and OL may be possible.

3. Theoretical Development

3.1. Requirements for a Theoretical Explanation

Existing research highlights the importance that knowledge plays in order for organizations to reap the rewards of new technologies. But knowledge, while necessary, may be insufficient to grant competitive advantage. What is required is unique organizational knowledge. While existing literature suggests organizational learning as the source for that knowledge, the unresolved theoretical question in existing literature is, why is learning, and not some other knowledge-related variable, necessary to produce the requisite knowledge? Learning would seem to play a role as it is one of the main processes by which organizations create knowledge but other perspectives look to alternative processes like absorptive capacity (Roberts et al., 2012) or innovation (Bueno et al., 2010; BolíVar-Ramos et al., 2012). Or perhaps even simpler explanations are applicable such as persistent organizational structures that accumulate from experience (such as management hierarchies), informational acquisition processes, or organizational memory? These six variables are all proposed mechanisms, but should they all be considered or are only some variables applicable to the issues of this study? It should be noted that all these proposed variables are in some way knowledge related so conflating their effects may serve to obfuscate any true observed relationships. A more specific theoretical argument is required.

3.1.1. Unique Organizational Knowledge

The first thing that a compelling theoretical explanation must offer is a mechanism to develop unique organizational knowledge necessary to endow it with a competitive advantage. As such, we can immediately discount more direct informational acquisition processes such as training or hiring as this would represent knowledge from outside of the organization. This condition also undermines the role that absorptive capacity may play for the organization as ‘peripheral knowledge’ which is more easily assimilated is more likely to be related to non-organizational specific applications. If knowledge is truly unique to the organization then it must be generated from within.

3.1.2. Non-linear Outcomes

In contemporary examples of applying new technologies for enhanced organizational performance, such as the abovementioned example of big data and analytics, it is also observed that a simple linear model of organizational technology is inadequate to explain all the difficulties organizations may face. A linear model presupposes that organizational capabilities remain qualitatively the same and so any improvement to the process would be relatively easily integrated into the organization. Yet, this is not always observed where the largest discrepancies between investments in technologies and organizational outcomes come in the form of qualitatively novel IT capabilities. For example, the implications of using predictive analytics with customer information would go beyond simply extending existing customer relationships as predictive analytics can offer entirely new ways of providing value which would require a re-working of the business models as well as the policies on how such technologies will be used. Consequently, there is a second condition necessary to explain the relationships involved with technological application: included variables must be able to describe how the choices of action, that new technologies enable, and the consequences of choices in technologies are connected. It is this interrelationship that must be successfully navigated each time a qualitatively novel capability is considered by organizations. Furthermore, this interaction overtime between technology and behavior, which leads to increasingly qualitatively novel technology and behavior, can lead to outcomes that were never anticipated, that deviate wildly from initial conditions, and exceed scales, scopes, or rates that could have been extrapolated from past behavior. Any successful theoretical explanation must also be able to explain these non-linear outcomes.

3.2. An Organizational Phenomenon

The works of Orlikowski (2001) and Kane & Alavi (2007) may aid a theoretical explanation as they study the broader implications of the use of technology on the behavioral changes of the organization and the people within it which is applicable to this situation. Choices in current technological application are chosen based on current organizational values and outlooks which serve to multiply future choices for organizations as their potential actions, within the same set of resources, are expanded. Faced with new opportunities, afforded by enhanced technological capability, organizations must decide which paths to follow and in doing so embody the values and priorities of that organization in their future choices. Accordingly, organizational values influence technological investment which in turn influences future choices that must be made on the basis of their organizational values. This process has large implications for the organization over time because this process propagates iteratively into the future allowing small scale changes to compound over time leading to large scale influences as the organization is forced to continually come up with new answers to questions such as 'what *can* we do' versus 'what *should* we do?'

Lacking a connection between time periods, each new time period would be treated no differently than what has come before and each new choice would be made on the basis of the current context alone. Viewed over a large time scale, organizations which do not exhibit such connections between time periods will not accumulate information from the past to inform future decisions. Such organizations may only be seen to vary slightly around large-scale trends in the organization's environment rather than follow a series of deliberate and purposeful decisions designed to execute the organization's long-term vision. Information needed to make informed decisions is limited to only the current time period resulting in an organization making a series of temporally myopic decisions rather than strategically calculated ones. Some sort of informational connection between time periods would be required to reach higher levels of performance such that organizations can get better over time.

3.3. Connections Between Time Periods

It might be thought that the simplest explanation for connecting information between time periods would be where organizational structures, such as management hierarchies, put in place in one-time period persist into the future thus influencing future behaviors and decisions. I refer to this as a 'structural relic' perspective whereby structural relics are any aspects of an organization that might endure into the future just by their existence alone as a 'building block' as opposed to something that requires effort to maintain or continually enact, like culture. Structural relics, consequently, tend to accumulate over time as they take more effort to dismantle than to persist because other organizational processes have been built upon them. Similarly, organizational memory may also connect information flows from the past into the future thus raising the question if learning really is the key process or if temporally persistent products of other more basic processes may explain observed patterns. However, only those situations which were identical as that which has happened before would be advantaged by these processes because such processes would not endow an organization with the ability to deal with novel circumstances, thus garnering only limited effect. Consequently, structural relics of an organizational past would tend to serve only a stabilizing effect in the organization, to diminish change and persist tradition and, as such, would not enable the non-linear outcomes observed over time.

A mechanism is required to be able to combine the lessons of experience from the past to influence future decisions. Memory alone is insufficient because it does not deal with novelty. But how can any prior experience inform future decision when the future is unknown? All that can be done is to generalize the experience from the past. Abstracting patterns from the past allows experience to be applicable to future scenarios, albeit only in a general way. That abstraction is what enables lessons learned from one situation to be applied to another, even if the specifics of two situations differ.

Such an operation of abstraction requires a cognitive element to be able to generalize which, in the organization, is given the term ‘informational interpretation.’ Informational interpretation is what enables an organization to process information at a higher level than simplistic rule or algorithm based information processing. Interpretation in combination with organizational memory allows more abstract patterns to be discerned from the past and not merely replicate it. The combination of memory and interpretation allows informational flows between a multitude of different situations. Indeed, this is very similar to the descriptive definition of organizational learning which includes informational interpretation and organizational memory such as in Real et al. (2006). Here, absorptive capacity (Roberts et al., 2012) is not a good explanation due to novelty of circumstance nor is innovation (Bueno et al., 2010) due to its utilization of, rather than production of, organizational knowledge.

Organizational learning is then the only variable left from those initially proposed by existing literature to be able to explain both required conditions. The abstraction from learning affords for much greater utility for the organization as its influence can be leveraged far more than other knowledge-related variables. While structural relics may serve to stabilize organizational change, learning would tend to leverage and accelerate change with new perspectives giving way to ever newer perspectives. “The significance of considering past, present and future for OL can be clarified by examining how prior experiences influence behavior.” (Berends & Antonacopoulou, 2014, p. 445).

If the structural relic perspective, and its related knowledge-based variables, were the greater overall organizational influence, then the application of new technology would only be made on the basis of temporally myopic decisions which are unable to foresee future trends and only able to understand what has already occurred. Thus, technological application would only be made to enhance existing business processes and application of that technology would be relatively straightforward as nothing would change qualitatively for the organization – the linear model of organizational technology. Yet, as I discussed earlier with the example of predictive analytics, this is not what is seen in modern organizations where technology is adopted that represents qualitatively divergent organizational capabilities which organizations then struggle to incorporate these new capabilities into their established cultures and values. If, on the other hand, OL was the greater organizational influence, then the application of the new technology could represent a qualitative change in the organization's possible behaviors and uncertainty over how to make best use of these new potentialities may cause pause for the core values and priorities of the organization itself which is more consistent with modern examples.

3.4. Observed Non-linear Organizational Outcomes

Senge (1990) supports the notion that learning may lead to large-scale or qualitative shifts over time. He describes how non-linear influences of learning may become very large and capable of drastic destabilization to the organization over time, so much so that they should be understood and managed. He studies these non-linear scenarios through a systems approach to organizational studies whereby systems interact with themselves such that outputs from one time period are the inputs of the next time period resulting in dynamic complexities of interactions over time. Senge warns of amplifying feedback capable of drastic consequences if not kept in check. An organization that exists within a changing environment may not only consider learning a need in order to continually adapt to changing circumstances, but also find that its effects can be powerful and highly influential over time. So significant may non-linear learning outcomes become that organizations facing change may exhibit feedback behavior that far exceeds or falls far short of a desired optimum and may be seen to fluctuate wildly over time. Mathematically chaotic organizational outcomes, such as this, may be exhibited by an organization as a result of compounding influences of the interactions of technology and learning over time making the situation highly sensitive to initial conditions and giving credence to behavioral feedback loops that amplify its effects which would indeed suggest greater understanding and management of the situation is necessary.

A pertinent question for any organization looking to adopt new technology would then be 'why?' If it is merely enhancing an existing business process, the linear model of organizational technology, then specific investments in specific technologies for specific purposes may be all that is needed. However, if it is to endow the organization with new capabilities, more existential questions will have to be tackled by the organization each time a qualitatively new technology is considered. In this latter view, the application of new technology would not be as easy as a simple purchase or investment but rather would require a period of reflection for the organization itself to make sense of these new uncertainties and update the values and goals of the organization to accommodate for changes in the way it operates. This is not to say that the former scenario never occurs, on the contrary, it should be expected to occur as a matter of course as structures and memories of the past will inevitably persist into the future and these structural relics provide a certain stability that guides the specific application of tools and technologies. However, it is to say that the latter scenario has the potential for far greater impact on the organization over time. This perspective explains some of the difficulties many organizations have in adopting new large scale technological systems, such as big data, as the limitation is not in making the investment but rather in the struggle to understand what that new abilities means for the organization and how to best use them to further its strategic goals. Thus, while other knowledge-based variables may show positive relationships to technological application, OL is theoretically, the most powerful mechanism by which organizational technology and behavior are connected over time.

4. Research Question and Hypotheses

Existing research into the relationship between technology and organizational performance leaves two main outstanding issues: lacking in-depth theoretical constructs and incomplete measurement of OL for this context. The former is necessary in an empirical investigation to argue why particular variables are pertinent and to rule out others; deeper theoretical constructs are needed to better propose, define, and interpret measurement models. In the previous section (3. Theoretical Development), I propose theoretical arguments for why organizational learning, and not other related constructs, is the key variable to measure in this context. The issue of measurement of OL, on the other hand, suggests that normative, rather than descriptive measures of OL will be a more precise measure to better discriminate patterns in data that are collected on this issue. Both issues build toward the research question and hypotheses that this study explores.

4.1. Research Question

The above discussion on applying technology in the organization lays the foundation for deeper investigation. The theoretical arguments provided describe the reasons why organizational learning, and not other knowledge-related variables, is the most important variable to include in an investigation of why technological application does not always garner the desired outcomes. A simple mediation model is therefore implied, and preferred compared with a more complicated model, with OL mediating the relationship between technology and performance. Additionally, these relationships may be more effectively quantified with the use of normative OL measures rather than descriptive OL measures. Together, these insights lead to the following research question: *do normative measures of OL provide more explanatory power in mediating the relationship between organizational technology and organizational performance than descriptive measures of OL?*

4.2. Hypotheses

To examine this research question, the following testable hypotheses have been formulated:

Hypothesis 1 (H1): That the relationship between IT and organizational performance is mediated by organizational learning.

Hypothesis 2 (H2): That normative measures of OL will explain a greater degree of variance in the relationships with IT and organizational performance than descriptive measures of OL.

H1 serves to ground this research in existing research contexts by replicating previous study's results which showed statistical evidence that OL is partially mediating the relationship between IT and organizational performance (Tippins & Sohi, 2003; Real et al., 2006). H2 serves to give greater insight into organizational learning in this context which may give researchers and practitioners alike more direction for future research and recommendations for practice.

4.3. Model Development

The model that will be used as a starting point for this study is Tippins and Sohi (2003) as it is the most relevant and utilizes three main variables: IT competency, organizational learning, and organizational performance. This model will form the basis for this study by first replicating its findings, and second, by building upon this model with a new measurement of learning. The models will first test the direct relationship between IT and performance as well as mediating models with OL between IT and performance.

To measure the relatively abstract concept of IT competency, Tippins and Sohi (2003) break IT into three main categories, each of which are measured through survey questions. IT objects, IT knowledge, and IT operations are each measured by a range of survey questions that load onto each latent variable. Then, the three categories of IT themselves load onto a single latent variable Tippins and Sohi (2003) refer to as "IT competency." As such, these measures reflect the presence of physical IT assets, the knowledge of how to use them, as well as their use in practice giving the second order latent variable a fairly comprehensive reflection of how IT is used in the organization.

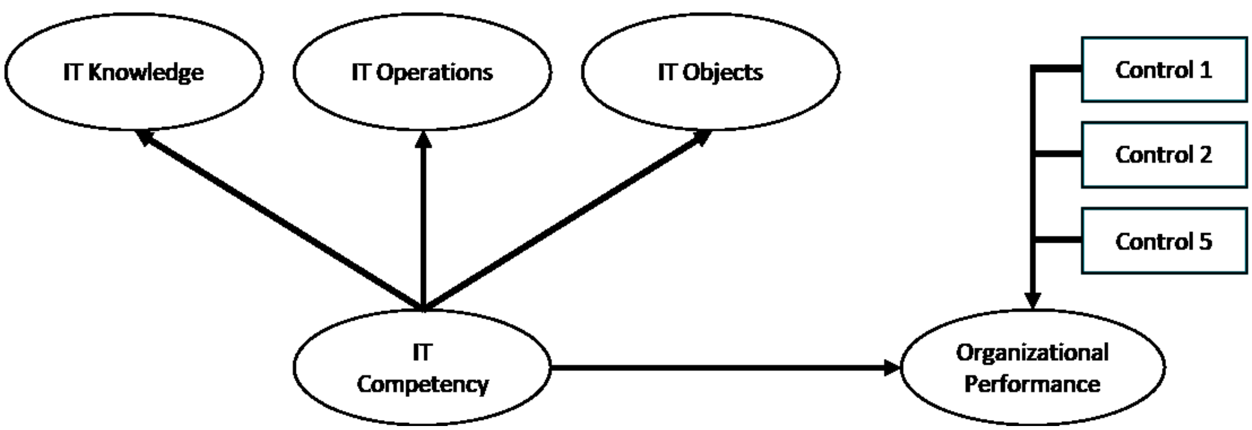
Organizational learning will be measured in two flavours: descriptive and normative. Each perspective of learning asks a series of survey questions which, just like the IT survey questions, first load onto a series of latent variables that represent the processes of learning which themselves load onto a second order latent variable that reflects overall learning in the organization. Descriptive measures include information acquisition, information dissemination, information interpretation, and organizational memory. Normative measures include clarity of purpose and mission, shared interpretation, experimentation, transfer of knowledge, and team and group problem solving.

Performance will be measured using high level survey questions that seek people's perceptions of organizational performance. This is due to the wide variety of organizational types that could be included in knowledge intensive industries which may not all define success in a similar manner. As such, performance will be measured as perceptions of organizational success at an individual level, group level, and organizational level which together will load onto a latent variable that represents all levels of performance. Each of the IT, learning, and performance questions are sourced from previously published and validated survey instruments and are further described in section 5.3 Measures.

There are three models that will be used in this study: the direct effects model that will form the basis of comparison for all other models, the mediation model with descriptive measures of OL, and the mediation model with normative measures of OL. The first figure below (figure 1a) describes the direct effects model which was created consisting of only two main variables, level of IT competency and organizational performance (in addition to the control variables) which model the latent variables as measured by the survey questions using factor analysis.

Figure 1a

SEM Diagram: Direct Effects Model



Next, I created two mediation models to test different variations of OL (descriptive/normative) on IT competency and performance (figures 1b and 1c). The first mediation model (figure 1b) uses the descriptive measure of OL as a mediating variable between IT competency and performance as discussed in existing literature (Tippins & Sohi, 2003; Real et al., 2006). The second mediation model (figure 1c) uses the normative measure of OL as the mediating variable.

Figure 1b

SEM Diagram: Mediation Model – Descriptive OL

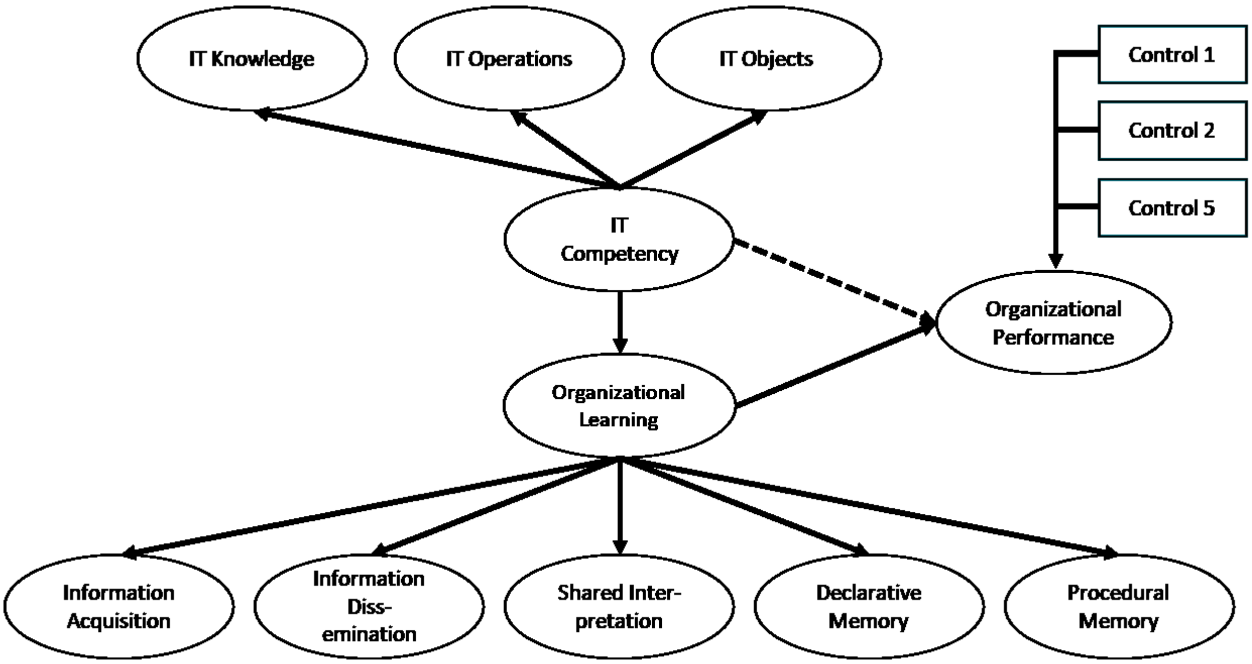
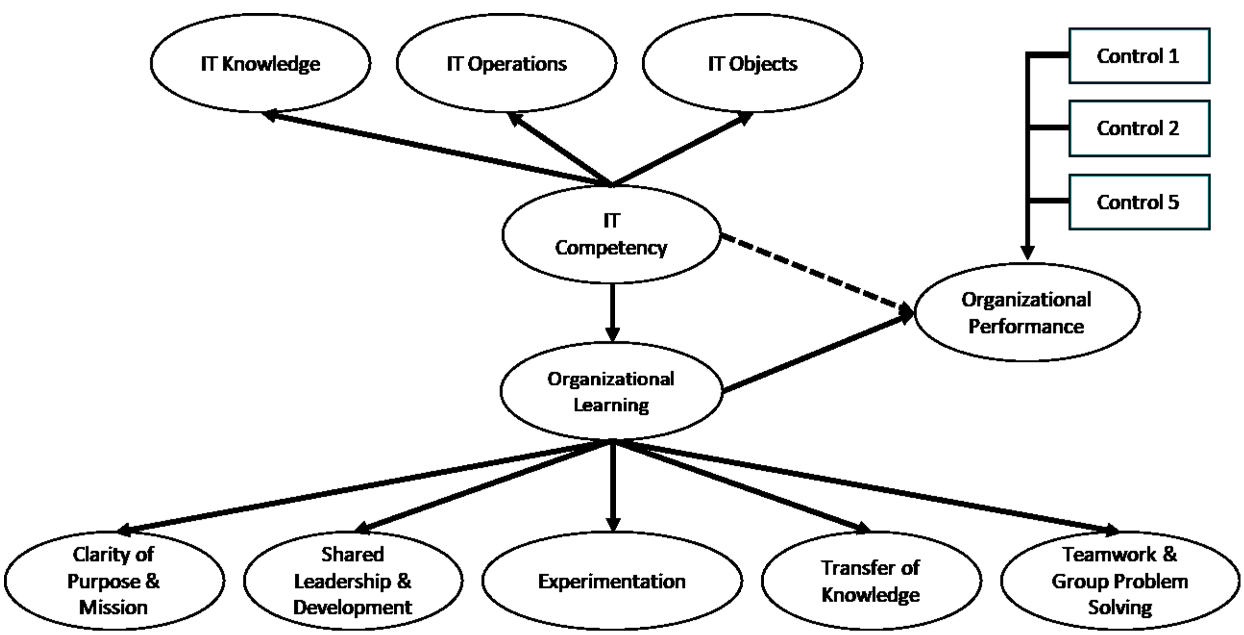


Figure 1c

SEM Diagram: Mediation Model – Normative OL



4.4. SEM Model Testing

Using IBM AMOS graphical structural equation modelling (SEM) software, various structural equation models were constructed. Multiple models were compared to examine the relationships and test hypotheses. (Refer to Appendix C for the full SEM diagrams for all three models.) The measured control variables are also shown in figures 1a-c with Control 1 representing organizational size, Control 2 representing market share, and Control 5 representing years of organizational experience of the survey respondent. (Control 3 and 4 were text based demographic questions used to produce reports for specific participating organizations and so are not applicable for this analysis.) Measured variables, as described in the survey questions, load onto the first level of latent variables (categories that make up IT competency, OL, and organizational performance, respectively) using factor analysis. Second level latent variables (IT competency, OL, and organizational performance) were calculated using the output from the first level latent variables also using factor analysis.

The proposed hypotheses (H1 and H2) will be confirmed or rejected based on the examination of the SEM output. H1 would be supported under the following conditions:

- One or both of the mediation models exhibits better overall SEM model fit than the direct effects model;
- One or both of the mediation models explain more variance in organizational performance than the direct effects model;
- There is a significant positive relationship between IT competency and OL in one or both of the mediation models;
- There is a significant positive relationship between OL and organizational performance in one or both of the mediation models; and

- The direct relationship between IT competency and organizational performance in one or both of the mediation models becomes lower in magnitude and significance compared to the direct effects model.

H2 will be examined by determining whether:

- The normative OL model exhibits better overall SEM model fit statistics than the descriptive OL model;
- The normative OL model is able to explain more variance in organizational performance than the descriptive OL model;

The normative OL model exhibits higher statistical significance for the relationships from IT competency to OL and from OL to organizational performance.

5. Methodology

5.1. Sample Selection

The selected research population is comprised of 'knowledge-intensive organizations' such as accounting firms, law firms, management consulting firms, engineering consulting firms and others (von Nordenflycht, 2010). Specifically, Canadian knowledge-intensive organizations (KIO's) represent the population of this study. Knowledge-intensive organizations have been selected due to their heavy emphasis on knowledge as an important resource within the organization. According to the Conference Board of Canada (2013), companies in this industry are characterized by their "intensive use of high technology" and/or they have a "highly skilled labour force necessary to use and exploit technological innovations." Furthermore, KIO's constitute an important sector of the Canadian economy which has been increasing over the last 25 years in size and importance (accounting for 18.1 per cent of GDP in 2006, up from 11.2 per cent in 1980). Because of KIO's reliance on knowledge for competitive advantage, it was expected that they should exhibit larger changes to organizational outcomes in response to varying levels of OL compared to other less knowledge-intensive industries. Such high reliance is expected to result in a potentially larger observable signal in data with which to measure a clear difference in performance between the two proposed measures.

Sampling selection was conducted through a sampling frame representing Canadian KIOs. In particular, survey responses were sourced from four organizations: Canadian Association of Management Consultants (CMC-Canada) (a large Canadian management consulting association), a large Canadian management consultancy, a small Canadian management consultancy, and Telfer School of Management MBA students. CMC-Canada covers a wide range of professional disciplines and geographies which provides a broad base of professional experience and perspectives. Membership for CMC-Canada is estimated to be approximately 3000 professionals. The large and small Canadian management consultancies focus on professional services for both private and public organizations and range in size from approximately 1100 members for the large consultancy to 65 for the small consultancy. Telfer MBA students were also included because they represent a wide range of professional experience prior to enrollment in the MBA program and represent a wealth of varied viewpoints among the 45 students. MBA students self-reported working in the following areas: professional services (33%), healthcare (23%), technology (21%), manufacturing (10%), public sector (8%), logistics (3%), and retail (3%). Considering professional services, healthcare, technology, and public sector to be knowledge intensive, which represents 84% of the sample MBA group. Of the remaining 16% of MBA respondents, all reported they were working in a management or administration capacity of some kind. Thus, I believe this sample group can be considered within a larger population of KIOs.

5.2. Sample Response Rate

Considerable effort was expended to attract enough responses from the participating organizations to conduct SEM data analysis. An online survey was created and sent to all available members of the participating organizations. Invitations to contribute to the survey were initiated by senior leaders of participating organizations to encourage survey participation and maintain the confidentiality and anonymity of the respondents. Reminder emails were also sent to increase response rates at each organization. Being a voluntary survey, each individual organization had relatively low response rates. As each organization was responsible for internal survey distribution, an exact response rate is not possible to calculate. However, based on approximations of organizational size by number of people, response rates ranged by organization from approximately 2% for CMC-Canada, 3% for the small management consultancy, 11% for the large management consultancy, and 80% of MBA students participated in the voluntary survey.

5.3. Measures

This study measured the following: level of organizational information technology (IT) capabilities, level of organizational learning (of which there are two varieties of organizational learning in the form of normative and descriptive), and the level of organizational performance. The method used for measuring these properties was a survey instrument based on previously validated survey questions. The resultant survey included a total of 75 survey questions across all three categories plus control questions. All questions used a seven-point Likert scale, from

"Strongly Disagree" to "Strongly Agree." Each section is described below (refer to Appendix B for a full copy of the questionnaire).

5.3.1. Information Technology Capabilities:

Tippins and Sohi (2003) measure technology in the organization in three categories: physical IT objects, knowledge of IT, and use of IT for business purposes. In their study, they call this measure an 'IT Competency.' Compared to other examined measures of IT, these categories best reflect the theoretical understanding from RBV, and its extensions, that just the possession of IT alone is not enough, that it needs to be combined with knowledge to create sustained value for the organization through its use in practice – an IT *capability*[1]. An organization which has invested in IT tools, has the knowledge of how to use them, and employs IT operationally is very close to representing the conceptual issues at hand as it holds both the physical tools as well as their knowledge in use. For this reason, the survey questions used by Tippins and Sohi (2003) to measure IT competency were adapted for this study as measures of IT from other studies do not reflect this understanding as comprehensively. In total, fifteen survey questions were included to measure the organization's IT competency through three latent variables (IT objects, IT knowledge, IT operations).

5.3.2. Descriptive Organizational Learning:

Descriptive measures of organizational learning were also sourced from Tippins and Sohi (2003) for their conceptual alignment with the descriptive definition of OL comprised of four subcategories: information acquisition, information interpretation, information sharing, and

---

[1] The word "capability" comes from the RBV, KBV, and dynamic capabilities literature and represents both the possession of resources and the ability to use them for organizational benefit. The term "IT competency" is the name of the measure from Tippins and Sohi (2003) to quantify the existence of IT resources, the level of knowledgeability, and ITs use in practice. IT competency is then a specific measurement used to measure the concept of an IT capability.

organizational memory. The latter is further delineated into declarative and procedural memory. Together, they represent the sub-processes necessary for OL to take place. Twenty-nine survey questions were used for the descriptive measure of OL across these categories.

5.3.3. Normative Organizational Learning:

Normative OL survey questions were sourced from Goh (2001), based on the work of Goh and Richards (1997), as these questions best fit the existing definitions and concepts of normative OL as discussed above. Twenty-one survey questions on the normative perspective of OL break down into the following five categories: clarity of purpose and mission, shared leadership and involvement, experimentation, transfer of knowledge, teamwork and group problem solving. Together, these categories represent the outcomes of learning espoused by normative perspectives on OL.

5.3.4. Organizational Performance:

Survey questions for measuring performance were sourced from Real et al. (2006) for perceptual measures of overall organizational success. It should be noted that the use of relative perceptions of performance is preferred (Goh, 2001; Real et al., 2006) due to the reluctance of most organizations to divulge potentially sensitive objective financial information (Tippins & Sohi, 2003) and is considered a reliable indicator based on statistical correlation with actual measures of financial performance (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Goh et al., 2012). Additionally, perceptions of performance may be more generally applicable as different types of organizations may employ different market strategies which define success differently. Real et al. (2006) measure performance using ten questions across three categories of individual, group, and organizational performance. These three perspectives of organizational performance cover a variety of organizational types and strategies.

5.4. Survey Structure

Survey questions were adapted for this study in the following ways. Tippins and Sohi's (2003) questions utilized the word "firm" to represent organizations. Since this study sought to survey professionals in a variety of knowledge intensive organizations, the word "firm" was replaced with the word "organization." In addition, two control variables were added from Tippins and Sohi (2003) to control for organizational size and relative market share for competitive organizations (five-point scale). One final control question was also added to account for the number of years of experience of the respondent and added to the survey as a numerical response question from 0-99 years. (Two more text-based control questions were added to the survey to report on demographic information for reporting back to participating organizations only.) Finally, only questions from the normative OL survey had items that were reverse coded. Due to this survey's length, a necessity to include both descriptive and normative OL questions, there is the chance of a respondent experiencing question fatigue and answering questions in a biased, patterned manner to complete the survey more quickly. To increase consistency across categories and to help prevent response bias, additional reverse coding was conducted such that there was at least one reverse-coded item in each survey category. The selection of which items to reverse code from within each subcategory were determined by computer generated random number. Reversed coded survey responses were later reversed back to their original scale prior to data analysis.

6. Data Analysis

Survey responses were tabulated, organized by topic (OL, IT competency, organizational performance, control questions) and their respective subcategories, and shown in Table 1. The total number of responses from all organizations was 218 completed surveys. For the purposes of the summary chart, individual category scores comprise the arithmetic mean of all survey questions for that category and individual topic scores comprise the geometric mean of all categories for that topic. This aligns with the previously validated survey questions which were selected from a larger group of questions for their ability to represent all relevant factors of the theoretical construct, to score similarly on a 7-point Likert scale, to be highly correlated within topics, and highly discriminant between topics. Mean, median, and standard deviation of the sample is also indicated as is the distribution of responses on the Likert scale. All survey questions were scored on a scale from 1 (strongly disagree) to 7 (strongly agree) except for the control questions for organizational size and market share which were each scored on a scale of 1-5 and the control question for years of experience which was numerical and so does not show a Likert scale distribution.

6.1. Survey Responses

Survey respondents tended to score slightly above a neutral response, typically 5 or 6, in each category. Distributions of responses on the Likert Scales showed good spread, no obvious signs of truncated distributions (with the possible exception of IT knowledge), no polarization of responses or multimodal distributions, and no outliers. Distributions appear to approximate normality assumptions.

Scatterplots of the three main topics (IT competency, descriptive OL, and normative OL) against the dependent variable of organizational performance on the 7-point Likert scale are shown below in figures 2a, 2b, and 2c.

Table 1

Summary of Survey Responses

n = 218

Topic Category	Mean	Median	St.Dev.	1	2	3	4	5	6	7
				Distribution of Likert Scale						
OL: Descriptive	**4.77**	**4.75**	**0.77**	**0%**	**0%**	**4%**	**34%**	**43%**	**17%**	**1%**
Information Acquisition	5.35	5.42	0.99	0%	1%	1%	17%	31%	37%	13%
Information Dissemination	4.08	4.00	1.19	0%	9%	19%	33%	23%	11%	4%
Shared Interpretation	4.81	4.80	1.03	0%	3%	6%	31%	29%	27%	4%
Declarative Memory	4.73	4.71	1.00	0%	1%	9%	29%	40%	17%	3%
Procedural Memory	5.28	5.40	0.86	0%	0%	1%	21%	35%	36%	7%
OL: Normative	**5.04**	**5.16**	**0.91**	**0%**	**0%**	**5%**	**20%**	**39%**	**31%**	**4%**
Clarity of Purpose and Mission	5.51	5.75	0.95	0%	2%	1%	7%	29%	44%	16%
Shared Leadership and Involvement	5.00	5.20	1.11	0%	4%	6%	21%	33%	31%	6%
Experimentation	5.06	5.20	1.11	0%	2%	8%	16%	32%	34%	7%
Transfer of Knowledge	4.90	5.00	1.02	0%	2%	5%	19%	42%	25%	6%
Teamwork & Group Problem Solving	4.97	5.00	1.09	1%	2%	5%	24%	33%	29%	6%
IT Competency	**5.22**	**5.38**	**1.04**	**0%**	**1%**	**6%**	**16%**	**33%**	**34%**	**9%**
IT Knowledge	5.60	6.00	1.26	0%	1%	7%	10%	17%	33%	33%
IT Operations	4.87	4.83	1.13	0%	2%	7%	25%	36%	22%	9%
IT Objects	5.36	5.60	1.24	0%	2%	8%	14%	21%	36%	19%
Organizational Performance	**5.72**	**5.97**	**0.90**	**0%**	**0%**	**3%**	**8%**	**20%**	**50%**	**19%**
Individual-level	5.48	6.00	1.11	0%	1%	5%	10%	25%	43%	16%
Group-level	5.87	6.00	0.94	0%	0%	3%	6%	11%	56%	22%
Organizational-level	5.90	6.00	0.98	0%	0%	4%	4%	18%	41%	34%
Control Questions										
Organizational Size	3.35	3.00	1.11	6%	14%	35%	28%	17%		
Market share	3.24	3.00	1.02	5%	16%	43%	23%	13%		
Years of Experience	4.47	3.00	5.05							

Mode

Figure 2a

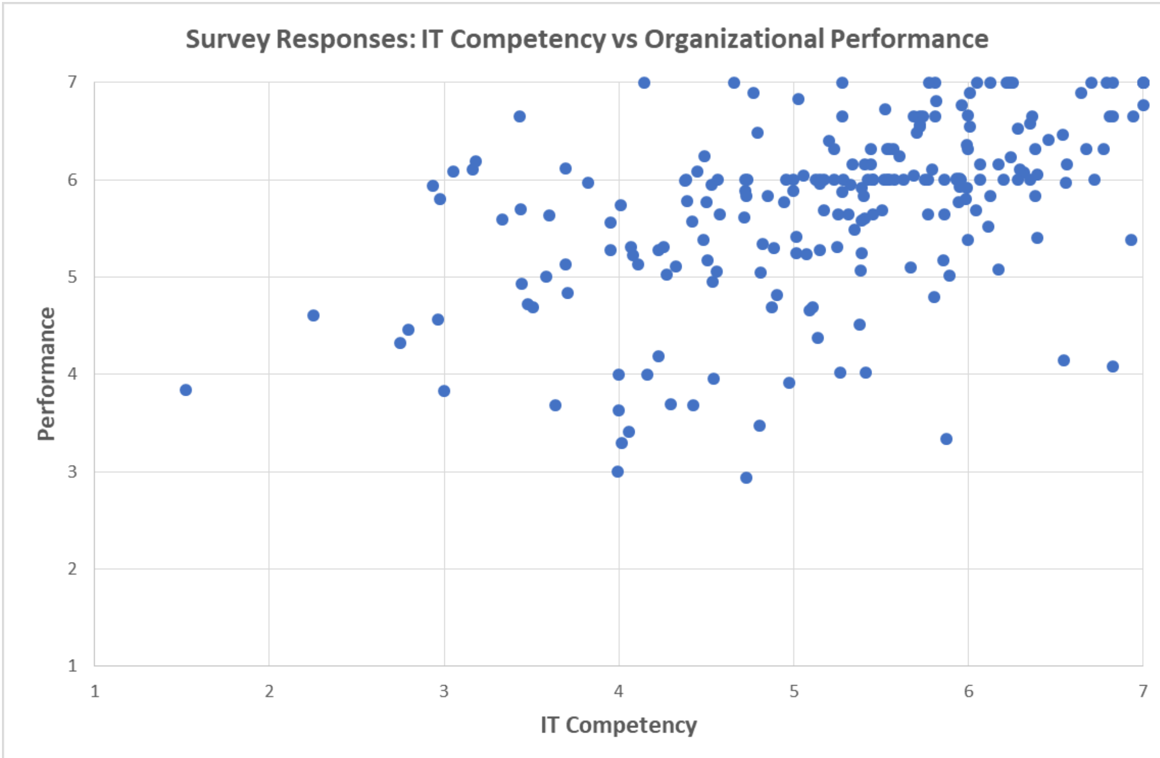


Figure 2b

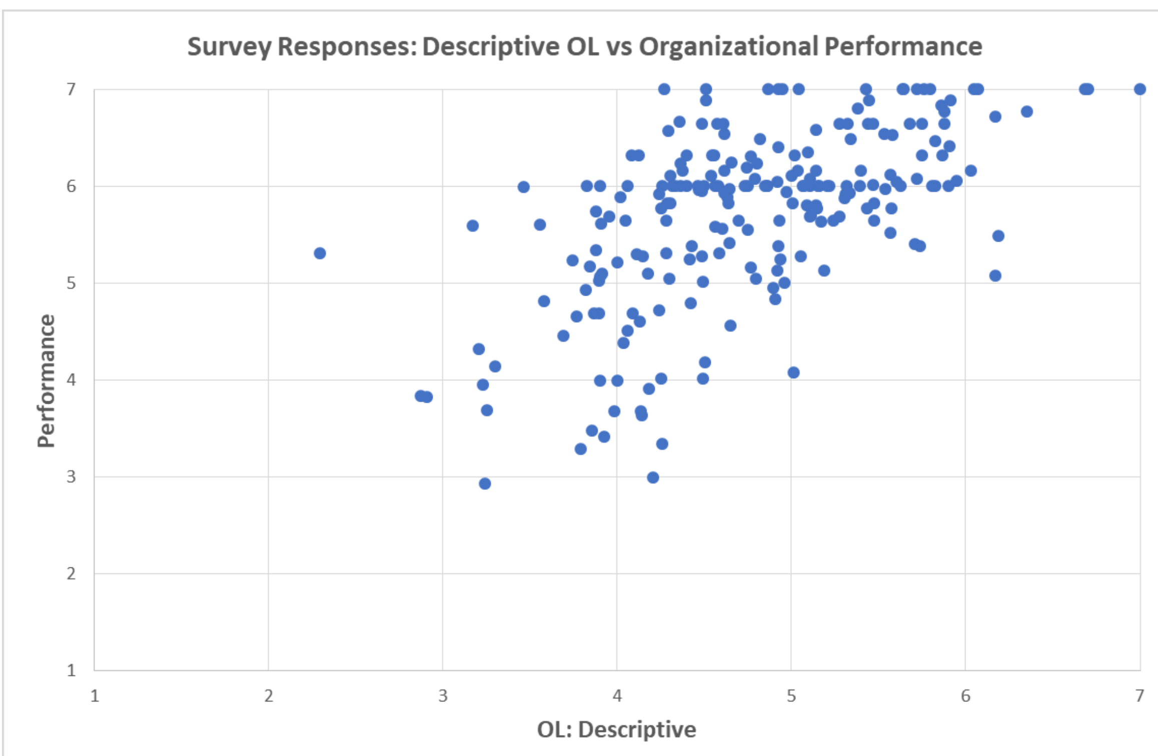
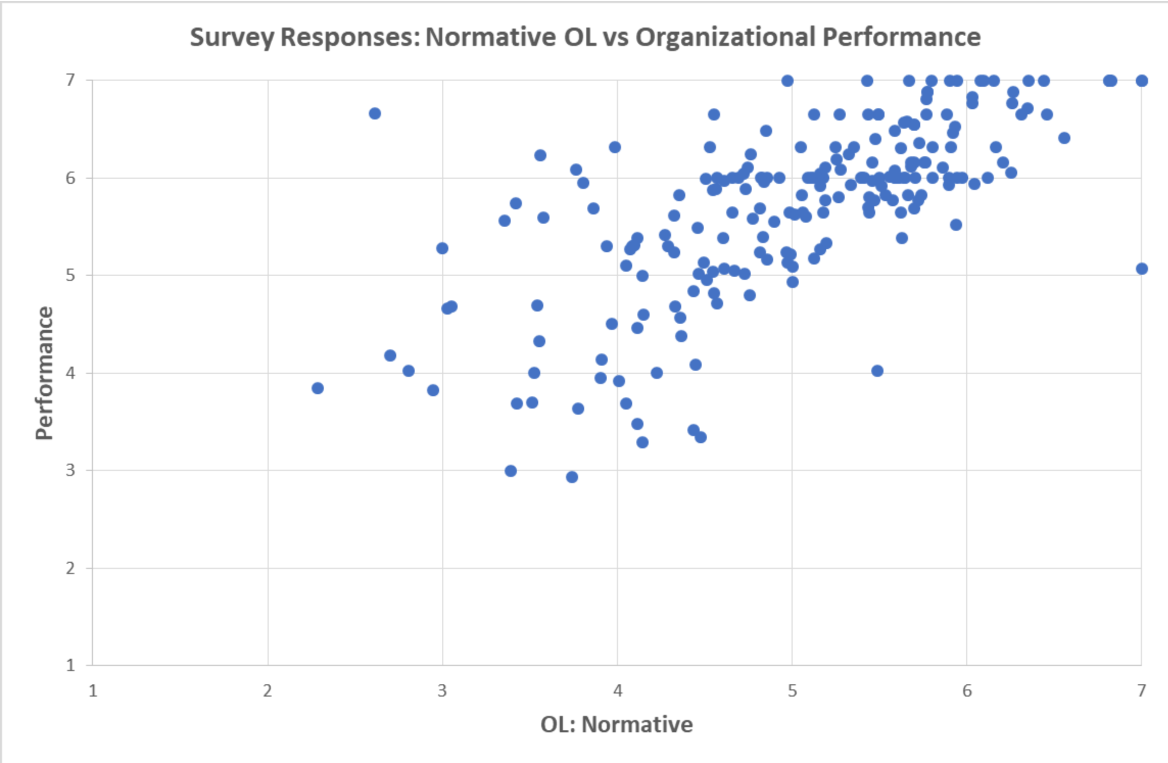


Figure 2c



6.2. Confirmatory Factor Analysis

Next, a confirmatory factor analysis was conducted. Construct reliability and average variance were extracted and calculated for each latent variable. (Refer to Table 2 for details.) Following Tabachnick & Fidell (2013), most factors demonstrated good construct reliability, at or above the 0.7 cut off. In examining average variance extracted, a few latent variables were lower than the 0.5 cut-off, however, most were within reasonable range. Tables with factor correlations between first and second order latent variables for all models is included in Appendix E. Based on these results, these factors were accepted for further analysis.

Table 2

Confirmatory Factor Analysis Summary

Factor	Construct Reliability	Average Variance Extracted
IT Competency	**0.843**	**0.643**
IT Knowledge	0.873	0.642
IT Operations	0.852	0.501
IT Objects	0.827	0.497
Organizational Performance	**0.860**	**0.672**
Individual Level	0.904	0.763
Group Level	0.873	0.697
Organizational Level	0.899	0.690
OL: Descriptive	**0.857**	**0.560**
Information Acquisition	0.818	0.441
Information Dissemination	0.815	0.452
Shared Interpretation	0.848	0.534
Declarative Memory	0.838	0.446
Procedural Memory	0.767	0.420
OL: Normative	**0.957**	**0.818**
Clarity of Purpose and Mission	0.758	0.445
Shared Leadership & Development	0.802	0.449
Experimentation	0.816	0.473
Transfer of Knowledge	0.671	0.340
Teamwork & Group Problem Solving	0.634	0.374

6.3. Model Fit Evaluation

The fit of the SEM model was evaluated using a number of statistics. These included the chi-square test statistic (χ^2 Test), the chi-square probability value (χ^2 P-value), the 'normed' chi-square statistic (χ^2 / DF) (chi-square test statistic divided by the degrees of freedom), and the root mean squared error of approximation (RMSEA). All measures were used to compare the relative performance of each of the SEM models. Chi-square p-values are often used as a starting point for evaluating SEM models. However, for models with large sample sizes or large number of variables, chi-square tends not to be accurate and so this measure should only be taken in context with the other measures of model fit (Tabachnick & Fidell, 2013). Conversely, χ^2 / DF and

RMSEA are preferable measures of fit for larger sample sizes than the chi-square test statistic (Tabachnick & Fidell, 2013, p. 725). A chi-square p-value of greater than 0.05 is expected for good model fit. A smaller value of chi-square divided by degrees of freedom is better where less than three shows adequate model fit and less than two shows good model fit. Tabachnick & Fidell (2013) also recommend that RMSEA should be less than 0.07 for a good-fitting model.

6.4. Verification of Model Assumptions

All three structural equation models were analyzed using IBM AMOS software. Maximum likelihood estimation was used for all models. The sample data had no missing values (data validation on the online survey ensured no missing values) and no outliers (all but one question was set to a fixed response scale). I examined normality using histograms of the surveyed variables and scatterplots of pairwise connections between variables. Summaries of the histograms and scatterplots may be seen in Table 1 (which contains a numerical representation of the histograms of the survey responses) and Figure 1, respectively. No measured inputs for the latent variables were highly skewed or kurtotic based on the histograms and scatterplots. I also used the scatterplots to ensure no non-linear patterns in the data. Plots show no outward signs of non-linearity or heteroscedasticity. Normality was further examined by looking at calculated values for skewness and kurtosis for all variables (see Appendix D) and confirmed no highly skewed or kurtotic input variables for factor analysis. Factor analysis model assumptions were thus met satisfactorily.

I should note that Appendix D shows there is one variable which does show signs of non-normality. The last control variable (Control5), which asked for the years of experience of the participant, which was a numerical response and not scored on a Likert scale, is indicating non-normal behavior showing a small amount of skewness (2.429) and a high kurtosis (6.717). Given that one would expect relatively more people in an organization to have fewer years experience and, fewer people would be expected with many years experience, I expected this variable to be somewhat skewed. However, the Control5 variable does not affect any factor analysis as the control questions relate directly to the organizational performance variable in the final SEM model. Regardless, normality is an assumption of all the variables in the SEM model and so I looked at the distribution of responses to see if a transformation was required to linearize the data. The control variable, unfortunately, showed signs of bimodality with a spike around 1 year of experience being the largest, dropping for years between one and ten, and then another smaller spike for greater than 10 years experience. Accordingly, I decided against a simple transformation of the data. I instead checked whether the influence of this variable on the data analysis output was large enough to warrant a more complicated transformation. Examination of the initial standardized regression coefficients of the control variables showed that this variable is near zero in the direct effects model (-0.023), drops in value for the descriptive OL model (-0.013), and drops again for the normative OL model (0.001) with no model reporting statistical significance at any level. Thus, I dropped the Control5 variable from further analysis.

7. Results

Having completed the initial data analysis and confirmatory factor analysis, the hypotheses were tested by examining the overall fit of the SEM models in addition to the regression outputs. A table summarizing the overall model fit statistics is shown below (Table 3). Here it may be seen that the chi-square p-values are all significant (beyond AMOS' ability to report). As discussed in the section 6. Data Analysis, this may be due to having greater than 200 observations for each variable and/or having complex SEM models. Consequently, the chi-square test was not reliable for this case and cannot be used to evaluate the relative performance of the SEM models. The normed chi-square test statistic, alternatively, takes into account the calculated degrees of freedom of the model and sample and demonstrates that the models have adequate degrees of freedom for calculating the statistical output. If degrees of freedom were too low, or model fit was poor, the $\chi 2$ / DF statistic would be greater than 3 and this is not the case in any model analyzed. The remaining test statistics also show that all theorized models perform better than their respective independent models on χ^2 / DF and RMSEA thus warranting further analysis.

7.1. Measures of Model Fit

Table 3

SEM Model Fit Summary

n = 218

SEM Model	χ2 Test	DF	χ2 P-value	χ2 / DF	RMSEA
Direct Effects Model	832.572	317	0.000	2.626	0.087
Independent	4136.338	351	0.000	11.784	0.223
OL: Descriptive	3156.093	1470	0.000	2.147	0.073
Independent	9078.319	1540	0.000	5.895	0.150
OL: Normative	2092.615	1066	0.000	1.963	0.067
Independent	7171.375	1128	0.000	6.358	0.157
				Best Model	

Next, each model was assessed to determine overall performance adequacy. The chi-square statistic divided by the degrees of freedom of the model (normed chi-square statistic) showed adequate to good values for all models: less than 3 for all models, and less than 2 for the normative OL model. The RMSEA shows borderline performance for the direct effects model at close to 0.09 but adequate performance for the descriptive OL model at 0.073 and good performance for the normative OL model at 0.067. The calculated confidence intervals for the RMSEA for the descriptive model is 0.070 to 0.076. The confidence interval for the normative model's RMSEA is 0.064 to 0.070. Thus, each model alone is performing well enough to continue with further analysis. Comparing the models directly, each can be ranked in ascending order of performance against both the χ^2 / DF statistic and the RMSEA statistic: direct effects model, descriptive OL model, and the normative OL model. Based on the previously discussed conventions for the measures of fit of the SEM models, only the normative OL model shows both a χ^2 / DF to be less than 2 and a RMSEA to be less than 0.07 indicating that it is the best performing model overall. Additionally, the confidence intervals of the RMSEA do not overlap which suggests the difference in overall model fit between the descriptive and normative models is significant.

7.2. SEM Path Analysis

I conducted further evaluation of the three SEM models by examining the regression path coefficients, regression p-values, and the coefficient of determination of the organizational learning and organizational performance latent variables. A table of all the numerical values for these statistical outputs may be found in Table 4. A summary of the above statistical outputs may be found in Figures 3a, 3b, and 3c. Each figure illustrates the high-level SEM path diagrams, standardized regression coefficients, p-values, and coefficients of determination and is discussed further below.

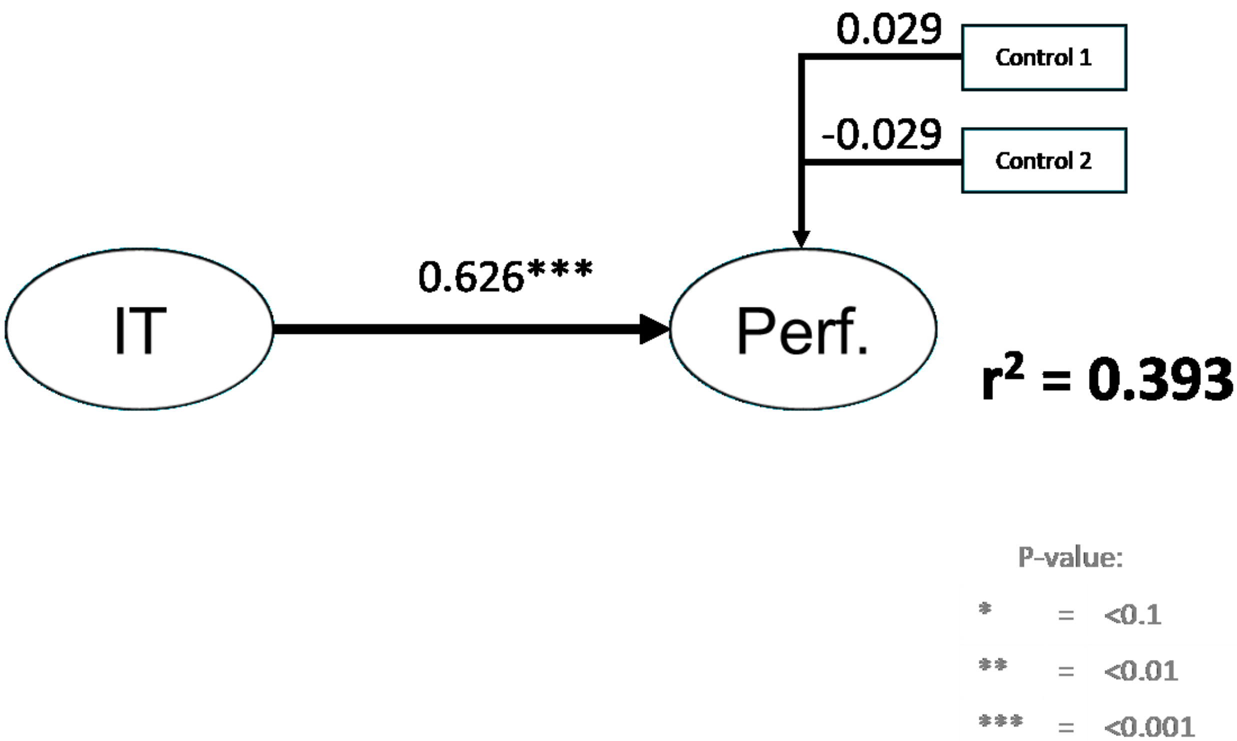
Table 4

SEM Path Relationships

Statistical Output	Direct Effects Model	Partial Mediation Model	
		OL: Descriptive	OL: Normative
Coefficient of Determination (R^2)			
Org. Performance	0.393	0.625	0.680
Org. Learning	-	0.416	0.420
Unstandardized Regression Coefficients			
IT Competency - Org. Performance	0.579	0.198	0.136
IT Competency - Org. Learning	-	0.652	0.500
Org. Learning - Org. Performance	-	0.611	0.916
Control 1 (Org. Size) - Org. Performance	0.021	0.028	0.069
Control 2 (Market Size) - Org. Performance	-0.024	-0.014	-0.029
Standardized Regression Coefficients			
IT Competency - Org. Performance	0.626	0.205	0.139
IT Competency - Org. Learning	-	0.645	0.648
Org. Learning - Org. Performance	-	0.641	0.722
Control 1 (Org. Size) - Org. Performance	0.029	0.038	0.087
Control 2 (Market Size) - Org. Performance	-0.029	-0.017	-0.034
P-values			
IT Competency - Org. Performance	0.000	0.024	0.128
IT Competency - Org. Learning	-	0.000	0.000
Org. Learning - Org. Performance	-	0.000	0.000
Control 1 (Org. Size) - Org. Performance	0.750	0.476	0.244
Control 2 (Market Size) - Org. Performance	0.738	0.752	0.638

Figure 3a

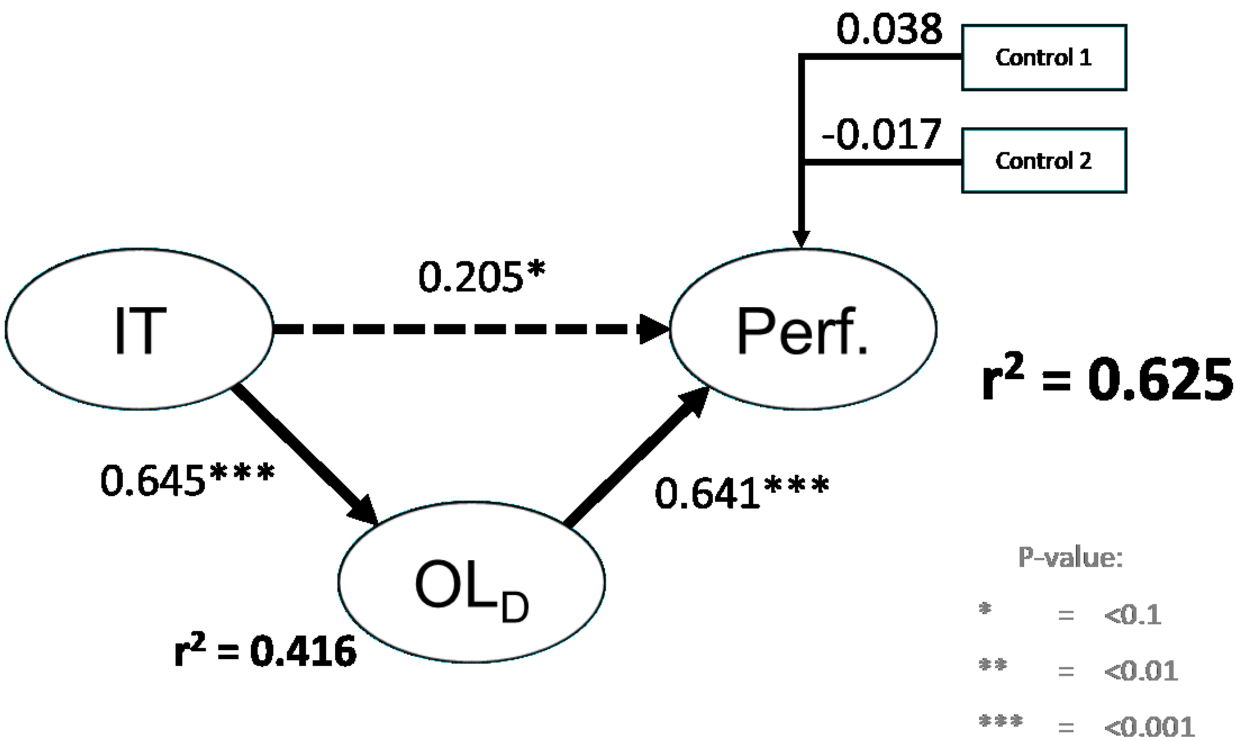
SEM: Direct Effects Model



The direct effects model demonstrates a statistically significant correlation between IT competency and organizational performance. However, the overall proportion of variance explained remains quite low and suggests this model is not an adequate explanation of the dependent variable. These results were expected as they are similar to previous studies which question a direct relationship between IT competency and organizational performance (Tippins & Sohi, 2003; Bhatt & Grover, 2005). It should also be noted that the coefficients for the control variables for organizational size (Control1) and market share (Control2) are both near zero and both control variables show no level of statistical significance at all.

Figure 3b

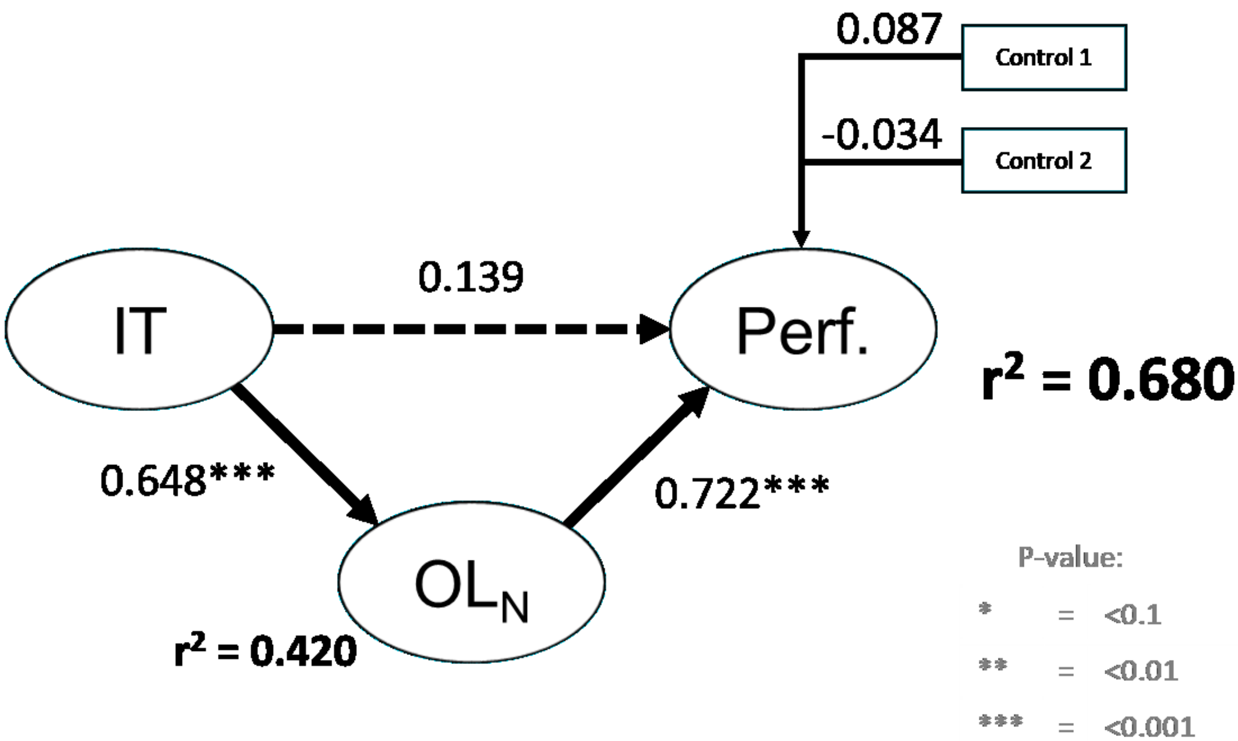
SEM: Mediation Model – Descriptive OL



The mediation model with descriptive OL shows a very different picture from the direct effects model. The relationship between IT competency and organizational performance has dropped in magnitude and significance. The relationship between IT competency and OL is positive and statistically significant as is the relationship between OL and organizational performance. Overall, the variance explained by the descriptive OL mediation model has improved substantially from the direct effects model from approximately 0.4 to 0.6. Together, these relationships support a partial mediation model presented by previous scholars (Tippins & Sohi, 2003; Real et al., 2006). The control variables once again show small coefficients and no statistical significance.

Figure 3c

SEM: Mediation Model – Normative OL



The mediation model with normative measures of OL shows the highest proportion of explained variance of all the models. Mediation is further supported with the relationship between IT competency and organizational performance dropping again in magnitude and significance, compared to the descriptive OL model, showing no level of statistical significance. There are also slightly increased coefficients between IT competency and OL, and between OL and organizational performance with both maintaining a very high level of statistical significance. The coefficient of determination for the OL variable is also higher compared to the descriptive model. However, the control variables, once again, show no significance despite their coefficients being slightly larger in this model. Thus, the normative OL model is the highest performing model of the three models presented and supports a full mediation model which is a novel contribution to research in this area.

7.3. Data Analysis Conclusions

Based on this analysis, the following conclusions can be drawn:

Conclusion 1 (C1): The control variables used were inadequate to account for significant variation in organizational performance in any model. As a result, the proportion of explained variance in each model is almost entirely accounted for by the independent variables of the models. Perhaps the relatively diverse sample of organizations contributed to the lack of power of the control questions wherein organizational performance was not defined in the same manner for all organizations. As such, controlling for performance will always be somewhat problematic with only general control questions being applicable for such a group. Future studies may narrow the sample to specific types of organizations which would allow more specific measures of performance and more appropriate control questions.

Conclusion 2 (C2): There is no strong direct relationship between IT competency and organizational performance, despite the model showing significance for the regression coefficient, based on poor performance of the coefficient of determination of organizational performance.

Conclusion 3 (C3): Both mediation models show better overall model fit and higher coefficients of determination in organizational performance than the direct effects model. Both mediation models show positive and significant relationships between IT competency and organizational learning and between organizational learning and organizational performance. Both mediation models show that the direct relationship between IT competency and organizational performance drops in strength and significance in the presence of organizational learning. Thus, the mediation model is supported confirming H1.

Conclusion 4 (C4): The normative OL model shows improved model fit compared to the descriptive OL model for all measures of overall model fit. The normative OL model supports a full mediation model compared to the descriptive OL model which is only able to demonstrate partial mediation based on the regression coefficients and levels of significance. The normative OL model shows a slightly higher coefficient of determination for organizational learning and organizational performance than the descriptive OL model. Thus, the normative OL measures showed better model fit to this data set than descriptive measures of OL supporting H2.

8. Discussion

The purpose of this study was to investigate the issues that hinder organizations from realizing the full value of technological investments. Big data and analytics was mentioned as one such example where modern organizations are attempting to qualitatively alter their IT capabilities but have only met with limited success. The role of organizational knowledge is key in understanding why organizations face difficulty in reaping competitive benefits from such IT tools. Organizational learning is then invoked as the key mechanism by which organizations create the knowledge necessary to successfully employ and gain benefits from new technology. This study found statistical support that organizational learning acts a mediating variable between IT competency (representing IT capabilities) and organizational performance. It also demonstrates that normative measures of OL better explain variation in this relationship than descriptive measures of OL.

8.1. Contributions to Research

Existing studies on the intersection between IT, OL, and organizational performance take the form of a computational model (Kane & Alavi, 2007), a case study (Dodgson et. al, 2013), a Literature review (Roberts et al., 2012), and statistical analyses (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006; Bueno et al., 2010; Schoenmakers & Duysters, 2010; Huang, 2011; Sanz-Valle et al., 2011; BolíVar-Ramos et al., 2012). After reviewing existing literature, I hope to complement the insights afforded by these other methods of inquiry while also building upon the statistical work done in this area as well. This study seeks to contribute to existing research on applying technology to enhance organizational performance in three ways: it replicates findings from existing studies, it introduces a deeper theoretical explanation of the dynamics at hand, and it introduces a new measure for learning in this context.

Previously published quantitative investigations into technological capability and organizational performance showed statistical support that knowledge related variables are important in understanding these dynamics. In particular, this study's replication supports the notion that OL acts as a mediating variable between IT and performance (Tippins & Sohi, 2003; Bhatt & Grover, 2005; Real et al., 2006). However, while Tippins and Sohi (2003) and Real et al. (2006) argue that OL is the mediator, and Bhatt and Grover (2005) argue that IT is the mediator. In this respect, this study presents empirical support that OL does indeed act as the mediator in the given relationships supporting both Tippins and Sohi (2003) and Real et al. (2006). Also, given that this study was sampling a completely different subset of organizations (KIOs) and in a different country (Canada), the fact that this study was able to replicate the finding that descriptive measures of OL act as a mediator between IT and performance lends credence to the relationships discussed being robust across industries and geographic regions. This study's replication of existing studies in a diverse context then reinforces existing research in this area.

This study does not stop with replication of existing findings, however. This study also provides an enhanced theoretical framework to explain the issues at hand. Previous studies introduce knowledge as an important variable (Tippins & Sohi, 2003) but fall short of explaining why learning and not some other variable is the key to creating knowledge. This study provides a deeper theoretical understanding that learning is the key variable because it is able to explain the source of unique knowledge as well as explain how learning and behavior can compound over time creating non-linear outcomes for organizations. No other proposed mechanism can fulfill these requirements making organizational learning the only variable able to do so. I argue that OL is the key variable because only OL is able to deal with novel circumstances and only OL can explain how and why past experiences can translate into qualitatively divergent future organizational paths. Simpler processes like organizational structural relics and organizational memory would only serve to diminish change. While alternative knowledge-based processes do not necessarily relate to unique organizational knowledge nor may they link the knowledge from the past into the future thus precluding the ability for knowledge gains to compound over time. Together, these insights explain why technological applications may be mediated primarily by learning and not other influences which is a novel contribution to theoretical understanding in this area.

The enhanced theoretical framework proposed in this study also gives greater insight into interpretation of relevant quantitative models. In some existing literature, additional variables are added to the three main variables of IT, OL, and performance. These additional variables take the form of technological distinctive competencies (Real et al., 2006; BolíVar-Ramos et al., 2012), tacit knowledge (Bueno et al., 2010), innovation (Bueno et al., 2010; Huang, 2011; Sanz-Valle et al., 2011; BolíVar-Ramos et al., 2012), invention (Schoenmakers & Duysters, 2010), and technological skill (BolíVar-Ramos et al., 2012). However, in one way or another, these additional variables are all knowledge related. In a quantitative model, such as SEM, this violates the assumption of variable independence and so reported relationship significance will be unduly affected. To minimize these overlapping effects of variables that have similar constructs, simpler models are preferred to more complex ones. Narrowing down the list of possible variables using the theoretical insight provided by this study, the appropriate knowledge related variables may be narrowed down to one: organizational learning.

Finally, this study makes a contribution to quantitate research in this area by proposing and testing a new measurement of organizational learning specifically for this context. All existing studies in this area use some form of descriptive OL measure for their measurement models. While the components of descriptive OL may be necessary for OL to take place, they may not be sufficient for organization's to functionally learn as all components must be working synergistically. The organizational learning literature would suggest that normative measures be more appropriate for this context as they seek to measure the outputs of learning which would only be present if the building blocks of learning are in place *and* working well together – a necessity for technology to be able to provide competitive advantage in an organization. This study showed that the use of a normative measure provides higher levels of statistical explanatory power, a novel approach not just in Canada but also in all known relevant literature.

8.2. Study Limitations

There are three main limitations of this study which are worth mentioning at this time. First is the use of a voluntary participation survey. The choice of voluntary participation was made primarily to maximize the number of survey responses. Negotiating with organizations to conduct a mandatory survey would have been much more difficult and resulted in lower overall survey responses as fewer organizations would have been willing to participate. However, voluntary participation precludes a random sampling of people within each organization thus limiting generalizability of each organization as a whole. Nevertheless, with a number of varied organizations and a variety of organizational experiences and perspectives, the diversity of the response group as a whole should be enough to generally reflect trends in the respondents surveyed. Regardless, generalizability towards an entire industry or geographic region may be problematic. The sample is still adequate, however, to compare between the different tested measures of organizational learning as all other variables were held constant making the comparison between measures fair.

A second limitation of the study is reflected through its use of cross-sectional data. Cross-sectional data misses the opportunity to see how relationships change over time which may prove important due to the theorized dynamic between changes in organizational IT capabilities and the necessary period of reflection the organization requires to determine how best to utilize the new capabilities. Such a dynamic would be expected to continuously alter the understanding and use of technology in the organization making a single snapshot in time only a small part of a larger picture.

A further limitation of this study is in the survey questions used to control for organizational performance. None of the sourced control questions were effective in accounting for any significant level of performance. This would negatively impact the ability of the structural equation model to predict organizational performance and may obscure underlying relationships. Even so, the performance of the best model showed nearly 70% of variance accounted for and strong support for the theorized mediation relationship which may demonstrate the overall importance of learning for organizational performance as discussed in previous studies (Goh et al., 2012). If this study is replicated with better control questions for organizational performance, higher levels of explained variance would be expected.

A final thought on the limitations of the study is that of the theoretical applicability to different organizational settings. Organizational learning would only be required in those situations that are unique to the organization where inimitable answers are required. For problems that are sufficiently similar to other organizations, industry standardized methodologies may be more easily applied. For example, learning from a textbook is faster than developing such knowledge by one's self. This means that organizations which only employ technology as a means to an end will, most likely, not benefit as much from organizational learning. Instead, a more efficient approach to acquiring the necessary knowledge in this context would be to obtain it directly through hiring the necessary expertise or participating in the necessary pre-established training protocols. In this case, the organizational processes remain unchanged; the organization is still pursuing its pre-established goals, just doing so more efficiently – a linear model of organizational technology. As a result, the organization is not faced with re-evaluating or re-defining its values for a new class of situations and its relationship with technology will be simpler and more direct. In this type of situation, there would be no feedback loop between the organization's choices of which technologies to employ and how best to use them and, consequently, the types of relationships theorized by this study may not be fully applicable in these situations thus limiting its generalizability.

I argue that situations with high rates of change, which induce high rates of uncertainty, would benefit more from a learning perspective than situations with low rates of change. Consequently, organizations that utilize more informational inputs and outputs, such as tertiary or quaternary organizations, may be more susceptible than most because it is faster to change informational inputs and outputs than it is to change physical ones. Knowledge-based industries, in particular, may find themselves predominantly affected. Accordingly, researchers studying these dynamics should expect to find applicability in knowledge-based areas to be higher than in others. Thus, the generalizability of this study is limited to organizations which are facing novelty.

8.3. Managerial / Practice Implications

The results from this study recommend managers adopt organizational learning practices to derive the most value from dynamic and complex IT capabilities. However, this recommendation may not apply to every organization. If an organization is merely adopting technology to enhance an existing business process, then only limited benefit may be found through learning. Contrarily, if an organization is adopting technology to endow it with qualitatively novel capabilities, then learning is essential.

Adopting new technology that offers novel capabilities for the organization would necessitate that it re-evaluates its own values and goals so that it then may understand how to best utilize its new abilities. I think this is why many modern organizations are having such a difficult time adopting new technologies such as big data and analytics. These technologies are offering new possibilities for organizations that they have never foreseen. For example, big data offers not only the potential for greater informational insight when making decisions but also forces the organization to deal with related issues never encountered at this scale before such as privacy of sensitive user data which has forced organizations to alter their relationships with their customers. If an organization's ability to learn and understand itself and its environment is not as proficient as its ability to acquire new capability-offering technology, then follies are bound to be made that do not best serve the organization's long-term interests. Only organizations with strong learning capabilities will have a good foundation of introspection upon which to base future decisions.

While the normative OL perspective showed superior performance in this study, both the normative and descriptive OL perspectives offer insight into how an organization may better position themselves for learning. Managers should heed the descriptive method of organizational learning to develop the building blocks to learning: information acquisition, information interpretation, information sharing, and organizational memory. But building blocks are not enough; these building blocks must also work well together. The normative perspective of OL gives more insight into how to develop and integrate these building blocks. Managers should ensure that all members of the organization understand and share in their understanding of their mission and that they all participate in helping the organization fulfill that purpose as this encourages people to think outside their 'silo.' Also, providing a safe space for people to experiment and try new ideas is critical for management when the correct answer is not already known. Finally, managers should encourage and facilitate knowledge sharing between members as it affords perspectives that exceed the sum of their individual outlooks. Knowledge sharing can create synergies which enable members to solve problems they would not be able to on their own. Together, managers that support these recommendations would situate their organization well for high-performing learning organizations necessary to make the best out of IT investments.

Results from this survey, however, indicate that OL practices may be more easily aspired to than practiced. For example, ‘knowledge dissemination’ consistently scored the lowest amongst all OL related measures. Considering that the sample consisted of knowledge-intensive organizations, this result is somewhat surprising. Organizations that cultivate a culture where people are encouraged to discuss issues beyond their own position is challenging. It is a difficult task to inspire new combinations of knowledge across specialized boundaries especially for knowledge-intensive organizations with high degrees of specialist positions. Perhaps this novelty by itself discourages such integrative approaches as it may be unknown how to best utilize this new insight resulting in questioning of its short-term return on investment. But the observations of OL research show that learning in the organization should not be viewed as a short-term issue. Learning enables larger long-term growth than any series of temporally myopic decisions would afford suggesting sharing of knowledge is indeed a worth-while effort.

Another observation from the results of this survey present one final piece of advice for managers. While some organizations showed very high scores in particular categories, the same organizations often demonstrated low scores in other categories. From the learning perspective, it is not enough to simply have one category of learning scoring well. Learning is an activity that encompasses all areas; deficiency in one area undermines overall learning capacity. This suggests that it may be more beneficial to bolster even modest performance in all categories rather than exceptional performance in only one.

The prototypical example that this thesis references, organizations struggling to employ big data and analytics (BDA) to enhance organizational performance, may find support from the above recommendations. First is to recognize that BDA represents qualitatively novel capabilities for most organizations. This requires that learning is an integral part of the process; managers should not be prescriptive about how to use a tool before the unique knowledge of how to best use this tool in that organization is developed. The development of this knowledge requires not just an understanding of the how the tools work, but also a solid understanding of the organization's values and priorities (clarity of purpose). This way, the organization is in a better position to engage in a period of self-reflection wherein they can decide, of the new possible actions now available to the organization, which ones would result in the best long-term outcomes for the organization.

To accomplish this task, the organization must be willing to invest in changes to internal structures and cultures that support long-term learning. In particular, there must be processes in place that enable informational acquisition both from external sources as well as the internal knowledge base of the organization's members. There must also be processes in place for informational interpretation which requires sharing and transferring information between a wide group of members. Additionally, the organization must afford the flexibility to members to experiment and problem solve within smaller decentralized groups with what that information may mean as this will not be known a priori and so no prior judgement or assumptions should be imposed resulting in a 'safe space' within which to fail in order to learn. The members, now reflecting on their shared experience with the new information, can collaborate on what this means for the organization and how to employ it sharing the leadership of the adoption of technology. Finally, once there is actionable knowledge that has been gained from the process, it should be recorded and codified so that it may be more easily stored, transferred, shared, and communicated. This 'memory' can then be used as the basis for future decisions and actions.

8.4. Implications for Future Research

Research into the relationships between IT and organizational performance has shown that simplistic models of the organization do not easily capture real-world dynamics of the use of IT in practice over time (Calvard, 2016). The continual process of learning what technology may offer an organization and what that means for the organization is, most likely, much more complex in reality than the simplified models examined within this study. Such a cyclical process of re-evaluation would compound over time creating the necessary conditions for complexity suggesting that these variables will interact with each other if studied longitudinally – the non-linear model of organizational technology. Due to the compounding nature of this cycle, causes and effects would be difficult to distinguish from one another if only studied at a single point in time making attribution of performance outcomes murky. It may not be possible to fully distinguish the effect of technology and performance separately from other factors if only a cross section is captured in research. Consequently, researchers looking to further elucidate these relationships will have to contend with such complexities where more integrative and longitudinal studies may prove fruitful research opportunities.

9. Conclusion

Organizations are increasingly relying on technology to inform decisions and create competitive advantage. However, this research proposes that simply possessing technology may not be enough to reap competitive rewards. Organizational learning is required to obtain the long-term knowledge necessary to satisfy the resource-based view conditions of IT as a competitive advantage. Existing research supports this view that OL mediates the relationship between IT and organizational performance. However, shortcomings of existing research in the conceptual models and the measurement of OL presented opportunities for future research.

This study aids the examination of how OL interacts with IT and mediates the relationship to organizational performance using normative and descriptive measures of OL. In replication of existing research, this study shows only a weak direct relationship between IT and organizational performance and supports the mediation model of OL. This study presents novel findings in the measurement of OL in that normative OL measures perform better than descriptive measures for understanding the mediation between IT and performance. This research also provides managers insight into how to achieve greater return on investment in IT infrastructure, especially in the face of ever greater reliance on data-based technologies, through the support of organizational learning perspectives.

Research on technology in the organization can learn from the complexities and plurality of perspectives that this study has only begun to incorporate. Technology may be viewed as a simple tool. However, technology is also more. It embodies our own values and decisions which then provide enhanced leverage to enact those values making technology an extension of ourselves. Researchers and practitioners alike should work towards building a comprehensive understanding that reflects these broad interdisciplinary issues. By crossing the traditional boundaries of operational experience and the siloed perspectives of organizational research specialties, a unified body of knowledge on the consequences of technology in the organization may be further illuminated aiding organizations well into the future.

10. References

Anand, V., Manz, C. C., & Glick, W. H. (1998). An organizational memory approach to information management. *Academy of Management Review*, *23*(4), 796-809.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization science*, *22*(5), 1123-1137.

Argyris, C., & Schön, D. A. (1978). *Organizational learning: A theory of action perspective*. Reading, MA: Addison-Wesley.

Argyris, C., & Schon, D. (1996). *Organizational Learning II: Theory, Method, and Practice.* Reading, MA: Addison-Wesley.

Bapuji, H., & Crossan, M. (2004). From questions to answers: reviewing organizational learning research. *Management Learning*, *35*(4), 397-417.

Berends, H., & Antonacopoulou, E. (2014). Time and organizational learning: A review and agenda for future research. *International Journal of Management Reviews*, *16*(4), 437-453.

Bhatt, G. D., Grover, V. (2005). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of management information systems*, *22*(2), 253-277.

BolíVar-Ramos, M. T., GarcíA-Morales, V. J., & GarcíA-SáNchez, E. (2012). Technological distinctive competencies and organizational learning: Effects on organizational innovation to improve firm performance. *Journal of Engineering and Technology Management, 29*(3), 331-357.

Bueno, E., Aragon, J. A., Paz Salmador, M., & García, V. J. (2010). Tangible slack versus intangible resources: the influence of technology slack and tacit knowledge on the capability of organisational learning to generate innovation and performance. *International Journal of Technology Management, 49*(4), 314-337.

Calvard, T. S. (2015). Big data, organizational learning, and sensemaking: Theorizing interpretive challenges under conditions of dynamic complexity. *Management learning*, 1350507615592113.

Conference Board of Canada. (2013). Knowledge-Intensive Services. Retrieved from http://www.conferenceboard.ca/hcp/details/innovation/knowledge-intensive-services.aspx

Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *Academy of management review*, *24*(3), 522-537.

De Geus, A. (1988). Planning as Learning. *HARVARD BUSINESS REVIEW, 66*(2), 70-74.

DiBella, A. J., Nevis, E. C., & Gould, J. M. (1996). Understanding organizational learning capability. *Journal of management studies*, *33*(3), 361-379.

Dodgson, M., Gann, D. M., & Phillips, N. (2013). Organizational learning and the technology of foolishness: The case of virtual worlds at IBM. *Organization science, 24*(5), 1358-1376.

Easterby-Smith, M., Antonacopoulou, E., Simm, D., & Lyles, M. (2004). Constructing Contributions to Organizational Learning Argyris and the Next Generation. *Management Learning*, *35*(4), 371-380.

Fiol, C. M., & Lyles, M. A. (1985). Organizational learning. *Academy of management review*, *10*(4), 803-813.

Gartner. (2015, September 15). Gartner Says Business Intelligence and Analytics Leaders Must Focus on Mindsets and Culture to Kick Start Advanced Analytics. Retrieved from https://www.gartner.com/newsroom/id/3130017

Garvin, D.A. (1993). Building a Learning Organization. *HARVARD BUSINESS REVIEW, 71*(4), 78-91.

Goh, S., & Richards, G. (1997). Benchmarking the learning capability of organizations. *European Management Journal*, *15*(5), 575-583.

Goh, S. C. (1998). Toward a learning organization: The strategic building blocks. *SAM Advanced Management Journal*, *63*(2), 15.

Goh, S. C. (2001). The learning organization: an empirical test of a normative perspective. *International Journal Organization Theory and Behavior*, *4*(3-4), 329-355.

Goh, S. C., Elliott, C., & Quon, T. K. (2012). The relationship between learning capability and organizational performance: a meta-analytic examination. *The learning organization*, *19*(2), 92-108.

Huang, H. C. (2011). Technological innovation capability creation potential of open innovation: a cross-level analysis in the biotechnology industry. *Technology Analysis & Strategic Management, 23*(1), 49-63.

Jiménez-Jiménez, D., & Sanz-Valle, R. (2011). Innovation, organizational learning, and performance. *Journal of business research*, *64*(4), 408-417.

Kane, G. C., & Alavi, M. (2007). Information technology and organizational learning: An investigation of exploration and exploitation processes. *Organization Science*, *18*(5), 796-812.

King, W. R. (2009). *Knowledge management and organizational learning* (pp. 3-13). Springer US.

Lant, T. K., Milliken, F. J., & Batra, B. (1992). The role of managerial learning and interpretation in strategic persistence and reorientation: An empirical exploration. *Strategic Management Journal*, *13*(8), 585-608.

Marchionni, C., & Ritchie, J. (2008). Organizational factors that support the implementation of a nursing best practice guideline. *Journal of nursing management*, 16(3), 266-274.

Miller, D. (1996). A preliminary typology of organizational learning: Synthesizing the literature. *Journal of management*, *22*(3), 485-505.

Mills, D. Q., & Friesen, B. (1992). The learning organization. *European Management Journal*, *10*(2), 146-156.

Myreteg, G. (2015). Organizational Learning and ERP Systems in the post-implementation phase: Where do we Stand? A Literature Review. *Electronic Journal Information Systems Evaluation Volume*, *18*(2).

Nevis, E.C., DiBella, A.J., & Gould, J.M. (1995). Understanding Organizations as Learning-Systems. *Sloan Management Review, 36*(2), 73-85.

Orlikowski, W. J., & Barley, S. R. (2001). Technology and institutions: What can research on information technology and research on organizations learn from each other?. *MIS quarterly*, *25*(2), 145-165.

Pemberton, J. D., Stonehouse, G. H., & Yarrow, D. J. (2001). Benchmarking and the role of organizational learning in developing competitive advantage. *Knowledge and Process Management*, *8*(2), 123-135.

Peteraf, M. A. (1993). The cornerstones of competitive advantage: a resource-based view. *Strategic management journal*, *14*(3), 179-191.

Popper, M., & Lipshitz, R. (1998). Organizational learning mechanisms a structural and cultural approach to organizational learning. *The Journal of Applied Behavioral Science*, *34*(2), 161-179.

Real, J. C., Leal, A., & Roldán, J. L. (2006). Information technology as a determinant of organizational learning and technological distinctive competencies. *Industrial Marketing Management*, *35*(4), 505-521.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive capacity and information systems research: Review, synthesis, and directions for future research. MIS quarterly, 36(2).

Romme, G., & Dillen, R. (1997). Mapping the landscape of organizational learning. *European Management Journal*, *15*(1), 68-78.

Sanz-Valle, R., Naranjo-Valencia, J. C., Jiménez-Jiménez, D., & Perez-Caballero, L. (2011). Linking organizational learning with technical innovation and organizational culture. *Journal of Knowledge Management, 15*(6), 997-1015.

Schein, E. H. (1993). SMR forum: How can organizations learn faster? The challenge of entering the green room. *Sloan Management Review*, *34*(2), 85.

Schoenmakers, W., & Duysters, G. (2010). The technological origins of radical inventions. *Research Policy, 39*(8), 1051-1059.

Senge, P.M. (1990). The Leader's New Work: Building Learning Organizations. *Sloan Management Review, 32*(1), 7-23.

Sidorova, A., Evangelopoulos, N., Valacich, J. S., & Ramakrishnan, T. (2008). Uncovering the intellectual core of the information systems discipline. *MIS Quarterly*, 467-482.

Stata, R. (1989). Organizational Learning - The Key to Management Innovation. *Sloan Management Review, 30*(3), 63-74.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. Boston: Pearson Education.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, 509-533.

Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: is organizational learning a missing link?. *Strategic management journal*, *24*(8), 745-761.

Tsang, E. W. (1997). Organizational learning and the learning organization: a dichotomy between descriptive and prescriptive research. *Human relations*, *50*(1), 73-89.

Von Nordenflycht, A. (2010). What is a professional service firm? Toward a theory and taxonomy of knowledge-intensive firms. *Academy of Management Review*, *35*(1), 155-174.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal*, *5*(2), 171-180.

Appendix A

Web of Science and ABI/INFORM Global were used to search for relevant scholarly articles. Many iterations of search terms were trialed but the terms that retrieved the best search results were “"organi?atio* lear*" AND ("big data" OR "analytic*")” and “"organi?atio* lear*" AND tech*” so that it covers variations of spelling in organizational learning as well as keywords for technology and popular topics in technologies use in the organization such as big data and analytics. The resultant articles range in year from 2001 to 2017 and represent the base for an academic investigation of the relationship between IT and learning.

Literature Review: Organizational Learning and Technology					
Article	Title	Key theoretical concepts	Methods of inquiry	Main findings	Issues and Implications
Orlikowski & Barley, 2001, MIS Quarterly	Technology and Institutions: What Can Research on Information Technology and Research on Organizations Learn from Each Other?	Technologies are both social and physical: technology reflects human agency by both embodying and expanding potential choice	Literature review, case study of telecommuting	OS has had more influence on tech than the reverse. IT would suggest a rise in prevalence afforded by technology but OS would suggest it is constrained by institutional factors. Neither perspective is enough to develop and integrated understanding. "Maintaining strong boundaries between fields that specialize in technology and organization is counter-productive" (p. 158).	The authors cite a narrow definition of telecommuting being used by others as merely the converse of working in an office. A more cross-disciplinary approach may be required to adequately investigate technology and organizations
Tippins & Sohi, 2003, Strategic Management Journal	IT Competency and Firm Performance: Is Organizational Learning a Missing Link?	Resource-based view: Usefulness of firm resources varies with changes in firm knowledge. Knowledge creation and integration constitute the ultimate source of competitive advantage.	Literature review, survey based instrument, statistical analysis, SEM	OL mediates the relationship between IT competency and firm performance. Positive relationship between IT competency and OL and between OL and firm performance. Significant relationship between IT competency and firm performance.	Considers the advantages IT only in relation to firm performance. Only private firms were considered. So results may only be relevant to firms engaged in competitive practices.

Bhatt & Grover, 2005, Journal of Management Information Systems	Types of Information Technology Capabilities and Their Role in Competitive Advantage: An Empirical Study	Resource-based view: IT resources alone are not enough for firm advantage because they are imitable. Must be combined with competitive capabilities	Literature review, survey based instrument, statistical analysis, SEM	IT did not relate directly to competitive advantage. Higher levels of OL did not have a direct effect on competitive advantage. Higher levels of the 'relationship infrastructure' had a strong positive effect on competitive advantage. Higher levels of OL strongly influenced the effect of IT.	Measurement of IT capabilities includes business experience which precludes firms that are not competition based. Measure of performance is not an absolute measure but rather a relative measure which would impact the level of significance and generalizability.
Real; Leal; Roldan, 2006, Industrial Marketing Management	Information technology as a determinant of organizational learning and technological distinctive competencies	Resourced-based view. OL as a system of stocks and flows of knowledge. IT as a means to enhance OL through which they create new knowledge.	Survey based instrument, statistical analysis, SEM	IT has a positive influence on OL. OL has a positive influence on development of IT competencies. IT competencies has a positive influence on performance. IT has an indirect positive influence on performance.	Only measures technology as IT infrastructure. Relationship from OL to IT was not examined.
Kane & Alavi, 2007, Organization Science	Information Technology and Organizational Learning: An Investigation of Exploration and Exploitation Processes	Based on March's (1991) concepts of exploration (the development of new knowledge) and exploitation (the use of existing knowledge) of organizational knowledge. Exploration and exploitation were modelled as stocks and flows of knowledge using three IT mechanisms: knowledge repositories, 'team rooms'/communication technologies, and 'groupware'/communities of practice.	Quantitative model	Both knowledge repositories and team rooms showed a rapid rise in performance which then plateaued. Knowledge levels in the electronic communities of practice tend to increase more slowly but don't tend to plateau. It is supported that knowledge heterogeneity is the source of exploration/exploitation dynamics. Knowledge repositories and communication technologies tend to promote exploitation by reducing knowledge heterogeneity leading to improved results in the short term only. Communities of practice cultivate exploration by preserving knowledge heterogeneity leading to improved long term results. Best results may be obtained from both exploration and exploitation methods.	Limited to the assumptions upon which the model was built. Does not go much beyond the boundary of the firm; would this relationship hold in different environments? Tools such as knowledge repositories may be used to both explore (by sharing new knowledge with the org.) and exploit.

Bueno et al., 2010, International Journal of Technology Management	Tangible slack versus intangible resources: the influence of technology slack and tacit knowledge on the capability of organisational learning to generate innovation and performance	Tangible versus intangible resources as they pertain to innovation, organizational learning, and organizational performance.	Survey based instrument, statistical analysis, SEM	Organizational learning is positively associated with innovation in technological firms where more OL leads to more innovation which in turn leads to more organizational performance.	OL is shown to enhance technical innovation in the organization. Poor measures of the organizational learning theoretical construct.
Schoenmakers & Duysters, 2010, Research Policy	The technological origins of radical inventions	Connecting the notion of radical versus non-radical inventions to theories of organizational knowledge	Discriminant analysis of patent applications	Radical inventions are based on a combination of mature and emergent technologies and existing knowledge.	Technology and organizational knowledge combine to create new technologies that are potentially drastically divergent from existing resources.
Huang, 2011, Technology Analysis & Strategic Management	Technological innovation capability creation potential of open innovation: a cross-level analysis in the biotechnology industry	Linking organizational learning mechanisms to technological innovation capability	Hierarchical linear modelling based on survey data	Learning strongly strengthens technological innovation capability.	Only measures OL as 'internal learning' which is only a subset of the larger theoretical construct of organizational learning.

Sanz-Valle et al., 2011, Journal of Knowledge Management	Linking organizational learning with technical innovation and organizational culture	Organizational learning enhances the knowledge capabilities of the organization which in turn enhances innovation within the organization, organizational culture may enhance or hinder learning	Survey based instrument, statistical analysis, SEM	Empirical evidence that OL supports technical innovation. Adhocracy culture positively supports OL, hierarchy is negatively associated with OL. OL mediates the relationship between culture and technical innovation.	Only a single organizational representative was used for each organization in the survey. This study goes farther than most in that it does not just show support for innovation through OL but that it shows support for technical innovation.
Bolı´var-Ramos et. al, 2012, Journal of Engineering and Technology Management	Technological distinctive competencies and organizational learning: Effects on organizational innovation to improve firm performance	Technology enhanced business processes, innovation as an exploitation of technological competency and knowledge through OL, the influence of management on technology and OL	Survey based instrument, statistical analysis, SEM	Management support positively influences technological skills, competencies, and learning. Each of these three components then positively influence organizational performance indirectly through innovation.	Uses same limited measures of OL as Bueno et al. (2010). Fails to adequately explain link between technology and learning using only memory as a linking concept. Instead, authors state that technological competencies require periodic updating to remain useful. OL becomes merely a consequence of management support for new technology. Authors recognize that a longitudinal study is required to assess the directionality of the relationships and possible reciprocal processes.

Roberts et al., 2012, MIS Quarterly	Absorptive Capacity and Information Systems Research: Review, Synthesis, and Directions for future Research	Perspectives on absorptive capacity as applied to technologies in the organization	Literature review	Absorptive capacity plays a role in information systems research in the following areas: business IT knowledge, knowledge transfer, IT assimilation, IT business value. IT is often absent from absorptive capacity research.	Reliance on a single primary reference for integration of OL concepts which do not adequately reflect knowledge processes of learning in the organization. Business-IT knowledge is proposed as a subset of an organization’s overall absorptive capacity which ignores many knowledge processes associated with learning.
Dodgson et al., 2013, Organization Science	Organizational Learning and the Technology of Foolishness: The Case of Virtual Worlds at IBM	March's (1976) concept of exploitation versus exploration as applied to technologies	Exploratory case study	Study shows that OL was technologically facilitated by virtualization technologies which aided with communication and experimentation.	Only a single organization was studied and in limited context. Only a single technology was studied making it difficult to generalize to other types of technologies.
Myreteg, 2015, Electronic Journal of Information Systems Evaluation	Organizational Learning and ERP Systems in the Post-implementation Phase	IT can enable/disable OL based on its relationship with org memory, communication, and discourse	Article review	Identified a dominance of studies concerning how to use ERP systems rather than investigate how IT can support the learning process. OL was found to be a critical success factor for ERP implementation.	Wider implications that many existing researchers have previously viewed technology as a means to an end and so have limited concepts of IT as applications of existing org processes. But this relationship needs to be examined the other way around as well.

Calvard, 2016, Management Learning	Big data, organizational learning, and sensemaking: Theorizing interpretive challenges under conditions of dynamic complexity	Sensemaking as a reduction in interpretive variety. Learning as an increase in interpretive variety. OL through big data may be seen as a continuous disruptive blend of induction, deduction, abduction, and sensemaking.	Article review	Four main challenges from learning from big data: simplexity as a balance between high-level simplicity and low-level complexity, interdisciplinarity is required to understand big data, ideological views of learning may clash (quantity over quality, correlation over causation, misinterpretations) etc., and domains of application (sources, processes, sectors, types of analysis).	Doesn't propose a unifying theory or consolidated body of knowledge.

Appendix B

Survey Questions

All items are on a seven-point Likert scale, from Strongly Disagree to Strongly Agree, with 3 being neutral (neither agree nor disagree) with the exception of the control variables (organizational size and market share) which are on a 5-point scale as described in the wording of the question itself.

OL: Normative	**Clarity of Purpose and Mission**	1	There is widespread support and acceptance of the organization's mission statement.
		2	I do not understand how the mission of the organization is to be achieved(r).
		3	The organization's mission statement identifies values to which all employees must conform.
		4	We have opportunities for self-assessment with respect to goal attainment.
	Shared Leadership and Involvement	5	Senior managers in this organization resist change and are afraid of new ideas(r).
		6	Senior managers and employees in this organization share a common vision of what our work should accomplish.
		7	Managers in this organization can accept criticism without becoming overly defensive.
		8	Managers in this organization often provide useful feedback that helps to identify potential problems and opportunities.
		9	Managers in this organization frequently involve employees in important decisions.
	Experimentation	10	I can often bring new ideas into the organization.
		11	From my experience, people who are new in this organization are encouraged to question the way things are done.
		12	Managers in this organization encourage team members to experiment in order to improve work processes.
		13	Innovative ideas that work are often rewarded by management.
		14	In my experience, new ideas from employees are not treated seriously by management(r).
	Transfer of Knowledge	15	I often have an opportunity to talk to other staff about successful programs or work activities in order to understand why they succeed.
		16	Failures are seldom constructively discussed in our organization(r).

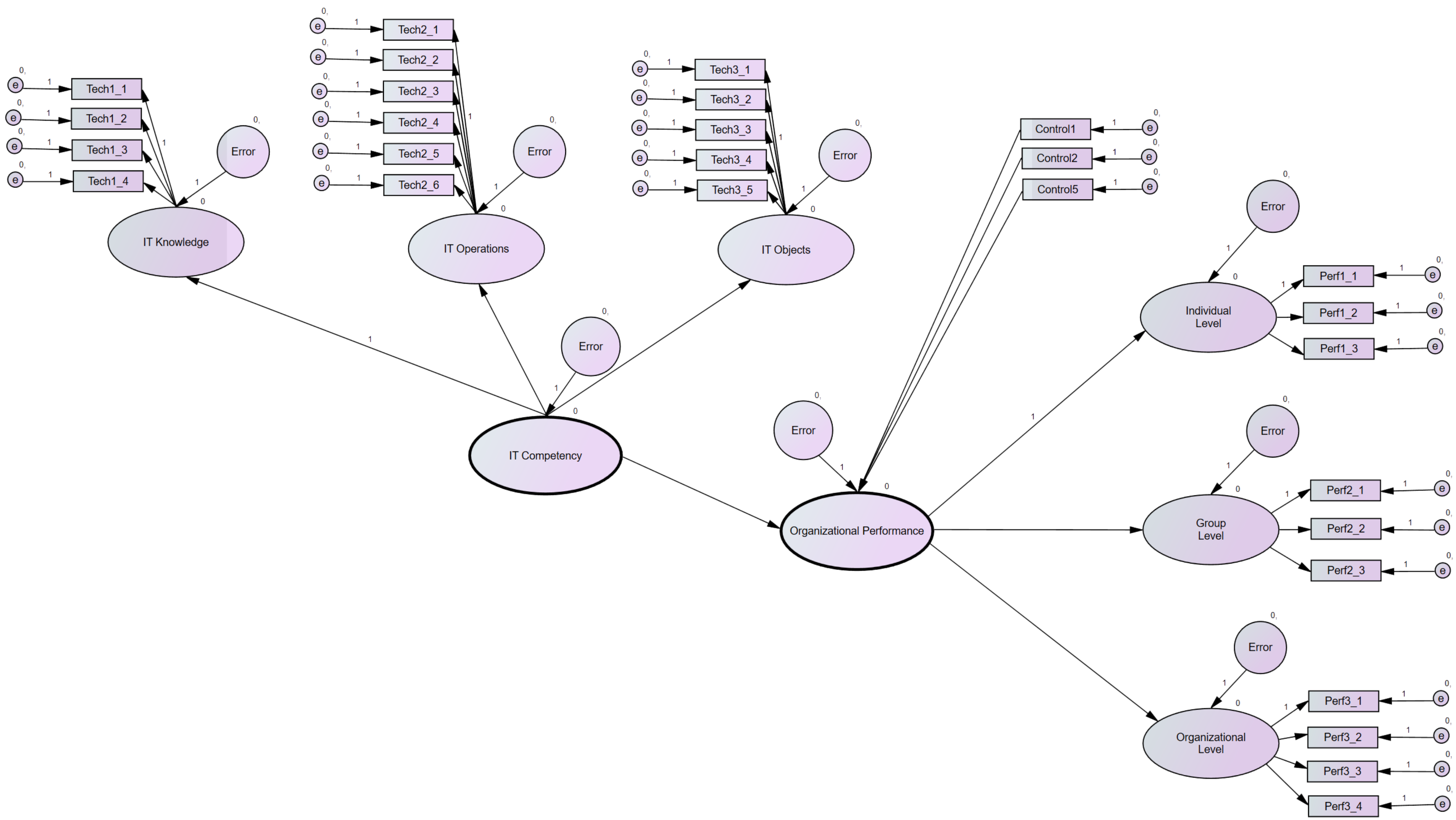
		17	New work processes that may be useful to the organization as a whole are usually shared with all employees.
		18	We have a system that allows us to learn successful practices from other organizations.
	Teamwork & Group Problem Solving	19	Current organizational practice encourages employees to solve problems together before discussing it with a manager.
		20	We cannot usually form informal groups to solve organizational problems(r).
		21	Most problem solving groups in this organization feature employees from a variety of functional areas.
OL: Descriptive	**Information Acquisition**	22	We rarely meet with our customers in order to find out what their needs will be in the future(r).
		23	We do a lot of in-house research that is directed at determining our customers' needs.
		24	We view our customers as a source of market information.
		25	We often ask our customers what they want or need.
		26	We regularly collect information concerning our customers' objectives.
		27	We often collect industry information from our customers by informal means (e.g., over lunch, at trade conventions).
	Information Dissemination	28	Within our organization, sharing customer information is the norm.
		29	Within our organization, information about our customers is easily accessible to those who need it most.
		30	Representatives from different departments within our organization meet rarely to discuss our customers' needs(r).
		31	Within our organization, customer information is rarely shared between functional departments(r).
		32	When one department obtains important information about our customers, it is circulated to other departments.
		33	Information concerning our customers is readily available to each department within our organization.
	Shared Interpretation	34	There is often disagreement among our organization's managers with regard to what our customers want(r).
		35	In our organization, we often experience conflicting opinions with regards to how best to satisfy our customers(r).
		36	When faced with new information about our customers, our managers usually agree on how the information will impact our organization.
		37	Managers in our organization tend to be on the same page when it comes to interpreting the needs of our customers.
		38	Managers in our organization tend to agree on how best to serve our customers.
	Declarative Memory	39	We retain information concerning our customers' overall business objectives.

		40	We retain information concerning which markets our customers compete in.
		41	We are knowledgeable about our customers' strengths and weaknesses.
		42	The competitive positions of our customers are unknown to us(r).
		43	We possess information concerning our customers' R&D efforts.
		44	We know a lot about our customers' sales goals.
		45	We know what marketing strategies our customers have used in the past year.
	Procedural Memory	46	We have a set procedure for handling routine purchase orders from our customers.
		47	We have learned from past experience how best to deal with 'hard to please' customers.
		48	We have standard procedures that we follow in order to determine the needs of our customers.
		49	We do not have a standard procedure for effectively dealing with customer complaints(r).
		50	Experience has taught us what questions to ask our customers.
Technology	**IT Knowledge**	51	Overall, our technical support staff is knowledgeable when it comes to computer-based systems.
		52	Our organization possesses a high degree of computer-based technical expertise.
		53	We are very knowledgeable about new computer-based innovations.
		54	We do not have the knowledge to develop and maintain computer-based communication links with our customers(r).
	IT Operations	55	Our organization is skilled at collecting and analyzing market information about our customers via computer-based systems.
		56	We rarely utilize computer-based systems to access market information from outside databases(r).
		57	We have set procedures for collecting customer information from online sources.
		58	We use computer-based systems to analyze customer and market information.
		59	We utilize decision-support systems frequently when it comes to managing customer information.
		60	We rely on computer-based systems to acquire, store, and process information about our customers.
	IT Objects	61	Our organization does not have a formal MIS department(r).
		62	Our organization employs a manager whose main duties include the management of our information technology.
		63	Every year we budget a significant amount of funds for new information technology hardware and software.
		64	Our organization creates customized software applications when the need arises.

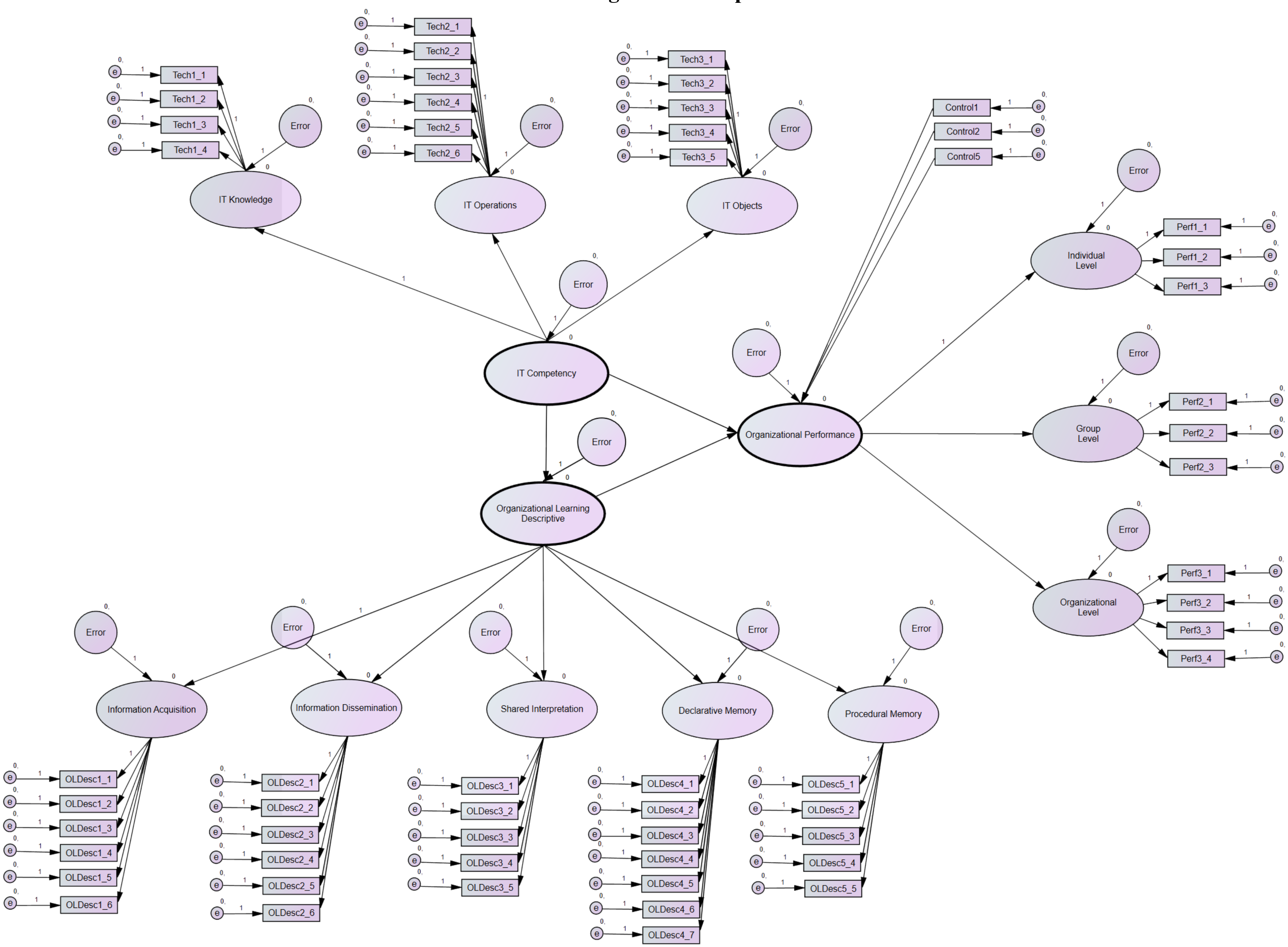
		65	Our organization's members are linked by a computer network.
Perceived Organizational Performance	**Individual-level**	66	Individuals are satisfied working here
		67	Individuals are generally happy working here
		68	Individuals are satisfied with their own performance
	Group-level	69	Our group makes a strong contribution to the organization
		70	Our group performs well as a team
		71	Our group meets its performance targets
	Organizational-level	72	Our organization is successful
		73	Our organization meets its clients' needs
		74	Our organization's future performance is secure
		75	Our organization is well-respected within the industry
Control Variables	**Organizational Size**	76	"Relative to our firm's largest competitor, we:" 1 - "Are much smaller" 2 - "Are smaller" 3 - "Are comparable" 4 - "Are larger" 5 - "Are much larger"
	Market share	77	"Relative to our firm's largest competitor, we:"(r) 1 - "Have a much larger market share" 2 - "Have a larger market share" 3 - "Have a comparable market share" 4 - "Have a smaller market share" 5 - "Have a much smaller market share"

Appendix C

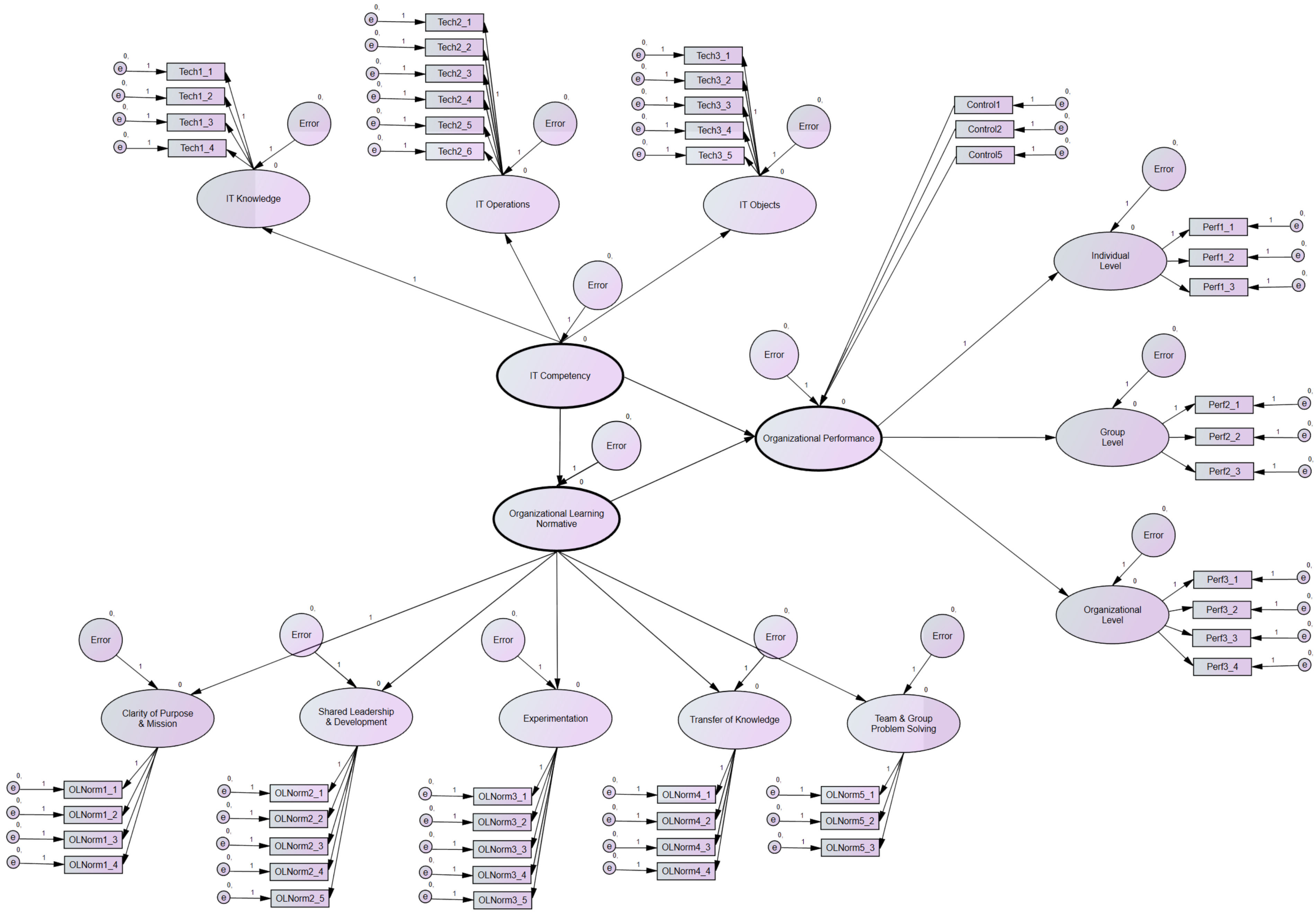
IBM AMOS SEM Diagram: Direct Effects Model



IBM AMOS SEM Diagram: Descriptive OL Model



IBM AMOS SEM Diagram: Normative OL Model



Appendix D

Variable Skewness and Kurtosis

Variable	Min.	Max.	Skew	C.R.	Kurtosis	C.R.
Control5	0	30	2.429	14.640	6.717	20.244
Control2	1	5	-0.022	-0.135	-0.341	-1.027
Control1	1	5	-0.263	-1.584	-0.505	-1.523
OLNorm1_1	1	7	-1.366	-8.237	2.351	7.085
OLNorm5_3	1	7	-0.727	-4.383	-0.208	-0.628
OLNorm5_2	1	7	-0.530	-3.192	-0.745	-2.244
OLNorm5_1	1	7	-0.895	-5.396	0.390	1.175
OLNorm4_4	1	7	-0.576	-3.472	-0.567	-1.708
OLNorm4_3	1	7	-1.082	-6.521	0.637	1.921
OLNorm4_2	1	7	-0.093	-0.563	-1.056	-3.182
OLNorm4_1	1	7	-0.942	-5.677	0.252	0.760
OLNorm3_5	1	7	-0.539	-3.251	-0.543	-1.638
OLNorm3_4	1	7	-0.991	-5.973	0.472	1.423
OLNorm3_3	1	7	-0.804	-4.848	-0.122	-0.368
OLNorm3_2	1	7	-0.657	-3.961	-0.654	-1.972
OLNorm3_1	1	7	-1.532	-9.235	2.980	8.982
OLNorm2_5	1	7	-0.787	-4.742	-0.209	-0.631
OLNorm2_4	1	7	-1.407	-8.478	1.901	5.730
OLNorm2_3	1	7	-0.469	-2.825	-0.782	-2.356
OLNorm2_2	1	7	-1.095	-6.599	0.565	1.703
OLNorm2_1	1	7	-0.614	-3.698	-0.833	-2.511
OLNorm1_4	1	7	-1.387	-8.361	2.065	6.224
OLNorm1_3	2	7	-1.251	-7.540	1.527	4.601
OLNorm1_2	1	7	-0.684	-4.125	-0.595	-1.793
Tech3_1	1	7	-0.529	-3.191	-0.911	-2.744
Tech3_2	1	7	-1.250	-7.536	0.722	2.177
Tech3_3	1	7	-0.881	-5.309	-0.146	-0.441
Tech3_4	1	7	-1.056	-6.364	0.117	0.354
Tech3_5	1	7	-1.789	-10.786	3.673	11.069
Tech2_1	1	7	-0.834	-5.026	-0.100	-0.301
Tech2_2	1	7	-0.291	-1.756	-1.007	-3.034
Tech2_3	1	7	-0.281	-1.697	-0.304	-0.915
Tech2_4	1	7	-0.658	-3.969	-0.037	-0.111
Tech2_5	1	7	-0.468	-2.819	-0.291	-0.878
Tech2_6	1	7	-0.674	-4.061	0.089	0.268
Tech1_1	1	7	-1.643	-9.904	2.843	8.568
Tech1_2	1	7	-1.339	-8.072	0.954	2.876
Tech1_3	1	7	-1.178	-7.101	0.420	1.266
Tech1_4	1	7	-0.828	-4.988	-0.384	-1.157
Perf3_2	2	7	-1.257	-7.577	2.021	6.091

Perf3_3	1	7	-1.096	-6.604	0.875	2.636
Perf1_3	2	7	-1.109	-6.686	1.158	3.489
Perf1_1	1	7	-1.330	-8.016	2.073	6.247
Perf1_2	1	7	-1.118	-6.741	0.928	2.798
Perf3_4	1	7	-1.583	-9.545	2.632	7.933
Perf3_1	2	7	-1.367	-8.241	2.535	7.639
Perf2_3	2	7	-1.206	-7.271	1.697	5.113
Perf2_1	1	7	-1.752	-10.559	3.590	10.820
Perf2_2	2	7	-1.341	-8.082	2.262	6.818
Multivariate					516.130	53.896

Appendix E

Factor Correlations

Direct Effects Model	IT Competency	Performance	IT Objects	IT Operations	IT Knowledge	Individual Level Performance	Org. Level Performance	Group Level Performance
IT Competency	1.000							
Performance	0.626	1.000						
IT Objects	0.777	0.486	1.000					
IT Operations	0.777	0.487	0.604	1.000				
IT Knowledge	0.849	0.532	0.660	0.660	1.000			
Individual Level Performance	0.435	0.696	0.338	0.338	0.370	1.000		
Org. Level Performance	0.578	0.924	0.449	0.449	0.491	0.643	1.000	
Group Level Performance	0.517	0.825	0.401	0.402	0.439	0.574	0.762	1.000

Descriptive OL Model	IT Competency	OL (Descriptive)	Performance	IT Objects	IT Operations	IT Knowledge	Memory - Procedural	Memory - Declare	Info. Dissemination	Info. Acquisition	Shared Interpretation	Individual Level Performance	Org. Level Performance	Group Level Performance
IT Competency	1.000													
OL (Descriptive)	0.645	1.000												
Performance	0.619	0.774	1.000											
IT Objects	0.760	0.490	0.470	1.000										
IT Operations	0.825	0.532	0.511	0.628	1.000									
IT Knowledge	0.815	0.526	0.504	0.620	0.673	1.000								
Memory - Procedural	0.560	0.869	0.672	0.426	0.463	0.457	1.000							
Memory - Declare	0.498	0.773	0.598	0.379	0.411	0.406	0.672	1.000						
Info. Dissemination	0.240	0.372	0.288	0.183	0.198	0.196	0.324	0.288	1.000					
Info. Acquisition	0.553	0.857	0.663	0.420	0.456	0.451	0.745	0.663	0.319	1.000				
Shared Interpretation	0.489	0.758	0.587	0.372	0.404	0.398	0.659	0.586	0.282	0.650	1.000			
Individual Level Performance	0.432	0.541	0.699	0.329	0.357	0.352	0.470	0.418	0.201	0.463	0.410	1.000		
Org. Level Performance	0.560	0.700	0.904	0.425	0.462	0.456	0.608	0.541	0.261	0.600	0.530	0.632	1.000	
Group Level Performance	0.523	0.654	0.845	0.398	0.432	0.426	0.568	0.506	0.244	0.561	0.496	0.591	0.764	1.000

Normative OL Model	IT Competency	OL (Normative)	Performance	IT Objects	IT Operations	IT Knowledge	Team & Group Prob. Solving	Transfer of Knowledge	Shared Leadership & Development	Clarity of Purpose & Mission	Experimentati on	Individual Level Performance	Org. Level Performance	Group Level Performance
IT Competency	1.000													
OL (Normative)	0.648	1.000												
Performance	0.607	0.812	1.000											
IT Objects	0.756	0.490	0.459	1.000										
IT Operations	0.792	0.513	0.481	0.599	1.000									
IT Knowledge	0.853	0.553	0.518	0.645	0.676	1.000								
Team & Group Prob. Solving	0.578	0.892	0.725	0.437	0.458	0.493	1.000							
Transfer of Knowledge	0.633	0.976	0.793	0.478	0.501	0.540	0.871	1.000						
Shared Leadership & Development	0.626	0.967	0.785	0.473	0.496	0.534	0.863	0.944	1.000					
Clarity of Purpose & Mission	0.498	0.769	0.625	0.377	0.395	0.425	0.686	0.751	0.743	1.000				
Experimentation	0.586	0.904	0.734	0.443	0.464	0.500	0.807	0.883	0.874	0.695	1.000			
Individual Level Performance	0.453	0.606	0.745	0.342	0.358	0.386	0.540	0.591	0.585	0.466	0.547	1.000		
Org. Level Performance	0.537	0.719	0.885	0.406	0.426	0.458	0.641	0.702	0.695	0.553	0.650	0.660	1.000	
Group Level Performance	0.499	0.667	0.822	0.377	0.395	0.426	0.596	0.652	0.645	0.513	0.603	0.612	0.727	1.000