Impact of Working Capital on Firm Performance: Does IT Matter?

Abstract

Although prior research in Operations Management (OM) has explored the working capital – firm performance relationship, the results from these studies remain inconclusive, with studies finding positive, curvilinear, or even insignificant relationships. This is largely due to contingent factors that make this relationship both complex and idiosyncratic. To strengthen the beneficial effect of working capital on performance, firms must therefore make appropriate investments that would foster more objective, informed, and firm-specific working capital choices. This paper examines one such investment, namely in Information Technology (IT), that can allow firms to optimize the working capital–firm performance relationship. This is important, as the role of IT in this relationship is yet to be explored. Using proprietary IT data from the Harte Hanks database, and based on a sample of 1,054 US-based manufacturing firms during 2011–2013, we find that IT investment positively moderates the performance effects of inventory, payables, and receivables cycles, and that these moderating effects vary by the type of IT investment, namely IT infrastructure and IT labor. Drawing on the theory of the Smart Machine, we explain how IT infrastructure and IT labor perform distinct roles that can help *automate* (i.e., use technology to increase the speed and accuracy of process execution) and/or *informate* (i.e., use technology to create new information), thereby moderating the working capital–firm performance relationship. We argue and find evidence that, due to the largely transactional nature of working capital processes, IT infrastructure has a relatively stronger moderating effect on performance than IT labor.

Keywords: Working Capital Management, Informate, Automate, Days Inventory Outstanding, Days Payables Outstanding, Days Sales Outstanding, IT Infrastructure Intensity, IT Labor Intensity, Tobin's *q*

1. INTRODUCTION

The management of working capital, defined as a firm's current assets less its current liabilities, involves three primary components: inventory, accounts payables, and accounts receivables. These working capital components provide operational and financial metrics that measure a firm's ability to manage its supply chain processes by funding internal operations, providing trade credit to supply chain partners, and managing its inbound logistics and outbound sales activities (Bendig et al., 2017; Hofmann & Kotzab, 2010). To achieve superior cash flow management capabilities that enable the quick conversion of resources into cash flows, firms must optimize their supply chain through efficient internal operations and streamlined communication processes with suppliers and customers. However, increasing competition combined with prevalent uncertainties in demand have increased a firm's exposure to supply chain risks in the form of longer supply chains, greater number of suppliers, greater product variety and technological uncertainty, etc., making the management of working capital a complex and dynamic decision with salient implications for firm performance (Esenduran et al., 2022).

One stream of prior research indicates that firms can improve performance by aggressively managing their working capital (i.e., reducing inventory and accounts receivables cycles, and increasing accounts payables cycle) (Capkun et al., 2009; Kroes & Manikas, 2014). The general premise here is that shorter cash conversion cycles (i.e., the time taken to convert working capital investments into cash flows) foster an improvement in firm performance (Deloof, 2003; Grosse-Ruyken et al., 2011), as the focal firm can transfer its capital costs and credit risks to other supply chain members by delaying payables (to suppliers) or aggressively following up on receivables (from buyers) (Hofmann & Kotzab, 2010), or even by taking advantage of financing mechanisms such as receivables financing, reverse factoring and payables discounting (Huff & Rogers, 2015; Rogers et al., 2020).

But delaying payables excessively, or unduly shortening the receivables cycle, can make the supply chain vulnerable, and an optimum balance between aggression and passivity must be found to optimize firm performance (Esenduran et al., 2022). Likewise, although a firm ties up its cash and incurs carrying costs by holding too much inventory, holding too little inventory can also result in stockouts that can have adverse performance effects (Barker et al., 2022). These trade-offs between too high versus too low levels of working capital imply that firms may have an optimal level of working capital that maximizes firm performance. This has led many researchers to propose a non-linear relationship between supply chain-related working capital and firm performance. For example, Baños-Caballero et al. (2014) and Wetzel and Hofmann (2019) suggest an inverted U-shaped relationship between working capital and firm performance. Along similar lines, Modi and Mishra (2011) found inventory resource efficiency to be positively related to firm performance, but with diminishing returns. But other studies highlight that there is no universally optimal working capital–firm performance relationship, and that the optimal relationship is contingent on various firm and industry-level characteristics and, therefore, unique to each firm (Eroglu & Hofer, 2011; Lazaridis & Tryfonidis, 2006).

These inconclusive findings lead us to infer that the working capital–performance relationship is complex and idiosyncratic and a 'one size fits all' approach may not yield the desired results. Firms therefore need to make the investments appropriate to their own needs to set up robust processes and control frameworks, and hire the right personnel, to be able to take better-informed and more objective working capital decisions that will strengthen their working capital–performance relationship. IT represents one such critical investment that firms need to make (Burton-Jones, 2014; Kohli & Devaraj, 2003). However, extant literature has not examined if, and how, IT investments moderate the performance effects of supply chain-related working capital measures. This is a gap both in the operations management and information system literatures, and this study attempts to shed some light on this gap.

Adding to this body of work is important because, though prior research broadly acknowledges the importance of working capital management in benefiting firm performance, the specific performance implications are complex and idiosyncratic, pointing to the role of complementary investments, such as IT, that can add more certainty, strength, and firm-specificity to the positive working capital–performance relationship, enabling firms to gain a competitive advantage over their rivals. We additionally contribute to the literature by taking a nuanced view of IT investment based on two distinct facets of IT: (a) IT infrastructure investment, and (b) IT labor investment (Bharadwaj, 2000; Bharadwaj et al., 1999). IT infrastructure investments include spending in IT assets such as servers, hardware, and other artifacts that support the processing and dissemination of information, while IT labor investments entail hiring and training IT employees to develop their technical and managerial skills.

IT investments can strengthen the working capital–performance relationship in multiple ways. For instance, robust IT infrastructure can help automate processes, such as inventory control; enable faster information-processing and seamless information exchange; ensure better process coordination and accurate demand forecasting; improve supplier risk assessment; and facilitate spend analysis through superior customer relationship management, thus, enhancing performance through optimal management of the cash flows (Bharadwaj, 2000; Rai et al., 2006). IT can also improve the visibility of business information across the supply chain, enabling the focal firm to collaborate with partners and take decisions that optimally balance the needs of all supply chain partners in a way that reduces the focal firm's risk exposure while improving its performance (Esenduran et al., 2022; Lam & Zhan, 2021). IT human capital investment can also strengthen the effects of working capital on performance by applying human knowledge, skills, experience, and judgment to make sense of tacit data; facilitate holistic decisions that integrate bits and pieces of complementary information; better communicate, coordinate, and negotiate with supply chain partners; and make flexible, dynamic alterations to standardized inventory or credit collection policies as contingencies arise (Bharadwaj, 2000).

We rely on the theory of the Smart Machine, which describes the two distinct roles of IT: automate or automating technology, and informate or informating technology (Burton-Jones, 2014; Zuboff, 1988, 1985). We argue that, while IT infrastructure helps both to “automate” (i.e., superior process execution by doing multiple tasks speedily and accurately) and “informate” (i.e., collecting data–which may be tacit–about underlying processes to create new information towards learning and improvement, and holistic decision-making), greater IT labor investment plays more of an informating role. Following prior studies (Aral & Weill, 2007; Bharadwaj, 2000; Galbraith, 1974), we also argue that for largely 'transactional' firm processes (i.e., processes involving more structured data), such as working capital management, IT infrastructure spending is more compatible than IT labor and; therefore; it has a stronger moderating effect than IT labor on the working capital-firm performance relationship.

We pose the research question: *does IT investment strengthen the effects of supply chain-related working capital measures on firm performance and, if so, does this effect vary for IT infrastructure and IT labor*? To test our predictions, we used proprietary data from Harte Hanks' (HH) Ci Technology Database to build a sample of 1,054 US-based manufacturing firms (3,020 firm-year observations) over a 3-year time frame between 2011 and 2013. Our study contributes to the OM literature by showing that IT investments augment the performance effects of working capital metrics such as inventory, accounts payables and accounts receivables, although these effects vary by the nature of IT investment.

2. LITERATURE REVIEW

We review the relevant literature from three broad perspectives: the impact of working capital management on firm performance; IT capability and working capital management; and the theory of the Smart Machine.

2.1 Working capital management and firm performance

Working capital metrics provide critical inputs to top management for assessing the effectiveness of the focal firm in managing its supply chain network (Gunasekaran et al., 2001). Although these metrics are measured at the firm level, they not only indicate how well the focal firm is managing its own operations, but also its overall supply chain health (APICS, 2017). The three metrics that drive a firm's working capital performance are (i)

Days Inventory Outstanding (DIO), which represents the firm's inventory on-hand at the current sales rate, (ii) Days Payables Outstanding (DPO), which represents the period of time that a company takes to pay off its suppliers, and (iii) Days Sales Outstanding (DSO), which represents the period of time between the sale of goods and the collection of revenue by the company (Huff & Rogers, 2015).

The impact of working capital on firm performance has been studied both in the OM and finance literatures (Aktas et al., 2015; Peng & Zhou, 2019; Zeidan & Shapir, 2017). Some early studies suggested that a less aggressive working capital management style – involving extended inventory and receivables cycles, and/or a shortened payables cycle – can improve firm performance. For instance, Blinder and Maccini, (1991) found that larger inventories can lower supply costs and price swings; eliminate production process interruptions; and avoid commercial losses brought on by a scarcity of products. Likewise, extending the receivables cycle can boost a company's sales because it can effectively act as a price reduction mechanism (Peterson and Rajan, 1997); encourage customers to purchase goods during periods of low demand; and strengthen long-term relationships and customer loyalty (Ng et al., 1999; Wilner, 2000).

Most later studies, however, found that an aggressive working capital management style–involving reduced inventory and receivables cycles and/or an extended payables cycle–was more likely to lead to enhanced firm performance (e.g. Capkun et al., 2009; Kroes & Manikas, 2014). Deloof (2003), in a study of Belgian firms, found that by reducing the number of days that inventories and accounts receivables are outstanding, firms can increase their profitability. In another study, Kieschnick et al. (2013) argued that lower working capital levels reduce the chances of firm bankruptcy. The general idea in most of these studies is that, by delaying payables (to suppliers) or aggressively following up on receivables (from buyers), firms can transfer their capital costs and credit risks to other supply chain members (Grosse- Ruyken et al., 2011, Hofmann & Kotzab, 2010).

Taking into account these divergent findings, another stream of research proposes a more nuanced relationship between working capital and firm performance. The crux of their proposition is that there is an optimal level of working capital beyond which it becomes too much of a good thing, with deleterious effects on firm performance. For example, Esenduran et al. (2022) found that where the focal firm overly delays its payments, it weakens the supply chain, eventually causing worse outcomes for the focal firm itself. Other studies, such as Baños-Caballero et al. (2014), Eroglu and Hofer (2011), and Wetzel and Hofmann (2019), have found a concave relationship between working capital management and firm performance. Mishra et al. (2013) also derived similar insights, finding diminishing payoffs from inventory resource efficiency. Singhania and Mehta (2017) found that firm profitability can be harmed both by an abundance, as well as a deficiency, of working capital.

Finally, a body of research contends that the optimum relationship between working capital and firm performance is idiosyncratic and depends on multiple factors at the industry and firm levels, implying that the precise nature of this relationship varies by firm (Eroglu & Hofer, 2011; Lazaridis & Tryfonidis, 2006; Sharma & Kumar, 2011). Some of the firm-level factors that earlier work has found to act as moderators of the working capital–firm performance relationship include firm size (Dalci et al., 2019), family ownership (Abdullah et al., 2022), corporate governance practices (Ahmad & Javaid, 2016), and supplier leanness (Barker et al., 2022).

Our literature review thus shows that these divergent strands of research have not established conclusive evidence on the precise nature of the relationship between working capital and firm performance, and this relationship continues to be both complex and idiosyncratic to firms. It follows that every firm, depending on its unique context, needs to put in place the necessary processes, practices, personnel, and decision-making frameworks that would enable it to make better working capital decisions in order to maximize firm performance. We propose that IT represents one such critical investment that firms must make in order to make informed, objective, and firm-specific working capital decisions that would result in improved performance (Burton-Jones, 2014; Kohli & Devaraj, 2003).

2.2 IT capability and working capital management

While the focus of our paper is on the role of IT in moderating the working capital-firm performance relationship, the majority of extant studies have examined the direct relationship between IT and working capital management. For instance, prior work has observed that enhanced IT capability can confer the necessary visibility to improve working capital management (Hofmann & Belin, 2011; Wuttke et al., 2019). Advanced IT capabilities also make it easier for supply chain partners to coordinate among themselves (Banker et al., 2006; Dehning et al., 2007; Gelsomino et al., 2016). A recent study, by Gill et al., (2022), showed that IT investment improves working capital management by decreasing inventory holding periods and cash conversion cycles.

Unlike these studies that address the direct effects of IT on working capital, there is little, if any, research that highlights the moderating impact of IT on the relationship between working capital-related variables and firm-level outcomes. A study that comes close is by Lam & Zhan (2021), who note how IT capability strengthens the role of supply chain finance initiatives in reducing service providers' financial risks. Our current study adds to this mostly unexplored stream of research on the moderating impact of IT on the relationship between working capital and firm outcomes.

But IT investments are often not a single, unified construct, and judicious investment in the right IT asset class may be more important than total IT investment in driving firm performance (Aral and Weill, 2007; Weill, 1992). Indeed, a stream of research has studied the performance implications of different IT investment categories, such as IT infrastructure and IT labor (e.g., Bharadwaj, 2000; Bharadwaj et al., 1999; Melville et al., 2004; Ravichandran & Lertwongsatien, 2005; Thomas & Dent-Micallef, 1997). But extant research has not explored the contingent effects of such IT categories on the relationship between supply chain-related working capital metrics and firm performance, which is an important research gap that we seek to address in this study. In this connection, we draw on Zuboff's theory of the Smart Machine (1988, 1985) to understand how investments in IT infrastructure and IT labor can moderate the relationship between working capital management and firm performance.

2.3 Theory of the Smart Machine

In a widely acclaimed book (Age of the Smart Machine: The Future of Work and Power), Zuboff (1988) expands on her earlier work (Zuboff, 1985) in outlining the theory of the Smart Machine and the dual role of IT in improving firm performance. This theory characterizes two possible roles of IT: automate or automating technology and informate or informating technology (Zuboff, 1985). 'Automate' describes how technology can help automation by facilitating superior process execution via the simultaneous performance of multiple tasks with speed (i.e., efficiency), accuracy (i.e., effectiveness), and limited human intervention. The ability to automate arises from the various machinery, artifacts, and algorithms that enable IT to complete tasks both efficiently and effectively (Burton-Jones, 2014). One of the primary benefits of automation using technology is that it "enables the same processes to be performed with more certainty and control" (Zuboff, 1988:p.9).

'Informate,' the second role of IT, focuses on using technology to create new information that firms can use to learn and develop. The informating technology perspective entails collecting, storing, and processing data pertaining to underlying processes, and subsequent conversion of this raw data into accurate, timely, and verifiable information that firms can use to improve old processes and develop new ones. What adds particular relevance to the informating role of IT is that much of the process or other work-related data are tacit, residing in the hearts and minds of employees (Zuboff, 1985) and it takes human skills; ingenuity; and the ability to integrate bits and pieces of complementary data over long periods of time in order to create new informational resources that companies can use to learn and improve (Karimi et al., 2007; Schwarz & Hirschheim, 2003; Zuboff, 1985).

Since that early work, the concepts underlying the Theory of the Smart Machine have been examined in varied contexts. Bravo et al. (2016) examined the automating and informating roles of IT in the context of Enterprise Resource Planning (ERP) users and used a questionnaire to assess the degree to which ERP systems allowed them to automate versus informate the organization. More specifically, the automation role included automating tasks; work routines; activities; and most common operations. Informating, on the other hand, involved consolidation; analysis; processing; and summarizing information.

Kim (2017) examined the effect of IT investments on initial bond ratings and yield spreads for U.S. firms and characterized the industries as automate, informate, or transform industries. They found support for a differential impact of IT investments based on the type of industries. They found that rating agencies and fixed income investors consider IT investments in the automation and information industries to be less risky than investments in transformational industries.

More recently, Jarrahi (2019) discuss Zuboff's work in the present day context of artificial intelligence (AI). They present a nuanced argument that, while AI might offer unique opportunities for automating cognitive work that once required high-skill workers, ironically, it might also be a source of unintended consequences such as cognitive complacency or de-skilling workers. Therefore, to offset such effects, the informating role and capabilities of AI can be called upon to equip workers with new sets of intellectual skills.

Even more recently, Seidel & Berente, (2020) extend the idea of Smart Machines to Smart Devices and add a third dimension–generate–where generate stands for generation of processes. The two stages from Zuboff's (1988) original work relate to automating and informating. IT allows firms to "replace the human body with a technology that enables the same processes to be performed with more continuity and control" (p. 9). On the other hand, informating explains how technology helps generate information about past or current processes in ways that help people make decisions and better monitor, adapt, and change processes. Finally, in the context of smart devices (internet of things or IoT), technologies can combine to generate new capabilities in processes and eventually new processes altogether. We contribute to the extant literature by analyzing the *automate* and *informate* roles played by different kinds of IT investments, and their contingent effect on the relationship between working capital and firm performance.

3. THEORY AND HYPOTHESIS

Our review of the literature – which we present in the form of a table summarizing the highly cited research articles related to our work (see Appendix A: Supplemental File) – shows that, by and large, aggressive working capital policies have a higher likelihood of generating cash flows that can improve firm performance (e.g., Kroes and Manikas, 2014). Therefore, a reasonable starting assumption for our hypotheses is that firms following aggressive working capital policies have a higher potential to perform well. But whether this potential will be realized might depend on a host of factors, such as a firm's business model; its specific supply chain configuration; and its supply chain risk exposure, making it hard to find the optimal level of working capital that maximizes performance (e.g., Grosse-Ruyken et al., 2011). This motivates us to study how investments in IT, by putting in place the right systems, processes, and personnel, can enable firms to harness vast amounts of data to make more informed, objective, and firm-specific working capital decisions that can strengthen the potential beneficial effects of working capital on firm performance.

We explain these relationships by drawing upon Zuboff's theory of the Smart Machine (Burton-Jones, 2014; Zuboff, 1988). Consistent with prior work in this area (Bharadwaj, 2000; Huang et al., 2013; Melville et al., 2004; Ravichandran & Lertwongsatien, 2005), we consider two types of IT investment: (i) IT infrastructure investment, denoting investment in IT assets such as high-end servers, communication hardware, and other artifacts that support the acquisition, processing, storage, and dissemination of information, and (ii) IT labor investment, denoting investment in IT assets such as hiring and training IT employees to develop human capital having the relevant technical and managerial skills.

Following our characterization of the dual role of IT as automate or automating technology and informate or informating technology (Zuboff, 1985; 1988), we argue that robust IT infrastructure would facilitate the dual role of IT, i.e., both automate and informate. That is because IT infrastructure investment can facilitate superior process execution by using technology to carry out tasks more efficiently and quickly with limited human intervention (Burton-Jones, 2014; Jarrahi, 2019), thus, acting as an automating technology. At the same time, IT infrastructure can also help firms generate; process; and disseminate new information about processes in order to monitor; adapt; and change old processes and develop new ones, thus, playing the role of an informating technology.

Unlike automating technologies that require limited human intervention (Burton-Jones, 2014; Zuboff, 1988, 1985), informating technologies–which involve making sense of complex data to generate new information that firms can use to learn and develop their processes, routines, and operations–often incorporate a strong role for human skills and ingenuity. Thus, while IT infrastructure can fulfil certain basic informating tasks (e.g., information generation and dissemination), human judgment and skills may be needed to perform certain other informating tasks, such as integrating bits and pieces of scattered information; communicating; coordinating and negotiating with relevant stakeholders inside and outside the firm; developing a holistic or comprehensive perspective about key operational and cash flow-related processes; applying cognitive capabilities to help with data interpretation, abstraction, and drawing explicit inferences; and providing information and analysis about key cash flow metrics to senior management (i.e., 'informate-up') and employees (i.e., 'informate-down') (Burton-Jones, 2014; Dehning et al., 2003;639; Jarrahi, 2019). We, therefore, argue that IT labor intensity, which entails investment in IT human capital, plays an important role as an informating technology.

3.1 Working capital metrics, IT infrastructure intensity, and firm performance

IT infrastructure intensity, which involves spending in IT assets such as servers, hardware, and other artifacts, can strengthen the association between working capital metrics (i.e., DIO, DPO, and DSO) and firm performance via multiple mechanisms. The major underlying mechanisms that strengthen the working capital–performance relationship include greater process automation, rapid response to customer and supplier requirements and better supply chain coordination; faster and more robust information-processing and exchange that enhance the accuracy of demand forecasts and supplier risk assessments; and, improved visibility and traceability of supply chain issues, along with better collaboration among supply chain partners (e.g., Esenduran et al., 2022; Lam & Zhan, 2021; Rai et al., 2006). This is consistent with Zuboff's (1985: p. 7) premise that managers harness IT to accomplish "three interdependent operational objectives - to increase the continuity (functional integration, enhanced automaticity, rapid response), control (precision, accuracy, predictability, consistency, certainty), and comprehensibility (visibility, analysis, synthesis) of productive functions."

Consider DIO, for example. The automation capabilities conferred by high IT infrastructure can enhance the speed and accuracy of inventory management processes, ensuring accurate demand forecasts; timely order fulfilment; and effective cost control, all of which can help improve firm performance. The integration aspect of IT also allows for easier coordination across firm processes. In such well-coordinated organizations, operational uncertainties can be reduced due to enhanced data capture that allows better inventory tracking, and the performance benefits from optimal inventory management are more likely to be realized (Lam & Zhan, 2021). IT infrastructure investments, such as high-performance servers and related platforms, also create superior information-processing capabilities (Bardhan *et al.*, 2013; Mitra, 2005). This can enhance the speed of information-sharing and ensure improved coordination among key supply chain stakeholders, mitigating any negative impact of the inventory cycle on firm performance.

As with DIO, the relationship between DPO / DSO and firm performance is also quite complex. Extending the payments cycle or reducing the receivables cycle might improve liquidity, but it can also cause harm to the firm's supplier and customer relationships (Fawcett et al., 2010; Kroes & Manikas, 2014). Superior IT infrastructure, by enabling automation of the payables and receivables management processes and improved real-time visibility and transparency of the cash flows, can help managers make optimal payables and receivables decisions that take effective vendor and customer management practices into consideration, thus improving firm performance (Barratt & Oke, 2007; Devaraj et al., 2007). Effective support from modern IT infrastructure can also improve firm performance through effective cash flow management that involves optimization of supplier trade credit; seller risk assessment; automated internal controls; and spend analysis through effective customer relationship management.

IT infrastructure can also mitigate any negative performance effects of suboptimal payables or receivables management through efficient processing of critical information, such as suppliers' or customers' current and future business potential and past payment history; risks faced by suppliers or customers; and regulatory changes. It can also lessen any untoward performance impact from sub-optimal receivables management by strengthening customer relationship management, for example, by offering suitable financing options to customers through integrated receivables management platforms, thereby meeting customer expectations and motivating them to reciprocate. On the payables side, IT infrastructure can also lead to better management of supplier relationships, as firms can now optimize their payment terms to mitigate the supplier's risks of bankruptcy, which would eventually enable the focal firm to better manage its supply chain risks and improve its financial bottom line (Esenduran et al., 2022). In general, IT infrastructure, by supporting real-time decisions, allows better tracking of possible financial disruptions along the supply chain that could otherwise impede the focal firm's performance (Lam & Zhan, 2021).

To summarize, IT infrastructure investment, by automating and coordinating the transactional processes that help translate optimal working capital management into superior firm performance, and by also ensuring better information sharing and visibility, has a beneficial impact on the relationship between supply chain-related working capital metrics such as DIO, DPO, and DSO, and firm performance.

H1a: ***IT infrastructure intensity mitigates the negative effect of Days Inventory Outstanding (DIO) on firm performance.***

H1b: ***IT infrastructure intensity strengthens the positive effect of Days Payables Outstanding (DPO) on firm performance.***

H1c: ***IT infrastructure intensity mitigates the negative effect of Days Sales Outstanding (DSO) on firm performance.***

3.2 Working capital metrics, IT labor intensity, and firm performance

The informating role of IT labor intensity, which involves investment in IT assets, such as hiring and training IT employees, can help improve the relationship between working capital metrics (i.e., DIO, DPO, and DSO) and firm performance. In recent times, the role of the IT Business Analyst has become critical in organizations. The roles of IT Business Analysts are typically data preparation/analysis, interpreting the data, and sharing the findings. Additionally, they are often called upon to program tools and data models to help visualize or monitor data. Thus, critical dimensions of IT labor include both technical skills (e.g., systems analysis and design) and managerial skills (e.g., interaction and coordination with the user community) that are often tacit and accumulate with experience (Bharadwaj, 2000). Multiple mechanisms can support the positive moderating role of IT labor on the working capital-firm performance relationship. First, IT managers can informate up and/or down, i.e., provide relevant information about the inventory, payables, or receivables cycles to both the top management and lower-level employees, enhancing firm competitiveness (Dehning et al., 2003).

Second, certain parts of the working capital process-related or supply chain partner-related information could be tacit and abstract and, therefore, may not lend themselves to automation. Besides, there may be several disjointed pieces of information that need to be integrated to maximize performance via optimal management of working capital processes. IT managers can use their experience, judgment, and insights to make sense of such tacit and fragmented information, and offer a holistic perspective that integrates information across various functions and processes associated with DIO, DPO, and DSO (Jarrahi, 2019), thus improving performance through better working capital decisions. Firm performance can also improve as IT managers continuously monitor, analyse, and evaluate process-based information pertaining to DIO, DPO, or DSO to facilitate learning, change, and the development of new working capital processes based on the unfolding needs of internal and external supply chain stakeholders (Bravo et al., 2016; Seidel & Berente, 2020).

Performance improvement can also happen when IT managers use their skills and ingenuity to make ongoing, flexible changes to working capital-related processes as the supply chain environment demands, or engage in regular communications with the relevant stakeholders to minimize change resistance and reduce risks. Skilled IT manpower can also use their technical and managerial competencies to keep abreast of the latest technological developments that can be applied to improve working capital processes, thus strengthening the working capital–firm performance relationship. On a related note, IT managers can also predict what new technologies may arise in the future, and how the associated opportunities and challenges can influence the working capital–performance relationship going forward. IT managers can also use their discretion and judgment to customize their DIO, DPO, or DSO policies for certain supply chain partners, or even prioritize certain partners over others to bring performance benefits to the firm.

In short, IT labor brings to the table certain skills, ability, expertise, and cognitive capabilities that can help strengthen the relationship between DIO, DPO, and DSO, and firm performance. Based on the above arguments, we hypothesize:

H2a: ***IT labor intensity mitigates the negative effect of Days Inventory Outstanding (DIO) on firm performance.***

H2b: ***IT labor intensity strengthens the positive effect of Days Payables Outstanding (DPO) on firm performance.***

H2c: ***IT labor intensity mitigates the negative effect of Days Sales Outstanding (DSO) on firm performance.***

3.3 Relative strengths of the moderating effects of IT infrastructure and IT labor

Using the lens of Zuboff's work (Burton-Jones, 2014; Zuboff, 1988, 1985), we have so far argued that while IT infrastructure represents a potent dual force due to its capability to automate processes as well as to informate, the primary role of IT labor is to informate. We build on this premise to suggest that the relative importance of automate versus informate would also depend on the underlying process where IT is being applied. Now, working capital management represents a *mostly* transactional process, meaning that although some aspects of the process may involve tacit or unstructured information, it, by and large, entails structured data. The mostly structured nature of the underlying data, in turn, underlines the salience of process automation in working capital management. This is unlike processes such as product innovation or new market entry, where the informating role can be relatively more prominent, since the largely loose, unstructured nature of the underlying data makes human analysis and interpretation the primary factor in converting such data into actionable information for learning and improvement.

Admittedly, and as hypothesized earlier, both IT infrastructure and IT labor have unique and important roles in strengthening the working capital–firm performance relationship. However, on a purely *relative* scale, in the working capital context the moderating impact of IT infrastructure as an automating technology vital to process speed and accuracy is likely to be stronger than the moderating impact of IT labor. This is consistent with findings in prior research (Aral & Weill, 2007; Bharadwaj, 2000; Galbraith, 1974), where IT assets such as high-end processing infrastructure have a relatively stronger influence in optimizing processes that usually deal with more structured information (leading to higher firm performance). Multiple mechanisms can support the stronger moderating role of IT infrastructure in the working capital–firm performance relationship, such as automation; rapid response; supply chain coordination; accuracy of demand forecasts; cost control; real-time visibility of the cash flows; robust internal controls; seller risk assessment; better tracking of supply chain disruptions; etc.

To be sure, although mostly structured, it is possible that some parts of the working capital process involve tacit or unstructured information. This makes it possible for skilled IT manpower, such as Business Analysts, to have their own unique role in informating up and/or down; making sense of tacit information; providing a holistic perspective; and dynamically responding to contingencies as they arise, all of which enable IT labor investments to play a useful role in strengthening the working capital–performance relationship. But because working capital metrics pertaining to the management of inventory, payables and receivables, represent largely transactional processes with more structured information, IT infrastructure, given its dual capability to automate processes as well as to informate, is likely to have a relatively stronger moderating effect compared to IT labor. This leads us to the following hypotheses:

H3a: ***IT infrastructure intensity mitigates the negative effect of Days Inventory Outstanding (DIO) on firm performance to a greater extent than IT labor intensity.***

H3b: ***IT infrastructure intensity strengthens the positive effect of Days Payables Outstanding (DPO) on firm performance to a greater extent than IT labor intensity.***

H3c: ***IT infrastructure intensity mitigates the negative effect of Days Sales Outstanding (DSO) on firm performance to a greater extent than IT labor intensity.***

4. METHODS

4.1 Data source

Data for this research was collated from four sources, for the period 2011–2013. First, we obtained data on the IT infrastructure budgets and number of IT employees of US-based manufacturing establishments from the Ci Technology database of HH (Gibbons et al., 2014; Huang et al., 2013; Luo et al., 2014). Second, we collected data on the firm-specific performance and operational parameters of publicly traded US firms from the COMPUSTAT Capital IQ North America (“Fundamentals Annual”) database. Third, we collected IT labor cost/wage information from the Bureau of Labor Statistics (https://data.bls.gov/). Finally, we obtained data on industry-level IT investments from the Bureau of Economic Analysis (https://www.bea.gov/).

The 2011–2013 time-period we chose was representative of broader trends in the US manufacturing sector. Thus, the US manufacturing sector output trend for 2011–2013 followed the general direction of the overall US manufacturing sector (covering a 20-year period) (Macrotrends, 2022; Thomas, 2021; Worldbank, 2022). The economic contribution of the manufacturing sector to the digital economy, in the form of investments in ICT infrastructure, services, and software, also followed the generic trend (Bureau of Economic Analysis report, 2022) during 2011–2013, as did the overall investment in broad IT categories such as IT infrastructure and IT labor. HH, on which we relied for the IT-related data, is an NYSE-listed (currently Aberdeen group) multinational company providing direct and targeted marketing information. HH Ci Technology database is one of the most comprehensive databases for IT Infrastructure and other IT expenditures like IT labor. The market intelligence division of HH monitors installed technology and IT spending at establishments based in North America, Europe, Asia-Pacific, and Latin America. HH surveys plants on a rolling basis within a span of 11 months. The survey includes details regarding hardware, software, IT employees, and other technology equipment at the plant level. Thus, at any given point, this data provides a comprehensive overview of the IT stock of a firm. HH conducts robust due diligence, both in data collection and data aggregation, and several prior studies have referred to it as the leading database for IT-related information (Huang et al., 2013; Luo et al., 2014). The HH Enterprise dataset comprises approximately 250,000 US firms, of which more than 95 percent are unlisted.

We could not directly merge the HH data with the COMPUSTAT Capital IQ database, as there was no common field identifier. The HH database provides a *Reference Database table* for integration with external data sources. The HH Reference Database table shows the mapping between the *Site ID* and the *Reference ID*. Site ID is a nine-digit numeric string that uniquely identifies HH site-level information, while Reference ID in the HH Reference Data table is the same as the *DUNS Number*. The DUNS Number, assigned and maintained by Dun & Bradstreet (D&B), is a unique nine-digit string widely used as a standard business identifier in D&B's Million Dollar Database (MDDB). The MDDB database also maps the *Ticker ID* with the DUNS number. The Ticker ID is a common identifier between the MDDB and capital IQ databases and is unique to all publicly traded firms. Hence, we followed multiple steps to compile our final dataset, as outlined in Table 1 below.

Table 1: Steps in creating the sample

Step 1	We merged the HH Reference Database with the MDDB database based on Reference ID. The MDDB database contains 5,320 publicly listed firms. We now obtained 11,080 firm-year observations (4,004 firms for 2011; 3,580 firms for 2012; 3,496 firms for 2013).
Step 2	The resulting file was merged with the HH enterprise database using Site ID. The HH Site-level Enterprise database provides data on IT budgets, installed technology, IT employees, and vendor presence for market intelligence. We did not experience any data loss at this step.
Step 3	We merged this new file with the HH IT Spend database (using Site ID). The HH IT Spend database provides the next level of details (IT spend on specific categories such as software and hardware) for these firms. We did not experience any data loss at this step.
Step 4	The latest file was merged with the COMPUSTAT Capital IQ NA (Fundamentals Annual) database using Ticker ID. At this stage we also integrated the information from the Bureau of Labor Statistics and the Bureau of Economic Analysis, both based on Standard Industrial Classification (SIC) codes. The resulting file contained 10,922 firm-year observations (3,917 firms for 2011; 3,541 firms for 2012; 3,464 firms for 2013).
Step 5	From the merged file, we retained firms in industries with SIC codes between 2000 and 3999 (i.e., manufacturing firms). Our dataset now comprised 3,710 firm-year observations (~33% of the total listed firms; 1,298 firms for 2011; 1,215 firms for 2012; 1,197 firms for 2,013).
Step 6	Finally, we cleaned the data by dropping duplicates (~1% loss of data), firms without revenue or sales figures (~ 2% loss of data), and firms without data on key independent or control variables (~17% data loss). Our final file was an unbalanced panel comprising 3,020 firm-year observations (1,054 firms for 2011; 982 firms for 2012; 984 firms for 2013).

For the final sample, we only retained manufacturing firms. This was to be consistent with the prior literature that suggests that the impact of working capital measures on firm performance is more relevant for manufacturing firms (Cai et al., 2016; Kovach et al., 2015). Our final sample was an unbalanced panel comprising 3,020 firm-year observations (1,054 firms for 2011; 982 firms for 2012; 984 firms for 2013). A more detailed year-wise break-up by the specific manufacturing sub-sector is also provided in Appendix B (Supplemental File). We next discuss the definitions and measurements of our dependent, explanatory (independent), and control variables.

4.2 Dependent variable

The dependent variable is firm performance, measured using Tobin's *q*. Investments in IT, both IT infrastructure and IT human capital, may take varying lengths of time to pay off, and such investments may not immediately translate into actual performance improvements. Hence, performance measures like Return on Assets (ROA) or Return on Equity (ROE) would not be appropriate for our research. In contrast, Tobin's *q* is primarily a market-based measure that "embodies the future performance expectations of analysts and investors and should reflect the expected value-added from investment irrespective of the number of years needed for pay off" (Deb et al., 2019, p. 189). Our approach is supported by earlier studies on the IT investment-performance relationship that measure performance in terms of Tobin's *q* (Bardhan et al., 2013; Bharadwaj et al., 1999). Tobin's *q* was measured using the ratio of the market value of assets (measured by the market value of the firm's outstanding debt and equity) to the cost of replacing these assets. We used the total book value of the firm as a proxy for the cost of replacement (Richard et al., 2009).

4.3 Explanatory variables

Three metrics, namely *Days Inventory Outstanding (DIO), Days Payables Outstanding (DPO)*, and *Days Sales Outstanding (DSO)*, were used as operational and/or financial measures of working capital. Following prior research (Jose et al., 1996), we defined DIO, DPO, and DSO in terms of the number of days. We took the average of the year-beginning and year-closing values of inventory, payables, and receivables to obtain the yearly averages. DIO, DPO, and DSO were defined as follows:

Days Inventory Outstanding (DIO) = 365(Average inventory / Cost of goods sold)*
Days Payables Outstanding (DPO) = 365(Average payable / Cost of goods sold*)
Days Sales Outstanding (DSO) = 365(Average receivables / Sales)*

We used two moderating variables, the first being *IT infrastructure intensity*, measured as the ratio of dollar investments in hardware, software, networks, servers, desktop, and related IT artifacts to the annual firm sales in dollars (Aral & Weill, 2007; Bharadwaj, 2000; Zhu, 2004). IT infrastructure provides the foundation for building applications and systems to support a firm's current processes and future growth aspirations (Aral and Weill, 2007), and superior IT infrastructure can give the firm a sustainable competitive advantage (Huang et al., 2013). Moreover, for publicly traded firms, information on robust IT investments can act as a strong signal of commitment and quality to market participants, such as analysts and investors (Chatterjee et al., 2002).

The second moderating variable was *IT labor intensity*. IT labor intensity is the total annual dollar value of investments on a firm's IT-specific employees, divided by annual firm sales (in dollars). In turn, the total annual dollar value of investments in IT employees was obtained by multiplying the number of firm IT employees with the corresponding industry's adjusted average annual wage for personnel engaged in computer-related or mathematical occupations (Huang et al., 2013). In line with prior studies (Huang et al., 2013), the adjustment to the industry's average annual wage was done using the ECEC (Employer Cost for Employee Compensation) multiplier and the ECI (Employment Cost Index) (please refer to https://www.bls.gov/opub/hom/ncs/calculation.htm, for additional details). The definitions and measurements of the independent and moderating variables are given in Table 2 below.

Table 2: Definitions and Measurements of Independent and Moderating Variables

Variable	Definition	Measurement	References
Days Inventory Outstanding	The average number of days inventory is held before it is sold	Natural logarithm of the average inventory cycle *[Days Inventory Outstanding=365*(Average Inventory/Cost of Goods Sold)]*	Capkun *et al.*, 2009; Jose *et al.*, 1996; Kroes and Manikas, 2014; Shin *et al.*, 2015
Days Sales Outstanding	The average number of days a firm takes to collect its sales revenues	Natural logarithm of the average receivables cycle *[Days Sales Inventory= 365*(Average Receivables/Sales)]*	Capkun *et al.*, 2009; Jose *et al.*, 1996; Kroes and Manikas, 2014; Shin *et al.*, 2015
Days Payables Outstanding	The average number of days a firm takes to pay its dues	Natural logarithm of average payables cycle *[Days Payables Outstanding=365*(Average Payables/Cost of Goods Sold)]*	Capkun *et al.*, 2009; Jose *et al.*, 1996; Kroes and Manikas, 2014; Shin *et al.*, 2015
IT infrastructure intensity	Investments in hardware, software, networks, servers, desktop and other IT- related infrastructure, scaled by annual firm sales	$\$(IT\ infrastructure)/\$(Sales)$	Aral and Weill, 2007; Bharadwaj, 2000; Zhu, 2004
IT labor intensity	Investment in IT- related labor (i.e., IT/IS labor and training costs), scaled by annual firm sales	$\$(IT\ labor)/\$(Sales)$	Aral and Weill, 2007; Bharadwaj, 2000

DIO, DPO and DSO are measured as their natural logarithms to address skewness

4.4 Control Variables

We used different variables to control for various firm- and industry-level effects that may influence the hypothesized relationships, and collected this data from COMPUSTAT. Prior research finds that firm size is negatively related to Tobin's *q* (Jayachandran et al., 2013; McConnell & Servaes, 1990), and large firms also require strong information processing capabilities that augment their need for investments in IT. Therefore, following prior studies that use Tobin's *q* as the dependent variable (e.g., Bharadwaj et al., 1999), we included *firm size* as a control variable. Size was measured as the natural logarithm of the firm's total assets (Mishra et al., 2013). Financial leverage (i.e., the debt-equity ratio) can negatively affect firm value, and firms with high leverage are often not well-perceived by investors. So, we followed prior research (e.g., Kim & Bettis, 2014; Mishra et al., 2013) to control for the effect of debt on firm value. The *debt-equity ratio* was measured as the ratio of total short-term and long-term debt to total shareholders' equity (Hull, 1999).

Current ratio is the next control variable. This ratio, defined as current assets by current liabilities, indicates the extent to which the current liabilities of a firm are covered by current assets. High current assets imply a firm's ability to absorb risk due to the presence of available slack (i.e., ready to deploy excess liquidity) (Bourgeois & Singh, 1983), which has a beneficial influence on firm performance (Bromiley, 1991; Lansing et al., 2017). We also controlled for the firm's year-on-year *sales growth* to isolate the impact of sales growth on performance. Sales growth shapes investor optimism and firm value and it has, therefore, been used as a control in prior studies (Deb et al., 2017). We measured sales growth as the compounded annual growth rate in sales, calculated as the natural logarithm of $\text{Sales}_{J,T}$ divided by $\text{Sales}_{J,T-1}$ for firm *J* in year *T* (Brush et al., 2000).

Early studies have also found a positive association between market share and firm performance (Montgomery & Wernerfelt, 1988; Szymanski et al., 1993), for example, due to greater market power (Smirlock et al., 1984). We, therefore, included *market share* as a control variable and measured it as the ratio of a firm's annual sales to the total annual sales of the industry (Bharadwaj et al., 1999). In line with prior empirical studies (e.g., Ehie & Olibe, 2010; Ravichandran et al., 2009), the next control variable we included was *R&D intensity*. R&D intensity is defined as R&D expenditure scaled by sales and where all missing values were replaced by zero (Hall, 1993). The next control variable was *return on assets* (ROA), defined as operating income before depreciation divided by total firm assets. Inclusion of ROA as control is also consistent with prior research on Tobin's *q* (Jayachandran et al., 2013; Vomberg et al., 2015).

The effect of *industry concentration* on firm performance has been a subject of much debate, with some studies predicting a positive relationship based on the idea of market power, and others predicting a negative relationship that suggests superior performance relies on efficiency and scale economies, rather than market power (for a discussion, see Bharadwaj et al., 1999). We, therefore, included industry concentration as a control variable and measured it using the Herfindahl Index, which is the sum of squared market shares (based on sales) of firms in the industry (Giroud & Mueller, 2011). Likewise, following earlier studies (Bardhan et al., 2013; Kim & Bettis, 2014), we included *capital intensity* as a control variable and measured it as capital expenditures scaled by total assets (Deb et al., 2017). Finally, we used dummies for industry (i.e., 4-digit SIC codes) and year to account for unobserved heterogeneity across industries and time periods.

4.5 Analysis

Our analyses focused on understanding the presence or absence of significant moderation effects, and the direction of these effects. We had an unbalanced panel dataset, as not all firms had IT investment information for all the three years in our study (i.e., 2011–2013). Unobserved heterogeneity due to multiple observations per firm is a common methodological issue in panel data analysis. Therefore, "(p)anel data models estimated with ordinary least squares (OLS) often experience problems with heteroscedastic error terms and autocorrelation, which can lead to biased and inconsistent results" (Martin *et al.*, 2013: p. 460), and fixed-effects or random-effects models are more common in panel data analysis.

In panel data, there could either be a within-firm or a between-firm effect. Fixed effects panel data models "use only within-firm variation in the dependent and independent variables" and, therefore, by not accounting for between-firm effects, a fixed effects model "prevents researchers from gaining any insights about between-firm relationship" (Certo et al., 2017; p. 1537; 1542). On the other hand, random effects models "combine both within- and between-firm variance when estimating the effects of independent variables on dependent variables" (Certo et al., 2017; pg. 1541). We focus on between-firm differences in the moderating effects of IT on the working capital–firm performance relationship, making random effects the more appropriate estimation method for our study.

To ensure that outliers are not driving our results, we followed precedent (Alti, 2006; Baker & Wurgler, 2002) and removed all Tobin's *q* values above 20. To further mitigate any effect of outliers without dropping more observations, we winsorized IT infrastructure intensity and the relevant control variables at the top and bottom 1% levels, and IT labor intensity at the 2% levels. However, for those variables that were highly skewed (i.e., non-normal) and/or had large absolute values, we took the additional step of transforming to their natural logarithm. These variables included DIO, DPO, DSO, firm size, and sales growth. A Cook's distance test we ran showed the absence of any influential outliers (Cook, 1977). Also, regressions with interaction effects are often affected by multicollinearity. We, therefore, tested the variance inflation factors (VIFs) (Chari et al., 2008) and found all VIF values to be below 2.5, thus, confirming the absence of multicollinearity in our dataset. We also report robust standard errors that are White's (1980) heteroskedasticity-consistent. Given the many known challenges of using standardized regression coefficients in a panel data setting, particularly in the presence of interaction terms (e.g., see Hayes, Glynn, & Huge, 2012; Moeller, 2015), we report unstandardized coefficients in all our models.

Table 3: Descriptive statistics and correlations

	Variable	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Tobin's *q*	2.07	1.79	1														
2	DIO	4.42	0.94	-0.02	1													
3	DPO	3.84	0.65	**0.32**	**0.14**	1												
4	DSO	3.89	0.51	**-0.06**	**0.16**	**0.28**	1											
5	IT Infrastructure	0.01	0.01	**0.12**	**0.07**	**0.17**	**0.05**	1										
6	IT Labor	0.38	0.32	**0.35**	0.02	**0.32**	**0.07**	**0.54**	1									
7	Firm Size	6.04	2.34	**-0.19**	**-0.05**	**-0.07**	-0.01	**-0.38**	**-0.57**	1								
8	Debt-equity	0.46	1.89	**-0.06**	**-0.03**	-0.01	-0.01	**-0.07**	**-0.07**	**0.14**	1							
9	Current Ratio	3.29	2.52	**-0.07**	**0.21**	**-0.25**	**0.04**	**0.10**	0.03	**-0.22**	**-0.10**	1						
10	Mkt. Share	0.02	0.05	**-0.06**	**-0.10**	**-0.04**	**-0.11**	**-0.12**	**-0.14**	**0.47**	**0.14**	**-0.17**	1					
11	R&D Intensity	0.12	0.79	**0.11**	**-0.07**	**0.19**	**0.08**	**0.19**	**0.27**	**-0.08**	**-0.06**	**0.05**	**-0.05**	1				
12	ROA	0.05	0.30	**-0.44**	**0.05**	**-0.38**	**-0.08**	**-0.27**	**-0.55**	**0.44**	**0.07**	**0.10**	**0.13**	**-0.21**	1			
13	Sales Growth	0.12	0.47	**0.22**	**-0.03**	**0.09**	**-0.16**	-0.01	**0.08**	**-0.04**	0.00	-0.02	**-0.04**	**0.11**	**-0.06**	1		
14	Ind. Concentration	0.11	0.07	**-0.12**	**-0.20**	**-0.21**	**-0.22**	-0.01	**-0.08**	**0.13**	**0.06**	**-0.10**	**0.39**	**-0.07**	**0.09**	**-0.04**	1	
15	Capital Intensity	0.04	0.03	**0.04**	**-0.09**	**-0.05**	**-0.12**	**-0.11**	**-0.13**	**0.12**	0.01	**-0.10**	**0.04**	**0.05**	**0.14**	-0.02	**0.10**	1

Statistically significant correlations ($p<0.1$), using two-tailed tests, are in bold.

5. RESULTS

The descriptive statistics and correlations for the measures used in this study are presented in Table 3. In the next table (Table 4), which presents the results of the random effects regressions, we first ran a partial regression model that included only the control variables. To this model, we first added the working capital-related explanatory variables (i.e., DIO, DPO, and DSO), and next added IT infrastructure intensity and IT labor intensity. Next, we additionally included the relevant interaction terms for DIO, DPO, and DSO, first with IT infrastructure intensity (H1a – H1c), and then with IT labor intensity (H2a – H2c). Finally, we added a model with all six interaction terms. We also ran Z-tests, and compared effect sizes, to test Hypotheses 3a – 3c (Clogg and Petkova, 1995; Paternoster, 1998). The models for Hypotheses H1a – H1c, and H2a – H2c, are shown below:

$$\textit{H1a – H1c: Tobin's q} = B_{10} + B_{11}{*}DIO + B_{12}{*}DPO + B_{13}{*}DSO + B_{14}{*}IT\ Infra + B_{15}{*}DIO{*}IT\ Infra + B_{16}{*}DPO{*}IT\ Infra + B_{17}{*}DSO{*}IT\ Infra + Controls \quad (1)$$

$$\textit{H2a – H2c: Tobin's q} = B_{20} + B_{21}{*}DIO + B_{22}{*}DPO + B_{23}{*}DSO + B_{24}{*}IT\ Labor + B_{25}{*}DIO{*}IT\ Labor + B_{26}{*}DPO{*}IT\ Labor + B_{27}{*}DSO{*}IT\ Labor + Controls \quad (2)$$

From Table 4, we observed that the main effect of DIO (i.e., inventory cycle) on firm performance is not statistically significant (see Models 2 and 3). The statistically insignificant relationship between DIO and firm performance appears indicative of the general differences in findings regarding the main effects of working capital components on firm performance (Cannon, 2008; also see Appendix A). Predictably, however, in both models 2 and 3, DPO (i.e., accounts payable cycle) was found to have a positive and significant effect, while the main effect of DSO was significantly negative. For the IT variables (Model 3), we found that both IT infrastructure and IT labor had a positive and significant direct effect on firm performance.

To test Hypotheses 1a, 1b, and 1c, we first ran a single random effects regression model that jointly included the following three interaction terms: DIO x IT infrastructure intensity, DPO x IT infrastructure intensity, and DSO x IT infrastructure intensity. These results are presented in Table 4, Model 4. We found positive and significant interaction effects of IT infrastructure intensity and DIO (i.e., H1a) ($\beta = 5.449$, $p < 0.01$), IT infrastructure intensity and DPO (i.e., H1b) ($\beta = 8.137$, $p < 0.01$), and IT infrastructure intensity and DSO (i.e., H1c) ($\beta = 4.136$, $p < 0.01$). Thus, hypotheses H1a, H1b, and H1c were all supported. This shows that IT infrastructure intensity can mitigate any possible negative effect of DIO and DSO on firm performance, while strengthening any positive effect of DPO.

Likewise, to test Hypotheses 2a, 2b, and 2c, we ran another random effects regression model that included the following three interaction terms: DIO x IT labor intensity, DPO x IT labor intensity, and DSO x IT labor intensity. These results are presented in Table 4, Model 5. This time, we found positive and significant interaction effects for IT labor with DIO (i.e., H2a) ($\beta = 0.101$, $p < 0.01$), and IT labor intensity with DPO (i.e., H2b) ($\beta = 0.263$, $p < 0.01$). However, the interaction effect of IT labor and DSO (i.e., H2c) was not statistically significant. Thus, while H2a and H2b were supported, H2c was not supported.

Finally, we ran a full model (Model 6) that included all six interaction terms in a single regression, and again found strong support for Hypotheses H1a – H1c, and H2a – H2b, but not H2c.

To test hypotheses H3a – H3c, which predicted a stronger moderating effect for IT infrastructure than for IT labor, we ran Z-tests comparing the interaction coefficients of IT infrastructure with those of IT labor. Thus, the DIO- IT infrastructure interaction term was compared with the DIO-IT labor interaction term; DPO-IT infrastructure with DPO-IT labor, and DSO-IT infrastructure with DSO-IT labor. These results are presented in Table 5. In all cases, the p-values were less than 0.05, indicating statistically significant differences in the interaction coefficients, with the interaction effects of IT infrastructure being much stronger than for IT labor.

Table 4: Random effects regression results

	Main Effects Dependent Variable – Tobin's *q*			IT Infra. interactions	IT Labor interactions	All interactions
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	4.106***	4.375***	2.939*	4.026***	4.763***	5.032***
	(1.654)	(1.730)	(1.687)	(1.604)	(1.659)	(1.605)
Control Variables						
Firm Size	-0.296***	-0.247***	-0.120**	-0.136***	-0.175***	-0.168***
	(0.044)	(0.044)	(0.047)	(0.045)	(0.047)	(0.045)
Debt-equity Ratio	-0.018	-0.016	-0.012	-0.011	-0.012	-0.011
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Current Ratio	-0.067***	-0.047**	-0.032	-0.031	-0.031	-0.031
	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.019)
Sales Growth	0.174***	0.055	0.087	0.146**	0.089	0.136**
	(0.062)	(0.066)	(0.064)	(0.063)	(0.065)	(0.063)
Mkt. Share	6.322**	4.871***	3.390	3.552	4.286*	3.992*
	(2.494)	(2.477)	(2.424)	(2.311)	(2.375)	(2.303)
R&D Intensity	0.157***	0.160***	0.122***	0.125***	0.293***	0.250***
	(0.038)	(0.038)	(0.041)	(0.040)	(0.046)	(0.046)
ROA	-1.543***	-1.538***	-1.747***	-1.871***	-1.727***	-1.837***
	(0.073)	(0.072)	(0.072)	(0.071)	(0.071)	(0.072)
Ind. Concentration	-1.066	-0.992	-1.019	-1.220	-1.270	-1.224
	(1.632)	(1.600)	(1.547)	(1.527)	(1.534)	(1.522)
Capital Intensity	0.396	-0.218	0.215	0.478	0.163	0.404
	(1.250)	(1.229)	(1.190)	(1.169)	(1.175)	(1.160)
Working Capital						
DIO		0.090	0.087	-0.045	-0.064	-0.099
		(0.063)	(0.069)	(0.068)	(0.075)	(0.073)
DPO		0.542***	0.457***	0.322***	0.243**	0.219**
		(0.089)	(0.088)	(0.091)	(0.103)	(0.100)
DSO		-1.047***	-0.750***	-0.675***	-0.509***	-0.508***
		(0.127)	(0.125)	(0.124)	(0.139)	(0.137)
IT Variables						
IT Infrastructure			8.358***	-7.876***	8.465***	-9.896***
			(0.622)	(2.613)	(0.622)	(2.791)
IT Labor			0.103*	0.114*	0.055	0.051
			(0.058)	(0.057)	(0.071)	(0.074)
Interaction Effects						
DIO x IT Infrastructure				5.449***		4.302***
				(0.669)		(0.701)
DPO x IT Infrastructure				8.137***		6.686***
				(0.925)		(0.985)
DSO x IT Infrastructure				4.136***		3.067**
				(1.460)		(1.477)
DIO x IT Labor					0.101***	0.074**
					(0.019)	(0.032)
DPO x IT Labor					0.263***	0.160***
					(0.039)	(0.040)
DSO x IT Labor					-0.037	-0.034
					(0.042)	(0.043)
Year Effects	Y	Y	Y	Y	Y	Y
Industry Effects	Y	Y	Y	Y	Y	Y
N	3020	3020	3020	3020	3020	3020
R^2	0.312	0.331	0.382	0.423	0.416	0.437

Tobin's *q* is the dependent variable in all models. The variables DIO, DPO, DSO, firm size, and sales growth are logged. Unstandardized coefficients are used, and robust standard errors are in parentheses. The p-values are indicated using "*" (*** p<0.01, ** p<0.05, and * p<0.1). Year and industry effects are not reported for brevity.

Table 5: Z-tests comparing the interaction coefficients of IT Infrastructure and IT Labor

	Interaction Term	Regression Coefficient	Standard Error	Z-stat	p-value
DIO	IT Infrastructure x DIO	4.302	0.701	6.03	0.000
	IT Labor x DIO	0.074	0.032		
DPO	IT Infrastructure x DPO	6.686	0.985	6.62	0.000
	IT Labor x DPO	0.160	0.040		
DSO	IT Infrastructure x DSO	3.067	1.477	2.10	0.036
	IT Labor x DSO	-0.034	0.043		

The p-values are indicated using "*" (*** p<0.01, ** p<0.05, and * p<0.1).

Our effect size calculations also provided support for H3. At high levels of DIO, an increase in IT infrastructure intensity from the 25th percentile to the 75th percentile was associated with an increase in Tobin's *q* equivalent to about 10 percent of median Tobin's *q*. The corresponding increase for the interaction of DIO with IT labor intensity was only about 4 percent. Similarly, at high levels of DPO, an increase in IT infrastructure intensity from the 25th percentile to the 75th percentile increased Tobin's *q* equivalent to about 13% percent of median Tobin's *q*. The corresponding number for IT labor intensity was about 7%. Finally, for DSO, only the interaction with IT infrastructure intensity was statistically significant, with an increase in Tobin's *q* of about 5% percent of median Tobin's *q*, as IT infrastructure intensity increases from the 25th percentile to the 75th percentile. These results show that, while both IT infrastructure intensity and IT labor intensity have a positive economic impact on firm performance, relatively speaking, the size of impact was higher for IT infrastructure intensity than for IT labor intensity.

The hypothesized relationships are shown in Figure 1. Figure 1.1 graphically represents the findings for H1a. As DIO increases, firms with high IT infrastructure show increased performance, while performance does not increase for firms with low IT infrastructure. Similarly, as shown in Figure 1.2 (i.e., H1b), as DPO increases, the increase in performance for firms with high IT infrastructure intensity is much sharper than firms with low IT infrastructure intensity. High IT infrastructure intensity is also able to largely offset the performance decline that follows an increase in DSO, as shown in Figure 1.3 (i.e., H1c).

Figure 1: Diagrams showing the interaction effects of IT infrastructure and IT labor

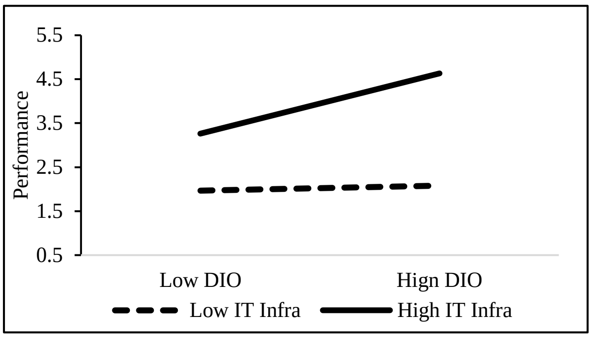

Fig. 1.1 IT Infrastructure and Inventory (DIO) – Interaction

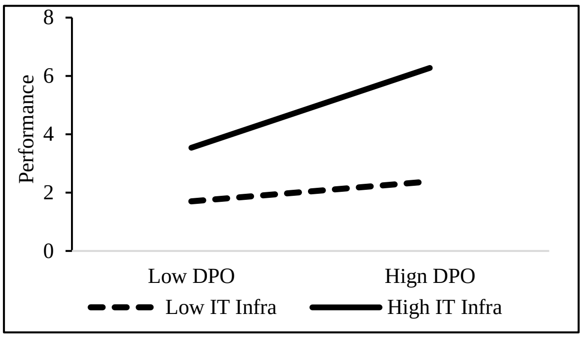

Fig. 1.2 IT Infrastructure and Payables (DPO) – Interaction

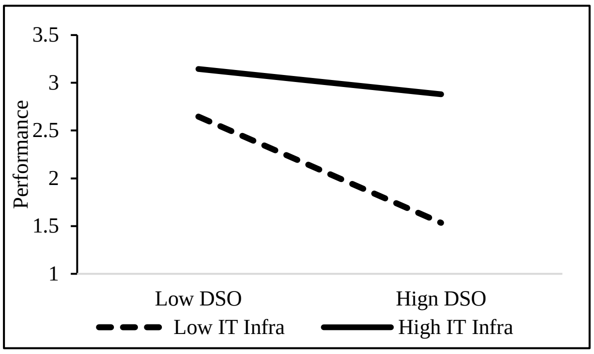

Fig. 1.3 IT Infrastructure and Receivables (DSO) – Interaction

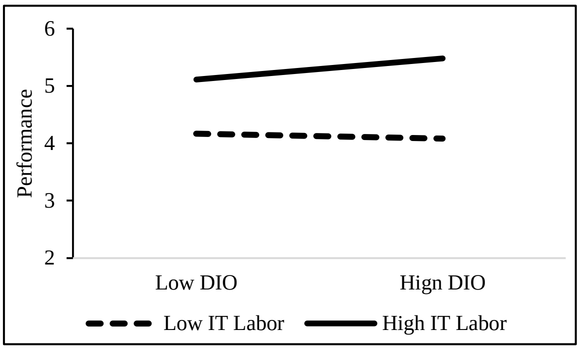

Fig. 1.4 IT Labor and Inventory (DIO) – Interaction

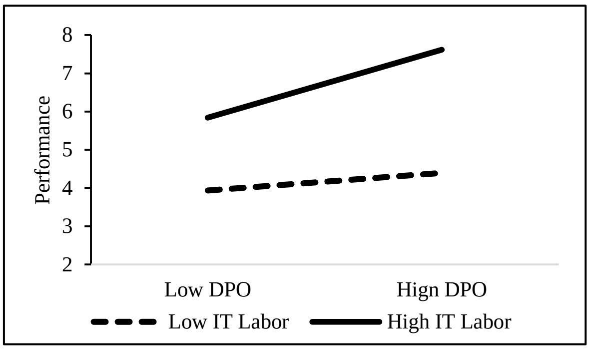

Fig. 1.5 IT Labor and Payables (DPO) – Interaction

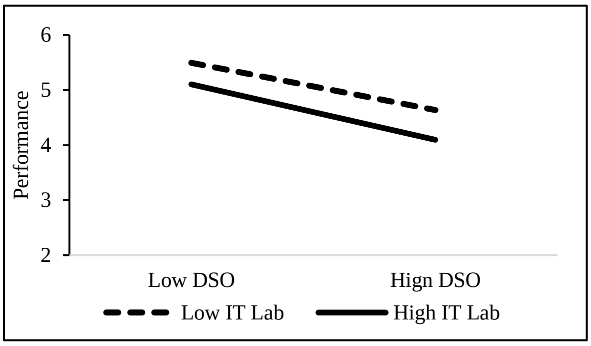

Fig. 1.6 IT Labor and Receivables (DSO) – Interaction

In each panel, the X-axis plots the marginal effects of working capital metrics (DIO, DPO and DSO) from 'mean - 1 std. dev.' to 'mean + 1 std. dev.' Lines labeled 'Low IT' and 'High IT' represent the respective variables at their 'mean - 1 std. dev.' and 'mean + 1 std. dev.' All other variables were held constant at their mean.

For IT labor, Figure 1.4 represents the findings for H2a. As DIO increases, firms with high IT labor intensity show improved performance, while performance actually shows a slight decline for firms with low IT labor intensity. Figure 1.5, which corresponds to H2b, shows that as DPO increases (i.e., as firms extend their payables cycle), the resulting increase in performance is much sharper for firms with high IT labor intensity than for firms with low IT labor intensity. Thus, the graphs shown in Figure 1 provide visual support for H1a, H1b, and H1c, and also H2a and H2b. Finally, Figure 1.6, corresponding to H2c, depicts the negative and statistically insignificant interaction effect of DSO and IT labor intensity on firm performance.

6. ENDOGENEITY

6.1 Approach to Analysis

"(A) persistent concern in the IT value literature has been establishing how much of the excess rate of return observed for IT investment is because of reverse causality or the endogeneity of IT investment" (Aral et al., 2006; ; Lee et al., 1997; Tambe & Hitt, 2012, p. 599). Thus, IT infrastructure intensity and IT labor intensity, the explanatory variables, could be potentially endogenous with the dependent variable (firm performance). For instance, while there is a possibility that high IT infrastructure / labor investments positively influence firm performance, it could also be that high-performing firms are more likely to invest in IT.

Our paper examines the moderating, rather than the direct, effects of IT investment. Recent research has shown that even in the presence of reverse causality, the coefficients of interaction variables (representing moderation effects) are consistent and efficient as long as the interaction term includes one exogenous and one endogenous variable (Bun & Harrison, 2019; Keum, 2021; Nizalova & Murtazashvili, 2016). For instance, if we could assume that while IT investment is potentially endogenous, DIO, DPO, and DSO levels are not directly affected by firm performance (i.e., potentially exogenous), we could argue that reverse causality is not a major concern in our models. To test this, we lagged the values of Tobin's q by a year, and regressed the current values of DIO, DPO, and DSO on lagged Tobin's q. Separately, we also tested to see if lagged Tobin's q influenced current values of IT infrastructure and IT labor investments.

Additionally, we addressed potential reverse causality/simultaneity issues by running two sets of two-stage least square (2SLS) estimates with instrumental variables (Wooldridge, 2017). In the first stage, we regressed IT infrastructure and IT labor on the chosen instruments and other covariates as a ‘reduced form equation,’ to be able to tease out the variation in IT that is uncorrelated with the error term (i.e., instrument exogeneity), while in the second stage (i.e., the ‘structural equation’) the resulting fitted value of IT is used in place of the endogenous regressor (Bascle, 2008). Exogeneity tests require us to have more instruments than endogenous regressors, and to also assume that at least one instrument is exogenous (Bascle, 2008). Another salient factor in instrument choice is relevance, implying that the instrument(s) must be sufficiently correlated to IT infrastructure and IT labor, the potentially endogenous regressors. However, “finding effective instruments for IT investment that can be applied to large samples of firms remains a persistent issue” (Brynjolfsson & Hitt, 2000; Tambe & Hitt, 2012, p. 602).

Despite these inherent limitations in finding perfect instruments, a large number of prior studies have argued that industry-level instruments were more likely to be exogenous (Bartelsman et al., 1994; Fu et al., 2020; Hitt, 1999; Larcker & Rusticus, 2010). Therefore, for the first instrument for IT infrastructure, following Loughran and Ritter, (2004), we created a dummy variable for technology firms (High IT = 1) that traditionally invest heavily in IT infrastructure.[1] Our second instrument for IT infrastructure was firm-level “hardware investment,” which has been used as an instrument for IT in prior studies that argue that although “hardware investment is highly correlated with IT investment, it does not directly influence firm performance (Rai et al., 1997) except through the effect of IT investments on performance (Lee & Mithas, 2014, p. 9).” We conducted a Sargan test to statistically validate instrument relevance and found both instruments to be valid ($p > 0.1$).

For IT labor intensity, the first instrument was “industry R&D intensity,” which is the R&D intensity of the median firm in the industry. R&D-intensive industries entail tacit knowledge, high

[1] High IT = 1 for firms with SIC codes 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, and 3845, and 0 otherwise.

uncertainty, unforeseeable volatility, a general absence of complete or holistic information, and the importance of process and product innovation, all of which bring the informating role of Business Analysts and other IT managers into sharper focus. IT labor intensity is also likely to be closely linked to the intensity of the firm's Selling, General, & Administrative (SG&A) expenses, i.e., SG&A to sales. That is because in addition to expenses such as advertising and rent, SG&A also includes expenses on salaries of employees such as those in IT, accounting, or payroll, who are not directly associated with production. As argued, industry-level variables were more likely to be exogenous, and so we used "industry SG&A intensity" as our second instrument for IT labor, by computing the industry-level median. A Sargan test statistically confirmed the validity of both instruments ($p > 0.1$).[2]

6.2 Results of Endogeneity Tests

To rule out reverse causality, we checked to see if prior firm performance–operationalized as values of Tobin's *q* lagged by one year–leads to higher current levels of IT infrastructure or IT labor investments, or DIO, DPO, and DSO. Our regression results show that lagged Tobin's *q* does not affect any of these five variables. These results are presented in Table 6, Models 1 – 5.

Table 7 presents the 2SLS-IV estimates. Model 1 presents the results for Hypotheses 1a – 1c. For the IV regressions, consistent with our earlier findings using random effects regressions, we found positive and significant interaction effects of IT infrastructure intensity and DIO (i.e., H1a) ($\beta = 5.965$, $p < 0.05$), IT infrastructure intensity and DPO (i.e., H1b) ($\beta = 9.017$, $p < 0.05$), and IT infrastructure intensity and DSO (i.e., H1c) ($\beta = 14.274$, $p < 0.05$). Thus, hypotheses H1a, H1b, and H1c were supported.

[2] We also ran another test for endogeneity based on the fitted values of IT infrastructure intensity and IT labor intensity. Due to space constraints, these results are presented in Appendix C of the Supplemental File.

Table 6: Effects of prior performance on working capital and IT

	Model 1 IT Infrastructure	Model 2 IT Labor	Model 3 DIO	Model 4 DPO	Model 5 DSO
Intercept	0.090*** (0.030)	0.253 (0.601)	2.803*** (0.514)	2.442*** (0.276)	2.674*** (0.270)
Tobin's *q* (t-1)	0.003 (0.002)	0.023 (0.019)	-0.003 (0.011)	0.007 (0.008)	0.003 (0.006)
IT Variables					
IT Labor	0.004* (0.002)		-0.006 (0.049)	0.132*** (0.023)	0.018 (0.017)
IT Infrastructure		1.242 (0.785)	0.043 (0.350)	0.681* (0.351)	-0.811*** (0.203)
Working Capital Variables					
DIO	-0.001 (0.002)	-0.008 (0.053)		0.092*** (0.031)	0.045** (0.019)
DPO	0.006 (0.005)	0.381*** (0.106)	0.256*** (0.098)		0.157*** (0.036)
DSO	-0.009 (0.007)	0.082 (0.080)	0.193*** (0.075)	0.243*** (0.050)	
Control Variables					
Firm Size	-0.008*** (0.002)	-0.281*** (0.032)	0.053*** (0.020)	0.021* (0.012)	0.035*** (0.009)
Debt-equity Ratio	0.001 (0.001)	-0.007 (0.004)	0.002 (0.004)	0.003 (0.004)	0.001 (0.003)
Current Ratio	-0.001 (0.001)	0.002 (0.009)	0.023* (0.013)	-0.033*** (0.007)	-0.007 (0.006)
Sales Growth	-0.001 (0.002)	-0.034 (0.096)	-0.123 (0.084)	-0.039 (0.041)	-0.232*** (0.044)
Mkt. Share	0.116*** (0.032)	4.479*** (0.824)	-2.475*** (0.944)	0.312 (0.399)	-0.801** (0.346)
R&D Intensity	-0.001* (0.001)	0.262*** (0.011)	-0.020 (0.014)	-0.028*** (0.009)	0.011* (0.006)
ROA	-0.003 (0.004)	0.158 (0.117)	0.139 (0.112)	-0.031 (0.029)	-0.005 (0.024)
Ind. Concentration	-0.082 (0.059)	4.163* (2.416)	0.770 (1.494)	-1.050 (1.048)	0.045 (0.835)
Capital Intensity	-0.022 (0.029)	-1.396** (0.656)	-1.280** (0.546)	0.638** (0.279)	-0.706*** (0.243)
Year Effects	Y	Y	Y	Y	Y
Industry Effects	Y	Y	Y	Y	Y
N	1903	1903	1903	1903	1903
R^2	0.250	0.470	0.287	0.487	0.471

Unstandardized coefficients are reported, and robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1; "(t-1)" indicates a one-year lag. Industry and year effects are not reported for brevity.

Table 7: Results of instrumental variables (IV) regressions

	IT Infrastructure	IT Labor
	Model 1	Model 2
Intercept	7.405***	8.957*
	(2.602)	(4.683)
Control Variables		
Firm Size	-0.303***	-0.547*
	(0.069)	(0.319)
Debt-equity Ratio	-0.014	-0.014
	(0.014)	(0.018)
Current Ratio	-0.064***	-0.005
	(0.020)	(0.028)
Sales Growth	-0.098	0.065
	(0.070)	(0.109)
Mkt. Share	5.361*	13.160*
	(3.140)	(7.594)
R&D Intensity	0.075*	0.462*
	(0.042)	(0.254)
ROA	-1.358***	-1.876***
	(0.130)	(0.127)
Ind. Concentration	-0.519	-4.022
	(1.452)	(2.917)
Capital Intensity	-0.852	-0.152
	(1.149)	(1.623)
Working Capital		
DIO	0.292	0.364
	(0.191)	(0.371)
DPO	0.182	0.585
	(0.133)	(0.448)
DSO	-1.416***	-0.285
	(0.211)	(0.418)
IT Variables		
IT Infrastructure	-6.664*	10.028***
	(3.719)	(1.473)
IT Labor	0.049	-6.773
	(0.067)	(4.463)
Interaction Effects		
DIO x IT Infrastructure	5.965**	
	(2.538)	
DPO x IT Infrastructure	9.017**	
	(3.526)	
DSO x IT Infrastructure	14.274**	
	(5.911)	
DIO x IT Labor		0.462*
		(0.254)
DPO x IT Labor		1.356*
		(0.767)
DSO x IT Labor		0.039
		(0.366)
Year Effects	Y	Y
Industry Effects	Y	Y
N	3020	3020

Tobin's *q* is the dependent variable in all models. The variables DIO, DPO, DSO, firm size, and sales growth are logged. Unstandardized coefficients are used. The instruments in model 1 are 'High IT' and 'hardware investment', while for model 2 the instruments are 'industry R&D intensity' and 'industry SG&A intensity'. The p-values are indicated using "*" (*** p<0.01, ** p<0.05, and * p<0.1).

Similarly, as depicted in Table 7, Model 2, we found support for Hypotheses 2a – 2b. Thus, the interaction effects for IT labor with DIO (i.e., H2a) ($\beta = 0.462$, $p < 0.1$), and IT labor intensity with DPO (i.e., H2b) ($\beta = 1.356$, $p < 0.1$), were both positive and significant. However, the interaction term between DSO and IT labor (i.e., H2c) was, as before, not significant statistically. Thus, H2a and H2b were supported, but H2c was not. We do not report R^2 values in Table 7, as R^2 is considered inappropriate as a measure of fit in the IV context (Pesaran & Smith, 1994). We also conducted Z-tests and found statistically significant differences in the interaction terms for IT infrastructure and IT labor, thus supporting H3a – H3b (results for H3a – H3b are available on request).

7. DISCUSSION AND CONCLUSION

The hypercompetitive business environment of today, in conjunction with uncertainties in the supply chain, constantly challenge a firm's working capital (e.g., reduced inventory, operational efficiency, better cash management, etc.), which in turn has direct implications for firm performance. Nonetheless, advancements in IT are enabling firms to meet this challenge by leveraging automation capabilities, as well as harnessing vast amounts of data for more effective decision-making. In this paper, our primary objectives were to investigate how investments in IT assets moderate the relationship between working capital metrics such as inventory, payables, and receivables cycle, and firm performance, and how the strength of this effect varies by the type of IT investment (IT infrastructure vs. IT labor).

Drawing on Zuboff's theory of the Smart Machine, we argued that IT assets, such as infrastructure, have the ability to both automate and informate, while IT labor, which involves investment in IT human capital, such as hiring and training IT employees, can primarily be seen as an informating technology. We hypothesized that both IT infrastructure and IT labor investments strengthen the relationship between working capital and firm performance, although in different ways. For instance, while the moderating effects of IT infrastructure intensity work via mechanisms such as automation, faster response time, more accurate forecasts, better supply chain visibility and coordination, etc., the moderating role of IT labor is performed through mechanisms such as making sense of tacit information, offering a holistic perspective, superior understanding of the supply chain environment, etc. We also argued that, although both IT infrastructure and IT labor play unique moderating roles in the working capital–firm performance relationship, the mostly structured and transactional nature of the data underlying working capital processes implies that, relatively speaking, the moderating effect of IT infrastructure will be stronger than that of IT labor.

Our empirical results, based on random effects models, provided strong support for these hypotheses. These findings were also supported using an instrumental variables approach that corrected for endogeneity, as well as another approach using fitted values of IT (see Appendix C). We found strong and consistent results for the moderating effects of IT infrastructure intensity. That is, we found that IT infrastructure intensity mitigates any negative effects of DIO and DSO on firm performance, while improving the positive effect of DPO. For IT labor intensity, we found that it too can mitigate any negative effect of DIO, while strengthening the positive effect of DPO. However, the coefficient sizes and statistical significance were lower than for IT infrastructure intensity, and these differences were statistically significant. We also found that IT labor intensity did not have a moderating effect on the DSO–firm performance relationship. We also examined and reported the effect sizes of IT infrastructure and IT labor intensity. As expected, we found that although both IT infrastructure and IT labor intensity had an economically significant moderating impact on firm performance, relatively speaking, the effect sizes were larger for IT infrastructure than for IT labor.

Managing inventory is a complex decision that impacts a firm's financial and operating performance. Inventory is an asset that firms carry to provide goods to their customers on time, but by holding inventory, cash is tied up and the firm incurs carrying costs. An optimal inventory level may free up capital that can be reinvested to increase sales and improve performance. Superior IT infrastructure helps automate several processes and decisions related to inventory control, enabling accurate demand forecasting, optimal order quantity determination, optimal warehouse capacity utilization, etc., thereby mitigating any negative performance effects of higher DIO. IT infrastructure also strengthens the link between accounts payables and receivables, and firm performance, for instance, by enabling automation of the payables and receivables management processes; improved real-time visibility and transparency of the cash flows; efficient processing of critical information relating to the risk profiles and payment histories of suppliers and customers; optimizing payment terms to mitigate the supplier's risks of bankruptcy; and offering appropriate financing options to customers via integrated receivables management platforms.

While the performance effects of working capital processes related to inventory, payables, and receivables are amplified by IT infrastructure due to the mostly structured nature of the underlying processes, IT labor–as an informating technology–can also have a unique role to play in the working capital–performance relationship. For instance, if the working capital data is less structured than usual, human judgment and skills may be needed to integrate bits and pieces of data to make a holistic assessment of the situation. IT Business Analysts, by facilitating communication and coordination with appropriate stakeholders, can help obtain complementary information or make sense of tacit data residing in the hearts and minds of other employees, customers, or suppliers. IT managers also apply their cognitive capabilities to interpret working capital data and draw explicit inferences, analyse key cash flow metrics, gauge the implications of changes in the supply chain environment for working capital management, etc., and share these insights with senior management (i.e., 'informate-up') and other employees (i.e., 'informate-down') (Burton-Jones, 2014; Jarrahi, 2019). They can also monitor and evaluate information pertaining to DIO, DPO, and DSO processes, and develop new processes based on the needs of relevant stakeholders (Bravo et al., 2016; Seidel & Berente, 2020).

7.1 Contributions

Our study contributes to the existing literature in operations management, supply chain management and information systems. First, we add to extant knowledge in supply chain digitization by showing that IT enables optimal working capital management through superior operational efficiency, improving overall firm performance. Next, we incorporate Zuboff's framework of technology for automation vs. transformation into the operations and supply chain management literature to explain how IT resources play a differential role in impacting the relationship between working capital metrics and firm performance. We additionally contribute to the longstanding discourse about IT's role in transactional processes involving more structured data. In particular, our study shows that IT infrastructure investment has a stronger performance impact than IT labor investment when it comes to the management of processes such as working capital that are mostly transactional in nature and involve more structured information. We believe this to be one of the first studies in OM to offer such a nuanced perspective about the role of types of IT.

7.2 Managerial Implications

Our study offers some managerial guidance to practitioners. First, operations and supply chain managers are constantly faced with the situation of optimizing working capital toward the eventual goal of improving firm performance. Our study provides evidence of another way of looking at this relationship – in the context of the technological environment, namely IT infrastructure and IT labor. They can view these as contextual levers to understand and influence the working capital to performance relationship. Next, supply chain managers often encounter a dilemma in situations where they are dealing with limited overall IT budget to allocate to various IT-related investments. In such situations, depending on the processes they plan to improve, managers can rethink the IT budget allocation strategy. If the objective is to improve processes dealing with transactional operational activities related to supply chain cash flows, allocating more funds for IT infrastructure would be a more appropriate strategy.

Finally, supply chain managers may use these research findings to support their case for investing in IT. When reporting returns that are solely focused on financial outcomes, the facilitating role of IT investments often goes unnoticed. Financial statements are unable to measure the more abstract beneficial effects of IT, such as increased visibility, quicker information distribution among key decision-makers, or drawing inferences from unstructured or scattered data. Our findings also have important financial implications. For instance, at higher levels of working capital, an increase in IT infrastructure intensity from the 25th to the 75th percentile is associated with a 13% increase in median Tobin's q for DPO, 10% for DIO and 5% for DSO. The corresponding numbers for IT labor are 7% for DPO and 4% for DIO. As businesses struggle to figure out how best to manage their working capital in times of environmental turbulence, it becomes more important than ever for managers to get buy-in from their superiors for any new IT investment. Our findings should therefore enable managers looking after working capital-related processes to justify making greater investments in IT and, particularly, in IT infrastructure.

7.3 Limitations and Future Research

The results of our study hold for the manufacturing sector given the sample employed, and should be evaluated across other industries. A possible extension of our study can be a focus on more granular industry segments within manufacturing, to investigate if the moderating effects are equally valid across these various segments. In this paper, we found IT labor investment, despite its unique role as a moderator, to be relatively less effective in influencing the performance impact of working capital. However, it is possible that IT labor has a delayed moderating effect on firm-level working capital management and firm performance. Such benefits may arise over time, given the capability of IT labor to codify tacit knowledge generated from supply chain processes. Hence, it would be interesting to study the long-term impact of IT labor on the working capital–firm performance relationship. Future research can also examine the role of IT in supplier-buyer financing mechanisms such as receivables financing, reverse factoring and payables discounting, and their implications for the working capital–firm performance relationship (Rogers et al., 2020).

Our study was conducted keeping a single focal firm as the unit of analysis. We anticipate that superior IT investments by the focal firm could also influence its supply chain partners owing to inter-firm information-sharing. For example, the focal firm's information- processing and sharing capabilities acquired though superior IT investments can inform both downstream and upstream supply chain partners about potential demand disruptions in the future, giving them time to plan their operations and working capital requirements in advance. Future research can also explore the inter-firm effects of IT investments, both IT infrastructure and IT labor. Indeed, empirically studying the moderating benefits of the focal firm's IT investment on the supply chain partner's working capital-firm performance relationship could be an interesting extension of our research.

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