The undersigned, approved by the Doctoral Dissertation Committee, have examined the dissertation titled

EXPLORING THE IMPACTS OF LOCATING CAPABILITIES TECHNOLOGIES ON HEALTHCARE PERFORMANCE

presented by Harun R. Musa

a candidate for the degree of Doctor of Business Administration

and hereby certify that in their opinion it is worthy of acceptance.

Balaji Sankaranarayanan, Ph.D.
Associate Professor
Committee Chair

SIGNATURE:________________________________

Aditya Simha, Ph.D.
Associate Professor
Second Committee Member

SIGNATURE:________________________________

K. Praveen Parboteeah. Ph.D.
Professor
Reader

SIGNATURE:________________________________

EXPLORING THE IMPACTS OF LOCATING CAPABILITIES TECHNOLOGIES ON HEALTHCARE PERFORMANCE

A Dissertation

Presented to

The Graduate Faculty of

The University of Wisconsin -- Whitewater

In Partial Fulfillment

Of the Requirements for the Degree

Doctor of Business Administration

By
HARUN R. MUSA

Dr. Balaji Sankaranarayanan, Dissertation Chair

DECEMBER 2022

DEDICATION

For my daughters, Laila and Amina, whose inspiration kept me going.

ACKNOWLEDGEMENTS

This work would not have come to fruition without the guidance, expertise, and encouragement of my dissertation committee members, Dr. Balaji Sankaranarayanan (Chair), Dr. Aditya Simha, and Dr. K. Praveen Parboteeah (Reader). In particular, I would like to thank Dr. Sankaranarayanan for the countless hours he spent guiding me to complete this work. You inspired me to understand the basics of research and what it takes to complete a dissertation. Thank you for your enthusiasm and patience in bringing me to this level. I will be forever grateful for all your efforts; you inspire me to follow in your footsteps someday.

Moreover, I would like to thank the faculty and staff at the University of Wisconsin–Whitewater who made the learning experience fun and rewarding for me. I would be remiss if I did not sincerely thank my fellow cohort members who motivated and inspired me throughout this process.

Most importantly, thank you to my daughters, Laila and Amina, whose support I relied on during the most challenging aspects of this experience. I know this journey has called for a significant sacrifice from each of you; from the bottom of my heart, I thank you.

EXPLORING THE IMPACTS OF LOCATING CAPABILITIES TECHNOLOGIES ON HEALTHCARE PERFORMANCE

HARUN R. MUSA

Dr. Balaji Sankaranarayanan, Dissertation Chair

ABSTRACT

Healthcare uses locating capabilities technologies (LCTs) such as radio-frequency identification and real-time location systems to track assets and people. Healthcare firms have struggled to understand LCTs' impact on firm performance. This dissertation explores the effects of LCTs by applying the dynamic capabilities theory and testing the hypothesized relationships. My dissertation is comprised of two essays.

In Essay 1, I focus on exploring LCTs' influence on healthcare organizations' financial performance by analyzing secondary data from healthcare firms that had and had not deployed LCTs using a matched-pair approach. I conducted independent sample t-tests and difference in differences analysis to compare the two groups. The results indicated that healthcare firms using LCTs did worse based on three financial measures: return on assets, net operating profit margin, and net income margin.

In Essay 2, I investigate the relationships between LCTs and healthcare performance by analyzing survey data from respondents with current or prior experience in healthcare decision-making. Drawing from the dynamic capabilities theory, I theorized: (a) location-based intelligence (LBI) capability as a second-order construct containing four lower-order constructs (location infrastructure capability, asset tracking capability, patient and staff locating capability, and information visibility capability); (b) LBI capability directly and indirectly positively affects healthcare performance (employee, patient, and technology benefits); (c) business process optimization (BPO) mediates the relationship between LBI capability and healthcare performance; (d) managerial capabilities have a direct and positive effect on BPO, which moderates the relationship between LBI capability and BPO; (e) employee and patient healthcare performance is a second-order construct comprised of employee and patient healthcare benefits, and (f) hospital characteristics such as size and location positively moderate the relationship between BPO and healthcare performance. The research model tested survey data from healthcare staff in the United States with current and prior experience in decision-making or using health information technology. The analysis results show that (a) LBI capability is a second-order construct that directly and indirectly affects healthcare performance; (b) BPO mediates the relationship between LBI capability and healthcare performance; (c) although managerial capabilities do not moderate the relationship between LBI capability and BPO, they have a positive and direct effect on BPO; (d) employee and patient healthcare performance is a second-order construct; (e) hospital size positively moderates the relationship between BPO and employee and patient healthcare performance; and (f), hospital location positively moderates the relationship between BPO and healthcare performance in technology.

This study's findings have significant research implications regarding LCTs impacting healthcare performance.

Keywords: locating capabilities technologies, location-based intelligence, RFID, RTLS, BLE, Wi-Fi tracking

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure Page

Exploring the Impacts of Locating Capabilities Technologies on Healthcare Performance

The World Health Organization declared Covid-19 a pandemic on March 11, 2020 (Cucinotta & Vanelli, 2020). As a result, states in the United States imposed lockdowns in March 2020 to curb the spread of the virus. Hospitals in the United States faced immediate strain on their capacities as the number of Covid patients increased quickly. Hospitals face many challenges, including locating available beds, equipment, staff, and patients in real-time, resulting in avoidable loss of life (Evans & Berzon, 2020). As the pandemic surged, hospitals realized they lacked the information technology (IT) capacity to locate assets and people at the necessary time. As a result, some hospitals could not deliver life-saving treatments (Evans, 2020). Not knowing the location of available beds and critical equipment, such as ventilators and intravenous pumps, meant the difference between life and death for critically ill patients. As the healthcare industry faced financial pressures to operate with limited resources, it had to make tough decisions in selecting IT projects for investment. While investments in modernizing electronic medical records systems increased, other endeavors, such as deploying locating capabilities technologies (LCTs), fell off the priority ladder (Evans & Berzon, 2020; “RFID: What’s the frequency,” 2019).

My experience in healthcare IT (HIT) suggests that hospitals face challenges in tracking critical medical information and optimally managing patient flows. Although some hospitals have begun attaching radio-frequency identification (RFID) tags to some medical equipment for tracking, they have not adopted this practice across all business areas. The focus has been on modernizing electronic health record systems (Evans & Berzon, 2020).

Unsurprisingly, during the Covid-19 pandemic in 2020, the federal government and the states raised alarm bells about the shortage of critical medical equipment such as ventilators and intravenous pumps (Evans & Berzon, 2020). However, two key questions remain: why would an industry that makes up a sizable portion of the U.S. gross domestic product have significant challenges in finding critical medical equipment? And is there an actual equipment shortage, or could healthcare not locate the equipment? In other words, is this a supply chain problem or a locational capability problem?

According to the Centers for Medicare & Medicaid Services (CMS) projection, healthcare spending in the United States will grow at an annual rate of 5.4% from 2019 to 2028, outpacing the gross domestic product growth rate of 4.3% annually (Advisory Board, 2020). The CMS estimates that healthcare spending reached $3.81 trillion in 2019 and will increase to $6.19 trillion by 2028 (Advisory Board, 2020). Expenditures on Information Technology projects such as locating capabilities technologies represent a sizable portion of the industry's operational budgets. ("RFID: What's the frequency," 2019)

The most prevalent locating technology used in healthcare is RFID (Vilamovska et al., 2009). However, LCTs such as real-time locating systems, Bluetooth low energy, and Wi-Fi location tracking are experiencing higher adoption. The RFID and real-time locating systems technologies employ tags such as employee badges and labels attached to physical items such as medical equipment and supplies for locating and tracking (Aboelmaged & Hashem, 2018; Álvarez López et al., 2018; Boulos & Berry, 2012; Gupta et al., 2015; Fosso Wamba, 2012; Fosso Wamba et al., 2013; Naresh et al., 2020). Although RFID arrived in healthcare about 15 years ago, the technology has had limited success (Fosso Wamba et al., 2013; Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014). Challenges healthcare firms face in adopting the technology include technological, data management, security, and financial issues (Fosso Wamba et al., 2013; Vilamovska et al., 2009).

Extant literature has suggested potential benefits of LCTs: efficiency gains, quality gains, and management gains (i.e., Boulos & Berry, 2012; Ting et al., 2011; Vilamovska et al., 2009); improving patient safety (Jones & Gupta, 2015; Naresh et al., 2020); increasing patient alone time and provider time (Arunachalam et al., 2016, 2017); improving logistical processes of surgical instruments (Moatari-Kazerouni & Bendavid, 2017); healthcare monitoring of diabetic patients (Alfian et al., 2018); and perioperative efficiency of anesthesiologists (Yeoh et al., 2019). With LCTs, healthcare organizations are presented with opportunities to enhance firm performance ("RFID: What's the frequency," 2019). However, decision-makers lack the tools to evaluate projects associated with deploying LCTs and make investment decisions (Wamba et al., 2013). Thus, healthcare firms must understand whether the use of LCTs translates into healthcare performance (Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014).

In their literature review of RFID-enabled healthcare applications, Fosso Wamba et al. (2013) called for future research that creates a mechanism for "developing a holistic performance measurement and management system to assess the value generated by RFID-enabled healthcare operation" (Wamba et al., 2013, p.883). As a result, this study answers this call by empirically examining the impact of LCTs on healthcare performance.

My dissertation applies dynamic capabilities (DC) theory to explore the impact of LCTs on healthcare performance. The concept of DC refers to "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p.516). Thus, DC enables firms to create and sustain competitive advantages. Rooted in the resource-based view (RBV) theory (Barney, 1991; Eisenhardt & Martin, 2000), DC theory accounts for how firms develop and configure resources in a dynamic environment. Resource attributes such as value, rarity, imperfect imitability, and non-interchangeability, according to RBV, allow forms to create and sustain competitive advantages (Barney, 1991). Three activities performed by organizations (sensing, seizing, and transforming) represent the foundation of DCs (Teece et al., 1997). While sensing enables firms to explore external opportunities, seizing activities allow firms to enhance their products and services through innovative business models. Transforming activities drive firms to adapt their business processes to meet market needs.

Recent studies have further affirmed the positive association between IT capabilities and firm performance: digital transformation (Reis et al., 2018), data analytics and competitive performance (Mikalef et al., 2020), Internet of Things (Côrte-Real et al., 2020), artificial intelligence capability (Mikalef & Gupta, 2021), IT architecture flexibility and governance (Mikalef et al., 2021), IT governance process capability (Joshi et al., 2022), and artificial intelligence investments on firm value (Lui et al., 2022).

Consistent with the dynamic capabilities perspective and extant literature arguments, this study posits a positive relationship between LCTs and sustained competitive advantage through enhanced healthcare performance.

Research Questions

Understanding the relationship between LCT use and firm performance (i.e., financial) is vital for healthcare firms. First, it is costly for these firms to deploy and use LCTs, potentially costing them millions of dollars (Boulos & Berry, 2012; Gupta, 2015; Yazici, 2014; Yeoh et al., 2019). As the healthcare industry struggles with tight margins and limited resources, prioritizing IT investments is vital (Boulos & Berry, 2012; Fosso Wamba et al., 2013). Second, prior studies have suggested that firms in healthcare appear to abandon or significantly minimize the use of LCTs in their business processes due to challenges in harnessing the technology (Arunachalam et al., 2016, 2017). Third, extant literature lacks empirical studies investigating LCTs' performance impacts (Fosso Wamba et al., 2013).

This study empirically investigated the impacts of LCTs on healthcare performance. Healthcare performance considers two aspects of performance: financial and efficiency. Financial performance indicators include return on assets, net operating profit margin, and net income margin. Efficiency indicators include improvement in asset utilization, reduction in time for employees (searching and inventorying equipment), reduction in time to log readings, and progress in rounding staff efficiency (in terms of compliance and improvement in staff documentation compliance). This study utilized both secondary and primary (survey) data to explore healthcare performance by comparing the financial performance of healthcare firms that implemented LCTs and those that did not, as well as investigating the perceptions of healthcare staff via a survey to explore the potential performance benefits of LCTs. Thus, this dissertation examines the following overarching research questions:

1. Do healthcare firms that implemented LCTs perform financially better than those that did not?
2. Does implementing LCTs positively impact business process optimization (BPO) and hospital performance?
3. Does BPO fully mediate the relationship between LCTs and performance?
4. Do managerial capabilities of hospitals have any positive relationship with BPO and moderate the relationship between LCTs and BPO?
5. Do hospital demographic variables such as hospital size and location play a moderating role between BPO and hospital performance?

Research Methods

This study employed primary and secondary data to explore the healthcare performance impacts of LCTs. In Essay 1, titled "Exploring the Impacts of LCTs on Healthcare Financial Performance," I analyze secondary data to compare the financial performance (return on assets, net operating profit margin, and net income margin) of firms that implemented LCTs and those that did not. This study aimed to understand whether there are differences between the firms and, if differences exist, whether they are positive or negative. The data set included the financial performance and LCT implementation information of healthcare firms billing Medicare for services. In Essay 2, titled "Exploring the Perceptions of Healthcare Staff on LCTs' Impact on Performance," I analyze survey data to investigate the performance perceptions of healthcare staff on LCTs, explore the relationship between LCTs and healthcare performance, and examine mediating and moderating factors.

Contributions

This study aimed to shine a light on the impacts of LCTs on healthcare performance. While LCTs hold a significant promise in their impact on enhancing the performance of healthcare firms, prior studies such as Fosso Wamba et al. (2013) have called for future empirical studies to investigate the impact of LCTs. To the best of my knowledge, this is the first study that explores the relationship between LCTs and healthcare performance by analyzing secondary data. As LCTs can cost healthcare firms millions in technology deployments and employee training, a richer understanding of LCTs' performance impacts can help healthcare firms invest their limited resources in IT projects that contribute positively to the bottom line.

Essay 2 focuses on filling the gap in the literature by surveying healthcare staff on their perceptions of LCTs' impact on performance. This study also aimed at identifying mediating and moderating factors that could offer healthcare firms an enhanced understanding of the factors impacting the successful deployment and use of LCTs.

Healthcare staff are critical for the successful adoption of LCTs. Prior studies have highlighted adoption challenges due to concerns of staff, such as security and privacy implications (Vilamovska et al., 2009; Fosso Wamba et al., 2013). The study's findings in Essay 2 empower leaders in healthcare to devise strategies for the successful deployment of LCTs by understanding the perceptions of their staff about LCTs. As implementing LCTs is costly, potentially involving millions of dollars, healthcare firms could make better investment decisions in the use of scarce resources.

References

Aboelmaged, M., & Hashem, G. (2018). RFID application in patient and medical asset operations management: A technology, organizational and environmental (TOE) perspective into key enablers and impediments. *International Journal of Medical Informatics*, *118*, 58–64. https://doi.org/10.1016/j.ijmedinf.2018.07.009

Advisory Board. (2020, April 3). *CMS: US health care spending will reach $4T in 2020*. (2020, April 3). https://www.advisory.com/daily-briefing/2020/04/03/health-spending

Alfian, G., Syafrudin, M., Ijaz, M., Syaekhoni, M., Fitriyani, N., & Rhee, J. (2018). A personalized healthcare monitoring system for diabetic patients by utilizing BLE-based sensors and real-time data processing. *Sensors*, *18*(7), Article 2183. https://doi.org/10.3390/s18072183

Álvarez López, Y., Franssen, J., Álvarez Narciandi, G., Pagnozzi, J., González-Pinto Arrillaga, I., & Las-Heras Andrés, F. (2018). RFID technology for management and tracking: E-health applications. *Sensors*, *18*(8), Article 2663. https://doi.org/10.3390/s18082663

Arunachalam, S. P., Marisamy, G., Sir, M., Nestler, D., Hellmich, T., & Pasupathy, K. (2016). Linking patient alone time and provider time to staffing levels and LOS at the emergency department: A RFID based study. In W.-T. Fu, L. Hodges, K. Zheng, G. Stiglic, & A. Blandford (Eds.), *2016 IEEE International Conference on Healthcare Informatics* (pp. 102–105). IEEE. https://doi.org/10.1109/ichi.2016.17

Arunachalam, S. P., Sir, M., Marisamy, G., Sadosty, A., Nestler, D., Hellmich, T., & Pasupathy, K. (2017). Identifying factors influencing patient alone time at the emergency department using RFID data: What is next? In S. T. C. Wong, M. D. Wang,

& A. F. Laine (Eds.), *2017 IEEE EMBS International Conference on Biomedical & Health Informatics* (pp. 225–228). IEEE. https://doi.org/10.1109/bhi.2017.7897246

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Boulos, M. N. K., & Berry, G. (2012). Real-time locating systems (RTLS) in healthcare: A condensed primer. *International Journal of Health Geographics*, *11*(1), 1–8. https://doi.org/10.1186/1476-072X-11-25

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2020). Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information & Management*, *57*(1), Article 103141. https://doi.org/10.1016/j.im.2019.01.003

Cucinotta, D., & Vanelli, M. (2020). WHO declares COVID-19 a pandemic. *Acta Bio Medica: Atenei Parmensis*, *91*(1), 157–160. https://doi.org/10.23750/abm.v91i1.9397

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3C1105::AID-SMJ133%3E3.0.CO;2-E

Evans, M. (2020, September 15). Hospitals failed to fully contain COVID-19 inside their walls. *Wall Street Journal*. https://www.wsj.com/articles/hospitals-failed-to-fully-contain-covid-19-inside-their-walls-11600176536

Evans, M., & Berzon, A. (2020, September 30). Why hospitals can't handle Covid surges: They're flying blind. *Wall Street Journal*. https://www.wsj.com/articles/hospitals-covid-surge-data-11601478409

Fosso Wamba, S. (2012). RFID-enabled healthcare applications, issues and benefits: An archival analysis (1997–2011). *Journal of Medical Systems*, *36*(6), 3393–3398. https://doi.org/10.1007/s10916-011-9807-x

Fosso Wamba, S., Anand, A., & Carter, L. (2013). A literature review of RFID-enabled healthcare applications and issues. *International Journal of Information Management*, *33*(5), 875–891. https://doi.org/10.1016/j.ijinfomgt.2013.07.005

Gupta, G., Kundu, T., & Codanda, A. A. (2015). An integrated conceptual framework for RFID enabled healthcare. *Independent Journal of Management & Production*, *6*(4), 946–961. https://doi.org/10.14807/ijmp.v6i4.356

Jones, E. C., & Gupta, S. (2015). Hospital supply chain management by implementing RFID. *International Journal of Supply Chain Management*, *4*(3), 1–6.

Joshi, A., Benitez, J., Huygh, T., Ruiz, L., & De Haes, S. (2022). Impact of IT governance process capability on business performance: Theory and empirical evidence. *Decision Support Systems*, *153*, Article 113668. https://doi.org/10.1016/j.dss.2021.113668

Lui, A. K., Lee, M., & Ngai, E. W. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), Article 103169. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., Pateli, A., & van de Wetering, R. (2021). IT architecture flexibility and IT governance decentralisation as drivers of IT-enabled dynamic capabilities and competitive performance: The moderating effect of the external environment. *European Journal of Information Systems*, *30*(5), 512–540. https://doi.org/10.1080/0960085X.2020.1808541

Moatari-Kazerouni, A., & Bendavid, Y. (2017). Improving logistics processes of surgical instruments: Case of RFID technology. *Business Process Management Journal*, *23*(2), 448–466. https://doi.org/10.1108/BPMJ-06-2016-0127

Naresh, V. S., Reddi, S., & Murthy, N. V. (2020). Secure lightweight IoT integrated RFID mobile healthcare system. *Wireless Communications and Mobile Computing*, *2020*, Article 1468281. https://doi.org/10.1155/2020/1468281

Reis, J., Amorim, M., Melão, N., & Matos, P. (2018). Digital transformation: A literature review and guidelines for future research. In Á. Rocha, H. Adeli, L. P. Reis, S. Costanzo (Eds.), *Trends and advances in information systems and technologies: WorldCIST'18 2018* (Vol. 1, pp. 411–421). Springer. https://doi.org/10.1007/978-3-319-77703-0_41

Reyes, P. M., Li, S., & Visich, J. K. (2016). Determinants of RFID adoption stage and perceived benefits. *European Journal of Operational Research*, *254*(3), 801–812. https://doi.org/10.1016/j.ejor.2016.03.051

RFID: What's the frequency, healthcare? (2019, August 23). Healthcare Purchasing News. https://www.hpnonline.com/sourcing-logistics/article/21092222/rfid-whats-the-frequency-healthcare

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Ting, S. L., Kwok, S. K., Tsang, A. H., & Lee, W. B. (2011). Critical elements and lessons learnt from the implementation of an RFID-enabled healthcare management system in a medical organization. *Journal of Medical Systems*, *35*(4), 657–669. https://doi.org/10.1007/s10916-009-9403-5

Vilamovska, A. M., Hatziandreu, E., Schindler, H. R., van Oranje-Nassau, C., De Vries, H., & Krapels, J. (2009). Study on the requirements and options for RFID application in healthcare identifying areas for radio frequency identification deployment in healthcare delivery: A review of relevant literature. *Directorate General Information Society and Media*, *13*(1), 223–238.

Yazici, H. J. (2014). An exploratory analysis of hospital perspectives on real time information requirements and perceived benefits of RFID technology for future adoption. *International Journal of Information Management*, *34*(5), 603–621. https://doi.org/10.1016/j.ijinfomgt.2014.04.010

Yeoh, C. B., Van Rooyen, C., Tan, K. S., Mascarenhas, J., Yang, G., Kerpelev, M., & Tollinche, L. E. (2019). Real time locating systems and sustainability of perioperative efficiency of anesthesiologists. *EC Anaesthesia*, *5*(8), 233–238.

ESSAY 1: EXPLORING THE IMPACTS OF LOCATING CAPABILITIES TECHNOLOGIES ON HEALTHCARE FINANCIAL PERFORMANCE

ABSTRACT

Healthcare uses locating capabilities technologies (LCTs) such as radio-frequency identification and real-time location systems to track assets and people. Firms in healthcare have struggled to understand LCTs' impacts, and this study explores the effects of LCTs by applying the dynamic capabilities theory. This study compares two matched groups of healthcare firms: those that used LCTs and those that did not. This paper uses secondary data to compare the two groups by performing independent *t*-tests and difference-in-differences analysis to compare the two groups' financial measures, such as return on assets, net operating profit margin, and net income margin. Findings from this study provide an understanding of LCTs' impacts on healthcare to empower decision-makers in prioritizing information technology investments.

Keywords: locating capabilities technologies, location-based intelligence, RFID, RTLS, BLE, Wi-Fi tracking.

Essay 1: Exploring the Impacts of Locating Capabilities Technologies on Healthcare Financial Performance

Healthcare spending will grow at an annual rate of 5.4% from 2019 to 2028 (Advisory Board, 2020). Expenditures on healthcare reached $3.81 trillion in 2019 and will reach $6.19 trillion by 2028 (Advisory Board, 2020).

Investments in information technology, such as locating technologies, account for a significant slice of IT budgets (“RFID: What’s the frequency,” 2019). While radio-frequency identification (RFID) has been the locating technology of choice in healthcare, other technologies such as real-time locating systems (RTLS), Bluetooth low energy, and Wi-Fi location tracking are becoming more common (Vilamovska et al., 2009). Location tracking technology works by attaching tags to people and objects that store location information that reader devices retrieve to determine the location of things (Aboelmaged & Hashem, 2018; Álvarez López et al., 2018; Boulos et al., 2012; Gupta et al., 2015; Fosso Wamba, 2011; Fosso Wamba et al., 2013, Naresh, 2020). While RFID determines the approximate location of mostly static objects, RTLS can track mobile targets such as ventilators, intravenous pumps, and people in real time (Aboelmaged & Hashem, 2018; Boulos & Berry, 2012; Ersol & Fescioglu-Unver, 2017; Fisher & Monahan, 2012; Naresh et al., 2020; Yeoh et al., 2019).

Although LCTs have been in healthcare for about two decades, firms have reported technological, data management and security, and financial adoption challenges (Fosso Wamba et al., 2013; Vilamovska et al., 2009). For the last ten years, most healthcare firms have dedicated their resources to modernizing their electronic medical record (EMR) systems and ICD-10 (International Classification of Diseases) conversions (“RFID: What’s the frequency,” 2019). As a result, most healthcare firms have not been investing in other IT projects, such as deploying LCTs ("RFID: What's the frequency," 2019).

Most healthcare firms are completing their EMR modernization projects (“RFID: What’s the frequency,” 2019). Consequently, these firms want to invest in new information technology (IT) to drive performance. However, healthcare decision-makers face significant challenges in evaluating IT projects such as LCTs due to a lack of tools for understanding the financial performance impacts of LCTs ("RFID: What's the frequency," 2019). Thus, it is vitally essential for these firms to determine whether LCTs translate into healthcare performance (Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014).

The extant literature suggests that healthcare can potentially gain these benefits from using LCTs: efficiency, quality, and management gains (Wamba et al., 2013). However, it is not clear whether the benefits exceed the financial expenditures involved in deploying LCTs (Vilamovska et al., 2009; Wamba et al., 2013). Understanding the relationship between using LCTs and firm financial performance is vital for healthcare. First, it is costly for these firms to deploy and use LCTs, potentially costing them millions of dollars (Boulos & Berry, 2012; Gupta et al., 2015; Yazici, 2014; Yeoh et al., 2019). As the healthcare industry struggles with tight margins and limited resources, prioritizing IT investments is essential (Boulos & Berry, 2012; Fosso Wamba et al., 2013). Second, prior studies have suggested that firms in healthcare appear to abandon or significantly minimize the use of LCTs in their business processes due to challenges in harnessing the technology (Arunachalam et al., 2016, 2017). Third, extant literature lacks empirical studies that investigate the performance impacts of LCTs by analyzing secondary data (Fosso Wamba et al., 2013).

This study postulated that using LCTs positively impacts healthcare firms' financial performance (return on assets [ROA], net operating profit margin [NOPM], and net income margin [NIM]), applying the dynamic capabilities (DC) theory. The secondary data analysis compared the treatment group of hospitals that implemented LCTs with the control group of hospitals that did not.

Literature Review

Locating Capabilities Technologies in Healthcare

The literature on LCTs concentrates on RFID and RTLS. While studies on Bluetooth low energy are lacking, the technology is finding application in wearable personal health devices; for instance, Alfian et al. (2018) used it to predict the onset of a diabetes diagnosis.

Healthcare uses RFID to manage assets, patients, and staff (Wamba et al., 2013). Fosso Wamba et al. (2013) reported that RFID-enabled asset management is considered one of the most critical applications due to its potential cost savings. The authors also reported improved patient and staff management benefits.

Healthcare organizations have faced challenges in deploying and using RFID-enabled applications due to technology, data management, security, privacy, financial, and organizational capability issues (Wamba et al., 2013). Technological problems involve a lack of network infrastructure that can support RFID-enabled applications, potential interference of RFID systems with medical equipment, difficulty in clearly defining the scope of RFID-enabled projects, and the technical realization of such tasks (Wamba et al., 2011). Data management, security, and privacy issues involve RFID data integrity and reliability, management of extensive data generated by RFID systems, and RFID-enabled business intelligence (Vilamovska et al., 2009). Organizational and financial issues involve conducting a cost-benefit analysis, managing changes, developing skills to support emerging RFID-enabled healthcare processes, controlling the complexity involved in integrating RFID with EMR and enterprise resource planning systems, and understanding healthcare organizational complexity, culture, and norms (Fosso Wamba et al., 2013).

Performance Impacts of Locating Capabilities Technologies on Healthcare

There are different ways to measure the performance impacts of LCTs in a healthcare setting. Yazici (2014) collected data from 81 operational directors and discovered that RFID as a locating capability is linked to hospital operation efficiency and increased patient satisfaction. This study also reported that staff capabilities, readiness, and IT investment contribute to the benefits. Arunachalam et al. (2016, 2017) studied the impact of RFID on patient management and reported that hospitals could monitor patient alone time and provider time to optimize staffing levels and reduce the length of stay.

Asset transfers and logistics processes are challenging in healthcare environments. Transfers involve exchanging medical devices such as ventilators and intravenous pumps between departments (Ersol & Fescioglu-Unver, 2017). Ersol and Fescioglu-Unver (2017) used sorting time series forecasting methods to arrive at optimal asset transfer policies, enhancing the efficiency of equipment use. Moatari-Kazerouni and Bendavid (2017) studied the logistics processes of surgical instruments and reported the performance benefits of tagging individual devices due to reduced re-processing time of soiled instruments and staff labor costs.

LCTs are evolving to further realize the performance benefits by bundling the technologies with the Internet of Things (IoT) and electronic data interchange. Amendola et al. (2014) bundled RFID with IoT to monitor patient health and gather environmental information such as temperature, humidity, and the presence of gases. Naresh et al. (2020) used physiological data from IoT sensors and RFID patient identification data to devise patient safety solutions. Bradley et al. (2018) bundled RFID with electronic data interchange to realize lower supply chain and human resource costs.

Another example of the evolution of locating capabilities is the study Asamoah et al. (2018) performed on using information visibility from RFID to provide real-time scheduling capability to patients, reducing long queue times and improving patient satisfaction. Jones and Gupta (2015) studied the impact of integrating RFID with enterprise resource planning systems and reported patient safety benefits resulting from properly handling medications and maintaining the stock of critical medicine and surgical supplies.

Table 1 below summarizes the performance impacts of LCTs in healthcare from the extant literature.

Table 1. Performance Impacts of Locating Capabilities Technologies on Healthcare from Extant Literature

Study	Performance Impacts of LCTs on Healthcare
Yazici (2014)	Improved hospital operation efficiency and patient satisfaction
Amendola et al. (2014)	Bundled RFID with IoT to monitor patient health and gathered environmental information such as temperature, humidity, and presence of gases
Jones & Gupta (2015)	Realized patient safety benefits by properly handling medications and maintaining the stock of critical medicine and surgical supplies
Asamoah et al. (2018)	Implemented real-time scheduling capability for patients, reducing long queues times and improving patient satisfaction
Arunachalam et al. (2016, 2017)	Optimized staffing levels and reduced length of stay by monitoring patient alone time and provider time
Ersol & Fescioglu-Unver (2017)	Optimized asset transfer policies by enhancing the efficiency of equipment used
Moatari-Kazerouni & Bendavid (2017)	Reduced re-processing time of soiled instruments and staff labor costs
Naresh et al. (2020)	Devised patient safety solutions using physiological data from IoT sensors and LCT-generated patient identification data

Note. LCTs = locating capabilities technologies; RFID = radio-frequency identification; IoT = Internet of Things.

Theoretical Background and Hypotheses Development

Dynamic Capabilities Theory

According to Teece et al. (1997), DC refers to "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p.516). Thus, DC enables firms to create and sustain competitive advantages. The DC theory extended the resource-based view (RBV) theory (Barney, 1991; Eisenhardt & Martin, 2000) to account for how firms develop and configure resources in a dynamic environment. Resource attributes such as value, rarity, imperfect imitability, and non-interchangeability, according to RBV, allow forms to create and sustain competitive advantages (Barney, 1991). Three activities performed by organizations (sensing, seizing, and transforming) represent the foundation of DC (Teece et al., 1997); sensing enables firms to explore external opportunities. Seizing activities allow firms to enhance their products and services through innovative business models, and transforming activities drive firms to adapt their business processes to meet market needs.

Teece et al. (1997, p.518) posited that

> the essence of competencies and capabilities is embedded in organizational processes of one kind or another. But the content of these processes and the opportunities they afford for developing competitive advantage at any point in time are shaped by the assets the firm possesses and by the evolutionary path it has adopted. Hence organizational processes are shaped by a firm's asset positions.

Consistent with these arguments, this study posits a positive relationship between LCTs as IT resources and sustained competitive advantage.

Dependent Variable: Healthcare Financial Performance

Healthcare financial performance considers three financial measures: ROA, NOPM, and NIM; ROA measures the extent to which a firm can generate profits using its assets, NOPM accounts for how much profit a company makes on a dollar of sales after paying for variable costs of products or services (such as wages before interest or tax payments), and NIM states how much a firm's net income is as a percentage of its revenues (Koen & Oberholster, 1999). Prior studies have identified financial performance indicators due to LCTs use, such as revenue growth and cost savings (Arunachalam et al., 2016, 2017; Jones & Gupta, 2015; Moatari-Kazerouni & Bendavid, 2017; Yazici, 2014).

Information Technology Capability and Firm Performance

Applying DC theory to the IT context, extant literature has demonstrated a positive relationship between the firm's specific IT capabilities and performance. Specifically, several researchers have established that IT infrastructural capabilities and embedded routines can enable firms to achieve competitive advantage (Bharadwaj, 2000; Mata et al., 1995; Pavlou & El Sawy, 2006; Ravichandran & Lertwongsatien, 2005; Ross et al., 1996). These include software, hardware, and communication systems and their capabilities that provide firm agility and performance, offering the ability to coordinate and dynamically reconfigure resources (Byrd & Turner, 2000; Sambamurthy et al., 2003).

Locating Capabilities Technologies

Applying the theoretical tenets of IT capabilities (Bharadwaj, 2000; Ravichandran & Lertwongsatien, 2005; Ross et al., 1996) in the healthcare domain, I argue that LCTs can enable healthcare organizations to coordinate and reconfigure their resources for sustained competitive advantage in a fast-changing environment. In this regard, RFID and RTLS are the two LCTs used to pinpoint and track patients, staff, and assets such as medical equipment and supplies. Therefore, this study argues for the capabilities generated by LCTs in healthcare firms for tracking patients, staff, and assets. To illustrate the use of LCTs in the healthcare setting, I present some example scenarios in the following paragraphs.

Extant literature has established a positive relationship between LCTs and firm performance in managing assets, patients, or staff (Aboelmaged & Hashem, 2018; Amendola et al., 2014; Arunachalam et al., 2016, 2017; Asamoah et al., 2018; Boulos & Berry, 2012; Bradley et al., 2018; Ersol & Fescioglu-Unver, 2017; Fisher & Monahan, 2012; Jones & Gupta, 2015; Moatari-Kazerouni & Bendavid, 2017; Naresh et al., 2020; Vilamovska et al., 2009; Volland et al., 2017; Yazici, 2014). By enabling tracking of patients, staff, and equipment, LCTs can improve staff scheduling and medical equipment usage by assigning resources where they are needed in real time (Arunachalam et al., 2016, 2017; Asamoah et al., 2018; Ersol & Fescioglu-Unver, 2017; Yazici, 2014), identify bottlenecks in their operations and devise solutions (Arunachalam et al., 2016, 2017; Yazici, 2014), and ultimately help patients in the process. The bundling of LCTs' capabilities with enterprise resource planning and EMR systems enables the streamlining of several real-time processes (e.g., the requisition process in the supply chain can track supplies in real time; Amendola et al., 2014). Integration with EMR systems can also enable healthcare organizations to identify cost-effective therapies by evaluating the flow of patients, supplies used, and providers involved in care delivery (Jones & Gupta, 2015; Moatari-Kazerouni & Bendavid, 2017; Yazici, 2014). These real-world uses illustrate that LCTs can empower healthcare firms to efficiently use resources such as staff, medical assets, and supplies, leading to optimal patient care and sustainable competitive advantages. Therefore, I hypothesize that:

H_1: LCTs are positively associated with ROA.

H_2: LCTs are positively associated with NOPM.

H_3: LCTs are positively associated with NIM.

Methodology

Sample Design

This study's data originated from a commercial healthcare data provider that provides paid subscription services for accessing its commercial intelligence solutions. In addition to collecting data from public sources such as the CMS, the provider collects data from healthcare firms via surveys and proprietary sources. The data in this paper covers 11 years of financial information (2010–2020) from hospitals that provide Medicare services. The data set also includes information on hospitals' IT investments, such as LCTs (i.e., RFID and RTLS) and medical record systems (i.e., Epic and Cerner).

Research Design and Methods of Data Collection

Matched-Pair Group Design

This study employed a matched-comparison group design with a treatment group containing hospitals that used LCTs and the matched control group that did not use LCTs to compare the performance between the two groups. Accounting, finance, and marketing research domains (i.e., Balakrishnan et al., 1996; Jain & Kin, 2022) have used this methodology widely to study the effects of variables on treatment groups. In the matched-pair comparison, two groups of firms (or any entities) are compared to each other. The treatment group refers to the group of firms that received the intervention (e.g., LCT investments), while the control group refers to the group of firms that did not receive the intervention. The researcher then selects a suitable match for each treatment group firm from among the control group firms. This selection can be based on criteria such as size, location, industry, and so forth and is informed by extant literature. The matched control group provides a benchmark for comparisons while reducing the confounding effects of extraneous variables such as market dynamics (Bharadwaj, 2000). In other words, matched-pair comparison serves to control for the influences of any confounds or other extraneous factors while testing for the hypothesized relationships.

Consistent with this approach, this study split the sample into a treatment group and a control group. The treatment group contained the hospitals which have implemented LCTs, while the control group contained the hospitals which have not implemented LCTs. In studies about healthcare organizations, prior work has used sizing schemes based on the number of staffed hospital beds, such as the effects of hospital size on patient satisfaction (McFarland et al., 2017) and hospital quality comparison (Geweke et al., 2003; Gowrisankaran & Town, 2003). In addition, prior studies have investigated the differences between rural and urban hospitals, including the impacts of Medicaid expansion (Kaufman et al., 2016), rural versus urban hospital performance (Garcia-Lacalle & Martin, 2010), and Medicaid expansion and hospital closures (Lindrooth et al., 2018). Hospital size and geographical classification have also been used as control variables in several studies, as they are argued to control for extraneous variability in hospitals (i.e., Geweke et al., 2003; Gowrisankaran & Town, 2003; Murphy & Wilson, 2021; Hamadi et al., 2021). Therefore, based on prior literature, two key criteria were chosen for the matched-pair comparison: the size of the hospital and the geographical classification (state, rural vs. urban) of the hospital. Hospitals were selected from the control group that matched the two criteria for each treatment group hospital. This study estimated hospital size by the number of staffed beds and location (state, rural vs. urban). Table 2, adapted from Tian (2016), depicts the hospital sizing scheme.

Table 2. Sizing Hospitals

Region and geographic classification (rural vs. urban)	Hospital bed size		
	Small	Medium	Large
Northeast			
Rural	1–49	50–99	100+
Urban	1–249	250–424	425+
Midwest			
Rural	1–29	30–49	50+
Urban	1–249	250–374	375+
Southern			
Rural	1–39	40–74	75+
Urban	1–249	250–449	450+
Western			
Rural	1–24	25–44	45+
Urban	1–199	200–324	325+

The primary difference between the two groups was whether they had used LCTs. The study determined hospital size by the number of patient beds and geographic area (state, rural or urban) to account for these firms' markets. As a result, it included 92 hospitals in each group for difference-in-differences (DID) and *t*-test statistical analysis to investigate the financial performance impacts of LCTs one, two, three, four, and five years after LCT implementation (deployment). The statistical analysis compared the two groups on financial performance measures such as ROA, NOPM, and NIM.

Results

Difference-in-Differences Analysis

The statistical analysis technique DID evaluates the impact of an event (i.e., deployment of LCTs) by comparing the treatment and control groups before and after the implementation of the event. Extant literature has used DID analysis widely to assess the impacts of policy changes and natural events (i.e., the Covid-19 pandemic; Wooldridge, 2015). This study performed the DID analysis using regression Equation 1.

$$Y= \beta 0 + \beta 1*[Time] + \beta 2*[Intervention] + \beta 3*[Time*Intervention] + \varepsilon \quad (1)$$

Table 3 shows the variables in the regression equation. Table 4 depicts the descriptive statistics on the variables in the DID analysis.

Table 3. Variables in the Regression Equation

Variable	Role in the Regression Equation
Y	The dependent variable, such as ROA (return on assets), NOPM (net operating profit margin), and NIM (net income margin)
Time	A categorical variable that denotes 0 for measurements before the event (implementation of LCTs) and 1 for financial performance measures after implementation
Intervention	A categorical variable that denotes the control group (without LCTs) with 0 and the treatment group (with LCTs) with 1
Time * Intervention	β3 represents the difference-in-differences using the interaction term between time and intervention (LCTs implementation)

Table 4. Descriptive Statistics: Return on Assets, Net Operating Profit Margin, and Net Income Margin

Financial Measure	Obs.	Minimum	Maximum	*M*	*SD*
ROA	1,100	-2.3537	6.9961	.040783	.3622972
NOPM	1,098	-1.4340	1.4610	-.041597	.1565971
NIM	1,099	-.9080	1.4860	.033748	.1157084

Note. *Obs. = observations; ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin (for both treatment and control groups).*

Difference-in-Differences Analysis Results on Return on Assets

Table 5 shows the regression analysis results using ROA as the dependent variable. β3, the coefficient representing DID, was negative (β3 = -0.045) at a 0.10 significance level. This result suggests that the treatment (LCTs implementation) negatively impacted ROA. Healthcare firms in the control group achieved better ROA. Thus, H_1 is not supported.

Table 5. Regression Results using Return on Assets as the Dependent Variable

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Significance
	β	SE	β		
(Constant)	0.038	0.027		1.412	0.158
Time	0.026	0.032	0.027	0.824	0.41
DID	-0.045	0.024	-0.061	-1.875	0.061

Note. DID = difference-in-differences.

Difference-in-Differences Analysis Results on Net Operating Profit Margin

Table 6 shows the regression analysis results using NOPM as the dependent variable. β3, the coefficient representing DID, was negative (β3 = -0.028) at a 0.01 significance level. This result suggests that the treatment (LCTs implementation) negatively impacted NOPM. Healthcare firms in the control group achieved better NOPM. Thus, H_2 is not supported.

Table 6. Regression Results using Net Operating Profit Margin as the Dependent Variable

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Significance
	β	SE	β		
(Constant)	-0.041	0.012		-3.554	0
Time	0.014	0.014	0.032	0.992	0.321
DID	-0.028	0.01	-0.089	-2.747	0.006

Note. DID = difference-in-differences.

Difference-in-Differences Analysis Results on Net Income Margin

Table 7 shows the regression analysis results using NIM as the dependent variable. β3, the coefficient representing DID, was negative (β3 = -0.020) at a 0.05 significance level. This result suggests that the treatment (LCTs implementation) negatively impacted NIM. Healthcare firms in the control group achieved better NIM. Thus, H_3 is not supported.

Table 7. Regression Results using Net Income Margin as the Dependent Variable

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Significance
	β	SE	β		
(Constant)	0.038	0.009		4.415	0
Time	0.005	0.01	0.016	0.501	0.617
DID	-0.02	0.008	-0.083	-2.556	.011

Note. DID = difference-in-differences.

Independent Samples *t*-Tests

Extant literature has used independent samples *t*-tests to compare the means of two sets of data (i.e., Bharadwaj's [2000] study on the performance impacts of IT). This study performed *t*-tests to compare the treatment group (with LCTs) and the control group (without LCTs). The analysis covered the financial performance measures (ROA, NOPM, and NIM) one, two, three, four, and five years after LCT implementation. Table 8 depicts the descriptive statistics of the financial performance measurements for the treatment group (Group 1: healthcare firms with LCTs) and the control group (Group 2: healthcare firms without LCTs). The results of the *t*-tests are in Appendix A.

The *t*-tests results suggest similarities with the findings of the DID analysis, where the treatment group (with LCTs) performed worse than the control group (without LCTs). Notably, during the five years after LCT implementation, the treatment group never achieved better financial performance than the control group. Table 9 shows the summary of the findings.

Table 8. Descriptive Statistics on Financial Measures for the Treatment and Control Groups

Financial Measure	Group	*n*	*M*	*SD*	*SE M*
ROA Year 1	1	92	.008807	.2028972	.0211535
	2	90	.053043	.1205737	.0127096
ROA Year 2	1	92	.096624	.7834319	.0816784
	2	91	.046189	.1632102	.0171091
ROA Year 3	1	92	-.016966	.2425249	.0252850
	2	92	.050455	.1196635	.0124758
ROA Year 4	1	92	-.001309	.1838126	.0191638
	2	92	.060140	.1747613	.0182201
ROA Year 5	1	92	.037461	.1827582	.0190539
	2	92	.109125	.7852099	.0818638
NOPM Year 1	1	92	-.062348	.1601641	.0166983
	2	90	-.030544	.1099964	.0115946
NOPM Year 2	1	91	-.029495	.1190749	.0124824
	2	91	-.022857	.1234606	.0129422
NOPM Year 3	1	92	-.072120	.1792815	.0186914
	2	92	-.032663	.1573221	.0164020
NOPM Year 4	1	92	-.069543	.1507068	.0157123
	2	92	-.027098	.1656524	.0172705
NOPM Year 5	1	92	-.045435	.1713032	.0178596
	2	91	-.024209	.2172221	.0227711
NIM Year 1	1	92	.025848	.1374677	.0143320
	2	90	.041244	.0789433	.0083214
NIM Year 2	1	91	.033088	.1091199	.0114389
	2	91	.040165	.0924946	.0096961
NIM Year 3	1	92	-.002848	.1554456	.0162063
	2	92	.040859	.0886646	.0092439
NIM Year 4	1	92	.015598	.1288432	.0134328
	2	92	.044804	.0944508	.0098472
NIM Year 5	1	92	.044587	.1171136	.0122099
	2	91	.045857	.1811189	.0189864

Note. *Group 1: Healthcare firms with locating capabilities technologies; Group 2: Healthcare firms without locating capabilities technologies. ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin.*

Table 9. Summary Results from the t-tests between Treatment and Control Groups

Financial Measure	Impact
Return on Assets (ROA)	ROA, 3 and 4 years after LCTs implementation, was lower for the treatment group at a 0.05 significance level
Net Operating Profit Margin (NOPM)	NOPM, four years after LCTs implementation, was lower for the treatment group at a 0.10 significance level
Net Income Margin (NIM)	NIM was lower for the treatment group 3 and 4 years after LCTs implementation at 0.05 and 0.10 significance levels

Note. LCTs = locating capabilities technologies.

Discussion

This study's data analysis did not support the three hypotheses positively linking the use of LCTs to financial performance (ROA, NOPM, and NIM). Further, the results revealed that healthcare firms using LCTs actually performed significantly worse year-over-year. At first glance, these results are surprising as they seem to run counter to the theoretical tenets of DC theory. Since the findings did not agree with what DC theory predicted, it is imperative to ask why and what factors might explain this discrepancy. Why does the use of LCTs adversely impact the financial performance of healthcare firms? Could there be factors (i.e., mediators and moderators) influencing the relationship between LCT use and firm financial performance?

Prior literature on applying the DC theory to firm contexts offers some tangible explanations. The extant literature argues that additional investments in technology do not necessarily translate into performance. Hitt and Brynjolfsson (1996) referred to this as the IT productivity paradox. Rather, it is how the technology is utilized in the firm that leads to performance (Carr, 2004). In this regard, several studies have stated that the link between technology capability and performance can be mediated or moderated by other factors. Some studies have found positive associations between firm capabilities and firm performance through the mediating role of business process optimization (Frei & Harker, 1999; Ramirez et al., 2010). Other studies have identified mediators between IT capabilities and firm performance, including senior leadership involvement (Armstrong & Sambamurthy, 1999), knowledge management (Tanriverdi, 2005), organizational capability (Liang et al., 2010), and absorptive capacity (Liu et al., 2013). In addition, the extant literature also has identified moderators related to managerial capabilities: problem-solving and handling complexity (Fainshmidt et al., 2016; Macher & Mowery, 2009; Schreyögg & Kliesch-Eberl, 2007); dominant managerial logic (Kor & Mesko, 2013); managing strategy, managing performance, resource planning and assignment, alliancing and networking, managing change, strategic decision-making, competence building, organizational learning, knowledge management (Bititci et al., 2011); and managerial cognition (Kor & Mesko, 2013). Therefore, the causal chain between LCTs' capabilities and performance needs to be explored further by considering potential mediators and moderators.

Further, the dataset used in this study did not provide enough insights into how the healthcare firms in the treatment group used LCTs; this suggests that LCT use in hospitals needs to be explicated further. Refining the LCT measurement would also help in clarifying the influence of LCTs and their associated capabilities on healthcare performance. Taken together, the findings of this study provide the impetus for the study in Essay 2, which measures LCTs' capabilities and explores potential factors (i.e., mediating and moderating) in the relationship between LCTs and healthcare performance.

Limitations of this Study

This study acknowledges certain limitations. First, the data set included only hospitals billing for Medicare services and reporting LCT implementation and the year implemented. The availability of data was the limiting factor in this study. As a result, future studies might find different results by examining financial measures from all healthcare firms in the United States.

Second, the data do not tell us how healthcare firms used LCTs. For example, are LCTs used in all departments in the organization or only in limited areas? Future studies could perform case study research to better understand the use of LCTs in healthcare.

Third, the data do not show the relationship between healthcare staff and LCTs. Prior studies have reported LCT adoption challenges (i.e., Gupta et al., 2015; Yazici, 2014). Future studies could employ survey research to understand the attitudes and perceptions of LCTs by those who use the technology.

Fourth, future studies may consider additional control variables such as hospital type (i.e., adult, pediatric, or both) and payer mix (government health plans vs. private insurance) to further explore LCT performance impacts in healthcare.

Finally, the financial measures used in this study were ROA, NOPM, and NIM because of data availability. Future studies might achieve differing findings by examining additional financial measures. This study sheds light on the financial performance of the impacts of LCTs in healthcare. Its conclusions could provide these firms with a better understanding of how to harness LCTs for optimal results.

Implications for Research

Although the extant literature has established a positive association between IT capabilities and firm performance, empirical research exploring the link between LCTs and healthcare performance is lacking (i.e., Vilamovska et al., 2009; Fosso Wamba, 2012; Fosso Wamba et al., 2013). Prior studies have suggested potential performance benefits of LCTs to include gains in efficiency, quality, and management (i.e., Boulos & Berry, 2012; Ting et al., 2011; Vilamovska et al., 2009) and improved patient safety (Jones & Gupta, 2015; Naresh et al., 2020). However, to my knowledge, no prior study has empirically investigated the financial performance impacts of LCTs in healthcare utilizing secondary data. The research contributions of this study are as follows.

First, this paper contributes to research by examining secondary data from a commercial data provider to determine whether healthcare firms that deployed LCTs performed better than those that did not. This study compared the two groups' financial performance one, two, three, four, and five years after deploying LCTs, offering insights into how LCTs impact the bottom line. Grouping the firms based on geographic location (state, rural vs. urban) and size provided a mechanism to control for differences between the groups other than the deployment of LCTs. Second, this study did not only explore whether there are differences between firms that deployed LCTs and those that did not, but it also examined whether the differences are significant by performing a DID analysis. Third, this paper contributes to research by applying the DC theory in the healthcare IT context, providing future researchers with a platform to explore factors potentially impacting IT capabilities on firm performance.

Implications for Practice

Healthcare firms contend with limited resources for IT projects, and decision-makers face significant challenges in prioritizing IT investments (Vilamovska et al., 2009; Fosso Wamba et al., 2013). This study has several practical implications. First, despite the findings of a lack of positive association between LCTs and hospital performance, hospitals should not refrain from investing in LCTs. Instead, this study recommends that healthcare organizations consider other factors (i.e., mediating and moderating variables) that may impact the relationship between LCTs and healthcare performance. As indicated previously, the extant literature, such as Brynjolfsson (1993), has discussed the IT productivity paradox where additional investments in technology do not contribute to improved performance. Later studies, such as Brynjolfsson & Hitt (1998), have posited that business process improvements mediate the relationship between IT and firm performance.

Second, this study seeks to provide an objective view of the financial impacts of LCTs on healthcare firm performance. LCTs' adoption and deployment costs within a hospital setting are high. Thus, healthcare firms need to learn from industry peers' best practices for LCTs deployment and use. Third, this study offers insights into how LCTs impact hospital performance over time. Healthcare decision-makers can use these insights to understand the time-to-value equation better, as this study's analysis examined performance five years after the deployment of LCTs. Finally, healthcare firms can also learn from peers who have successfully implemented LCTs to drive firm performance. The data set for this research included groupings of hospitals based on geographic location and size.

Conclusion

To the best of my knowledge, this is the first study examining secondary data related to the financial performance of healthcare firms that used LCTs. The results from the statistical analysis were surprising since they stood in stark contrast with the established research that positively links IT investments, such as the implementation of LCTs, with firm performance (i.e., Amendola et al.,2014; Jones & Gupta, 2015; Naresh et al., 2020; Yazici, 2014).

As the secondary data set included a few healthcare firms that enhanced their financial performance using LCTs, this paper recommends that future studies explore how these firms achieved this outcome via case studies (qualitative method). Healthcare could benefit from this endeavor in optimizing performance benefits from healthcare IT investments. Essay 2 of my dissertation focuses on identifying potential mediators and moderators in the relationship between LCTs and healthcare performance. Healthcare decision-makers could use the findings to advise their approach to deploy LCTs.

References

Aboelmaged, M., & Hashem, G. (2018). RFID application in patient and medical asset operations management: A technology, organizational and environmental (TOE) perspective into key enablers and impediments. *International Journal of Medical Informatics*, *118*, 58–64. https://doi.org/10.1016/j.ijmedinf.2018.07.009

Alfian, G., Syafrudin, M., Ijaz, M. F., Syaekhoni, M. A., Fitriyani, N. L., & Rhee, J. (2018). A personalized healthcare monitoring system for diabetic patients by utilizing BLE-based sensors and real-time data processing. *Sensors*, *18*(7), Article 2183. https://doi.org/10.3390/s18072183

Álvarez López, Y., Franssen, J., Álvarez Narciandi, G., Pagnozzi, J., González-Pinto Arrillaga, I., & Las-Heras Andrés, F. (2018). RFID technology for management and tracking: E-health applications. *Sensors*, *18*(8), Article 2663. https://doi.org/10.3390/s18082663

Amendola, S., Lodato, R., Manzari, S., Occhiuzzi, C., & Marrocco, G. (2014). RFID technology for IoT-based personal healthcare in smart spaces. *IEEE Internet of Things Journal*, *1*(2), 144–152. https://doi.org/10.1109/JIOT.2014.2313981

Armstrong, C. P., & Sambamurthy, V. (1999). Information technology assimilation in firms: The influence of senior leadership and IT infrastructures. *Information Systems Research*, *10*(4), 304–327. https://doi.org/10.1287/isre.10.4.304

Arunachalam, S. P., Marisamy, G., Sir, M., Nestler, D., Hellmich, T., & Pasupathy, K. (2016). Linking patient alone time and provider time to staffing levels and LOS at the emergency department: A RFID based study. In W.-T. Fu, L. Hodges, K. Zheng, G. Stiglic, & A. Blandford (Eds.), *2016 IEEE International Conference on Healthcare Informatics* (pp. 102–105). IEEE. https://doi.org/10.1109/ichi.2016.17

Arunachalam, S. P., Sir, M., Marisamy, G., Sadosty, A., Nestler, D., Hellmich, T., & Pasupathy, K. (2017). Identifying factors influencing patient alone time at the emergency department using RFID data: What is next? In S. T. C. Wong, M. D. Wang, & A. F. Laine (Eds.), *2017 IEEE EMBS International Conference on Biomedical & Health Informatics* (pp. 225–228). IEEE. https://doi.org/10.1109/bhi.2017.7897246

Asamoah, D. A., Sharda, R., Rude, H. N., & Doran, D. (2018). RFID-based information visibility for hospital operations: Exploring its positive effects using discrete event simulation. *Health Care Management Science*, *21*(3), 305–316. https://doi.org/10.1007/s10729-016-9386-y

Balakrishnan, R., Linsmeier, T. J., & Venkatachalam, M. (1996). Financial benefits from JIT adoption: Effects of customer concentration and cost structure. *Accounting Review*, *71*(2), 183–205.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, *24*(1), 169–196. https://doi.org/10.2307/3250983

Bititci, U. S., Ackermann, F., Ates, A., Davies, J., Garengo, P., Gibb, S., MacBryde, J., Mackay, D., Maguire, C., van der Meer, R., Shafti, F., Bourne, M., & Firat, S. U. (2011). Managerial processes: Business process that sustain performance. *International Journal of Operations & Production Management*, *31*(8), 851–891. https://doi.org/10.1108/01443571111153076

Boulos, M. N. K., & Berry, G. (2012). Real-time locating systems (RTLS) in healthcare: A condensed primer. *International Journal of Health Geographics*, *11*(1), 1–8. https://doi.org/10.1186/1476-072X-11-25

Bradley, R. V., Esper, T. L., In, J., Lee, K. B., Bichescu, B. C., & Byrd, T. A. (2018). The joint use of RFID and EDI: Implications for hospital performance. *Production and Operations Management*, *27*(11), 2071–2090. https://doi.org/10.1111/poms.12955

Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM*, *36*(12), 66-77. https://doi.org/10.1145/163298.163309

Brynjolfsson, E., & Hitt, L. M. (1998). Beyond the productivity paradox. *Communications of the ACM*, *41*(8), 49-55. https://doi.org/10.1145/280324.280332

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3C1105::AID-SMJ133%3E3.0.CO;2-E

Ersol, D., & Fescioglu-Unver, N. (2017). Heuristic policies for mobile asset sharing within hospitals. *Computers & Industrial Engineering*, *111*, 352–363. https://doi.org/10.1016/j.cie.2017.07.038

Frei, F. X., & Harker, P. T. (1999). Measuring aggregate process performance using AHP. *European Journal of Operational Research*, *116*(2), 436–442. https://doi.org/10.1016/S0377-2217(98)00134-9

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. *Journal of Management Studies*, *53*(8), 1348–1380. https://doi.org/10.1111/joms.12213

Fisher, J. A., & Monahan, T. (2012). Evaluation of real-time location systems in their hospital contexts. *International Journal of Medical Informatics*, *81*(10), 705–712. https://doi.org/10.1016/j.ijmedinf.2012.07.001

Fosso Wamba, S. (2012). RFID-enabled healthcare applications, issues and benefits: An archival analysis (1997–2011). *Journal of Medical Systems*, *36*(6), 3393–3398. https://doi.org/10.1007/s10916-011-9807-x

Fosso Wamba, S., Anand, A., & Carter, L. (2013). A literature review of RFID-enabled healthcare applications and issues. *International Journal of Information Management*, *33*(5), 875–891. https://doi.org/10.1016/j.ijinfomgt.2013.07.005

Garcia-Lacalle, J., & Martin, E. (2010). Rural vs urban hospital performance in a 'competitive' public health service. *Social Science & Medicine, 71*(6), 1131–1140. https://doi.org/10.1016/j.socscimed.2010.05.043

Geweke, J., Gowrisankaran, G., & Town, R. J. (2003). Bayesian inference for hospital quality in a selection model. *Econometrica, 71*(4), 1215–1238. https://doi.org/10.1111/1468-0262.00444

Gowrisankaran, G., & Town, R. J. (2003). Competition, payers, and hospital quality. *Health Services Research*, *38*(6 Pt. 1), 1403–1422. https://doi.org/10.1111%2Fj.1475-6773.2003.00185.x

Gupta, G., Kundu, T., & Codanda, A. A. (2015). An integrated conceptual framework for RFID enabled healthcare. *Independent Journal of Management & Production*, *6*(4), 946–961. https://doi.org/10.14807/ijmp.v6i4.356

Hamadi, H. Y., Martinez, D., Palenzuela, J., & Spaulding, A. C. (2021). Magnet Hospitals and 30-Day Readmission and Mortality Rates for Medicare Beneficiaries. *Medical care*, *59*(1), 6–12. https://doi.org/10.1097/MLR.0000000000001427

Hitt, L. M., & Brynjolfsson, E. (1996). Productivity, business profitability, and consumer surplus: Three different measures of information technology value. *MIS Quarterly*, *20*(2), 121–142. https://doi.org/10.2307/249475

Jain, B. A., & Kini, O. (2022). Venture capitalist participation and the post-issue operating performance of IPO firms. *Venture Capital*, 397-410. https://doi.org/10.4324/9781315235110-23

Jones, E. C., & Gupta, S. (2015). Hospital supply chain management by implementing RFID. *International Journal of Supply Chain Management*, *4*(3), 1–6.

Kaufman, B. G., Reiter, K. L., Pink, G. H., & Holmes, G. M. (2016). Medicaid expansion affects rural and urban hospitals differently. *Health Affairs*, *35*(9), 1665–1672. https://doi.org/10.1377/hlthaff.2016.0357

Koen, M., & Oberholster, J. (1999). *Analysis and interpretation of financial statements* (2nd ed.). Juta and Company Ltd.

Kor, Y. Y., & Mesko, A. (2013). Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic Management Journal*, *34*(2), 233–244. https://doi.org/10.1002/smj.2000

Liang, T. P., You, J. J., & Liu, C. C. (2010). A resource-based perspective on information technology and firm performance: A meta analysis. *Industrial Management & Data Systems*, *110*(8), 1138–1158. https://doi.org/10.1108/02635571011077807

Lindrooth, R. C., Perraillon, M. C., Hardy, R. Y., & Tung, G. J. (2018). Understanding the relationship between Medicaid expansions and hospital closures. *Health Affairs*, *37*(1), 111–120. https://doi.org/10.1377/hlthaff.2017.0976

Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, *54*(3), 1452–1462. https://doi.org/10.1016/j.dss.2012.12.016

Macher, J. T., & Mowery, D. C. (2009). Measuring dynamic capabilities: Practices and performance in semiconductor manufacturing. *British Journal of Management*, *20*(S1), S41–S62. https://doi.org/10.1111/j.1467-8551.2008.00612.x

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, *19*(4), 487–505. https://doi.org/10.2307/249630

McFarland, D. C., Shen, M. J., Parker, P., Meyerson, S., & Holcombe, R. F. (2017). Does hospital size affect patient satisfaction? *Quality Management in Health Care*, *26*(4), 205–209. https://doi.org/10.1097/QMH.0000000000000149

Moatari-Kazerouni, A., & Bendavid, Y. (2017). Improving logistics processes of surgical instruments: Case of RFID technology. *Business Process Management Journal*, *23*(2), 448–466. https://doi.org/10.1108/BPMJ-06-2016-0127

Murphy, W. H., & Wilson, G. A. (2021). Dynamic capabilities and stakeholder theory explanation of superior performance among award-winning hospitals. *International Journal of Healthcare*

Naresh, V. S., Reddi, S., & Murthy, N. V. (2020). Secure lightweight IoT integrated RFID mobile healthcare system. *Wireless Communications and Mobile Computing*, *2020*, Article 1468281. https://doi.org/10.1155/2020/1468281

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198–227. https://doi.org/10.1287/isre.1060.0094

Ramirez, R., Melville, N., & Lawler, E. (2010). Information technology infrastructure, organizational process redesign, and business value: An empirical analysis. *Decision Support Systems*, *49*(4), 417–429. https://doi.org/10.1016/j.dss.2010.05.003

Ravichandran, T., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of Management Information Systems*, *21*(4), 237–276. https://doi.org/10.1080/07421222.2005.11045820

Reyes, P. M., Li, S., & Visich, J. K. (2016). Determinants of RFID adoption stage and perceived benefits. *European Journal of Operational Research*, *254*(3), 801–812. https://doi.org/10.1016/j.ejor.2016.03.051

RFID: What's the frequency, healthcare? (2019, August 23). Healthcare Purchasing News. https://www.hpnonline.com/sourcing-logistics/article/21092222/rfid-whats-the-frequency-healthcare

Ross, J. W., Beath, C. M., & Goodhue, D. L. (1996). Develop long-term competitiveness through IT assets. *Sloan Management Review*, *38*(1), 31–42.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS quarterly*, 237-263.

Schreyögg, G., & Kliesch-Eberl, M. (2007). How dynamic can organizational capabilities be? Towards a dual-process model of capability dynamization. *Strategic Management Journal*, *28*(9), 913–933. https://doi.org/10.1002/smj.613

Tanriverdi, H. (2005). Information technology relatedness, knowledge management capability, and performance of multibusiness firms. *MIS Quarterly*, *29*(2), 311–334. https://doi.org/10.2307/25148681

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Tian W. An All-Payer View of Hospital Discharge to Postacute Care, 2013. 2016 May. In: Healthcare Cost and Utilization Project (HCUP) Statistical Briefs [Internet]. Rockville (MD): Agency for Healthcare Research and Quality (US); 2006 Feb-. Table 3, Hospital bed size categories. Available from: https://www.ncbi.nlm.nih.gov/books/NBK373736/table/sb205.t3/

Ting, S. L., Kwok, S. K., Tsang, A. H., & Lee, W. B. (2011). Critical elements and lessons learnt from the implementation of an RFID-enabled healthcare management system in a medical organization. *Journal of Medical Systems*, *35*(4), 657–669. https://doi.org/10.1007/s10916-009-9403-5

Vilamovska, A. M., Hatziandreu, E., Schindler, H. R., van Oranje-Nassau, C., De Vries, H., & Krapels, J. (2009). Study on the requirements and options for RFID application in healthcare Identifying areas for radio frequency identification deployment in healthcare delivery: A review of relevant literature. *Directorate General Information Society and Media*, *13*(1), 223–238.

Volland, J., Fügener, A., Schoenfelder, J., & Brunner, J. O. (2017). Material logistics in hospitals: A literature review. *Omega*, *69*, 82–101. https://doi.org/10.1016/j.omega.2016.08.004

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach* (6th ed.). Cengage learning.

Yazici, H. J. (2014). An exploratory analysis of hospital perspectives on real time information requirements and perceived benefits of RFID technology for future adoption. *International Journal of Information Management*, *34*(5), 603–621. https://doi.org/10.1016/j.ijinfomgt.2014.04.010

Yeoh, C. B., Van Rooyen, C., Tan, K. S., Mascarenhas, J., Yang, G., Kerpelev, M., & Tollinche, L. E. (2019). Real time locating systems and sustainability of perioperative efficiency of anesthesiologists. *EC Anaesthesia*, *5*(8), 233–238.

ESSAY 2: EXPLORING THE PERCEPTIONS OF HEALTHCARE STAFF ON LOCATING CAPABILITIES TECHNOLOGIES' IMPACT ON PERFORMANCE

ABSTRACT

Healthcare uses locating capabilities technologies (LCTs) to pinpoint assets and people. Although radio-frequency identification has been a ubiquitous technology for locating, real-time location systems, Bluetooth low energy, and Wi-Fi are finding broader applications. Healthcare firms have struggled to understand LCTs' impact on performance. This study aimed to explore the effects of LCTs by applying the dynamic capabilities theory. This paper collected and analyzed survey data from healthcare staff on their perceptions of the performance impacts of LCTs. This study's findings empower healthcare decision-makers to understand their staff's perceptions of the performance impacts of LCTs.

Keywords: Locating capabilities technologies, location-based intelligence, RFID, RTLS, BLE, Wi-Fi tracking.

Essay 2: Exploring the Perceptions of Healthcare Staff on Locating Capabilities Technologies' Impact on Performance

Locating capabilities technologies (LCTs) refer to information technology (IT) resources such as hardware, software, and business processes used to find and track objects, such as radio-frequency identification (RFID), real-time location system (RTLS), Bluetooth low energy, and wireless fidelity (Wi-Fi). These technologies locate and track objects by storing location information in tags attached to targets, such as employee badges and equipment labels. Reader devices read location information from the tags and send the data to servers throughout the enterprise. Users obtain location information via software applications visualizing the location data (Aboelmaged & Hashem, 2018; Álvarez López et al., 2018; Boulos & Berry, 2012; Fosso Wamba, 2011; Fosso Wamba et al., 2013; Gupta et al., 2015; Naresh et al., 2020). Healthcare firms face LCT adoption challenges as staff are reluctant to use the technology due to security and privacy concerns (Fosso Wamba et al., 2013; Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014). As most healthcare organizations are on the last stretch of the modernization of their electronic health record systems and ICD-10 code conversions, they are implementing LCTs to drive firm performance ("RFID: What's the frequency," 2019). However, healthcare leaders struggle to utilize their limited resources to invest in IT projects (Vilamovska et al., 2009). Thus, it is vitally essential for healthcare organizations to understand the potential performance impacts of LCTs according to their staff's perceptions (Fosso Wamba et al., 2013; Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014).

Extant literature has suggested efficiency, quality, and management gains are possible through LCT implementation (i.e., Asamoah et al., 2018; Boulos & Berry, 2012; Fisher & Monahan, 2012; Ting et al., 2011; Vilamovska et al., 2009; Yazici, 2014). However, empirical research examining the perceptions of healthcare staff on the performance impacts of LCTs is lacking (Fosso Wamba et al., 2013; Vilamovska et al., 2009).

This study answers the call by Fosso Wamba et al. (2013) in their literature review of RFID-enabled healthcare applications for future empirical studies to explore the performance impacts of LCTs. This study investigated the overarching research question: What impacts do LCTs have on healthcare performance? The sub-questions of the study were:

1. What are the dimensions of location-based intelligence (LBI) capability, and what role does LBI capability play in influencing healthcare performance?
2. Does business process optimization (BPO) mediate the relationship between LBI capability and healthcare performance?
3. What role do managerial capabilities play in influencing the relationship between LBI and BPO?
4. Do hospital characteristics such as size and location (rural vs. urban) positively moderate the relationship between BPO and performance?

The findings of this study empower decision-makers in healthcare organizations to objectively evaluate competing IT investment priorities and make informed decisions.

Literature Review

Locating Capabilities Technologies in Healthcare

Healthcare has primarily used RFID and RTLS as LCTs to locate and track objects (Vilamovska et al., 2009). While RFID identifies the approximate location of things, RTLS finds and tracks objects in real-time. Mobile objects such as ventilators, intravenous pumps, and people (staff and patients) require RTLS for real-time tracking (Boulos & Berry, 2012; Fosso Wamba et al., 2013). As healthcare firms make inroads in deploying LCTs, they face adoption challenges, such as staff resistance to adopting the technology due to privacy and security concerns and difficulties in optimizing business processes to harness the powers of LCTs (Fosso Wamba et al., 2013; Vilamovska et al., 2009).

Performance Impacts of Locating Capabilities Technologies on Healthcare

Extant literature has indicated performance benefits of LCTs, including hospital operating efficiency and patient satisfaction (Yazici, 2014), improved patient management and staff scheduling (Arunachalam et al., 2016, 2017), improved asset utilization (Ersol & Fescioglu-Unver, 2017), and improved efficiency in re-processing surgical instruments (Moatari-Kazerouni & Bendavid, 2017). Results from prior studies have also demonstrated performance benefits gained by bundling LCTs with other technologies, such as electronic data interchange and the Internet of Things; these benefits include monitoring patient health and gathering environmental information such as temperature and humidity (Amendola et al., 2014), improving patient safety (Naresh et al., 2020), and lowering supply chain and labor costs (Bradley et al., 2018).

Real-Time Locating Systems

Due to their ability to track objects inside and outside facilities and report real-time location information, RTLS are finding growing acceptance in the healthcare space (Boulos & Berry, 2012). This technology can offer many benefits, such as monitoring provider time with patients using the locate by associating capability (knowing who is near whom), monitoring the movement of patients for physical exercise compliance and safety, identifying bottlenecks that can cause long wait times, optimizing patient transfer times between departments, and locating medical equipment for maintenance and compliance certifications (Boulos & Berry, 2012).

Fisher and Monahan (2012) studied the impact of RTLS implementation in U.S. hospitals and reported substandard functionality of most RTLS and serious deployment obstacles due to material and organizational constraints. They also noted that asset tracking is the best use case for RTLS and that the success of RTLS depends on organization-wide deployment and centralized control of the system.

Successes and Challenges in the use of Locating Capabilities Technologies in Healthcare

In their study of critical enablers and impediments of using RFID systems, Aboelmaged and Hashem (2018) reported that technical advantages and organizational capacity enhance the supply and patient management performance, the effect of environmental competitiveness is evident only in managing patients, technical complexity and environment uncertainty contribute negatively to both asset and patient management, and organizational resistance do not influence the use of RFID in asset and patient management.

Yeoh et al. (2019) studied the application of RTLS on the efficiency of anesthesiologists for one year. They found that a measure of duration decreased between the time of operating room admission and the time of induction during the initial six months; this benefit dissipated during the last six months of the study, bringing into question the sustainability of the benefits.

Privacy and security issues have adversely impacted the adoption of locating capabilities technologies (Gupta et al., 2015; Reyes et al., 2016; Yazici, 2014). Katz and Rice (2009) conducted a national survey on RFID in the United States and reported high levels of interest in emergency services, much less interest in health information and monitoring services, and higher negative sentiment when the RFID modality is attached to the body as opposed to away from the body (e.g., via smartphones). Privacy concerns were the main reason behind the failed RTLS implementation reported by Boulos and Berry (2012), where a nurse tracking RTLS system was deployed at a hospital to enable nurses to alert security in cases of physical or verbal abuse; the nurses refused to wear their identification badges due to privacy concerns, highlighting the need to address privacy concerns before LCT deployments.

Factors Driving Adoption of Location Capabilities Technologies in Healthcare

Stating technology selection as one of the critical factors in the success of RTLS implementation, Budak and Ustundag (2015) proposed using the fuzzy analytic hierarchy process to select RTLS technology based on the needs of a healthcare organization under consideration. Ting et al. (2011) studied management issues in deploying RFID within healthcare organizations and developed a framework to consider before the deployment. The authors proposed 11 steps grouped into three categories: preparation, implementation, and maintenance.

Highlighting the importance of understanding the user adoption impact of RFID, Hossain & Prybutok (2008) used the technology acceptance model to explain the consumer acceptance of RFID. The authors reported higher perceived convenience of RFID technology leads to greater acceptance of this technology; societal beliefs, value systems, norms, and behaviors influence the extent of consumer acceptance of RFID technology; and higher perceived importance of and less willingness to sacrifice personal information security lead to lower intention to use RFID technology. Yazici (2014) reported the importance of aligning the information requirements of healthcare organizations with the perceived benefits of RFID to enhance user acceptance. The author also noted the importance of staff readiness and investment in IT on the adoption rate of RFID. Reyes et al. (2016) also studied RFID adoption; the adoption stage of RFID related to performance and firm size impacts perceived customer service and productivity.

Theoretical Background

Information Technology Capability and Firm Performance

Extant literature has firmly established a positive association between IT capabilities and firm performance (Bharadwaj, 2000; Mata et al., 1995; Pavlou & El Sawy, 2006; Ravichandran & Lertwongsatien, 2005; Ross et al., 1996). Prior studies have also investigated mediators between IT capabilities and firm performance, including knowledge management (Tanriverdi, 2005), organizational capability (Liang et al., 2010), and absorptive capacity (Liu et al., 2013).

Dynamic Capabilities Theory

Dynamic capabilities (DC) refer to the ability of firms to adapt their competencies in fast-changing business environments. Thus, DC's goal is to create competitive advantages and sustain them (Teece et al., 1997). Sensing, seizing, and transforming are firm activities to constitute DC; sensing enables firms to explore external opportunities, seizing activities allow firms to enhance their products and services through innovative business models, and transforming activities drive firms to adapt their business processes to meet market needs (Teece et al., 1997).

Teece et al. (1997, p.518) posited that,

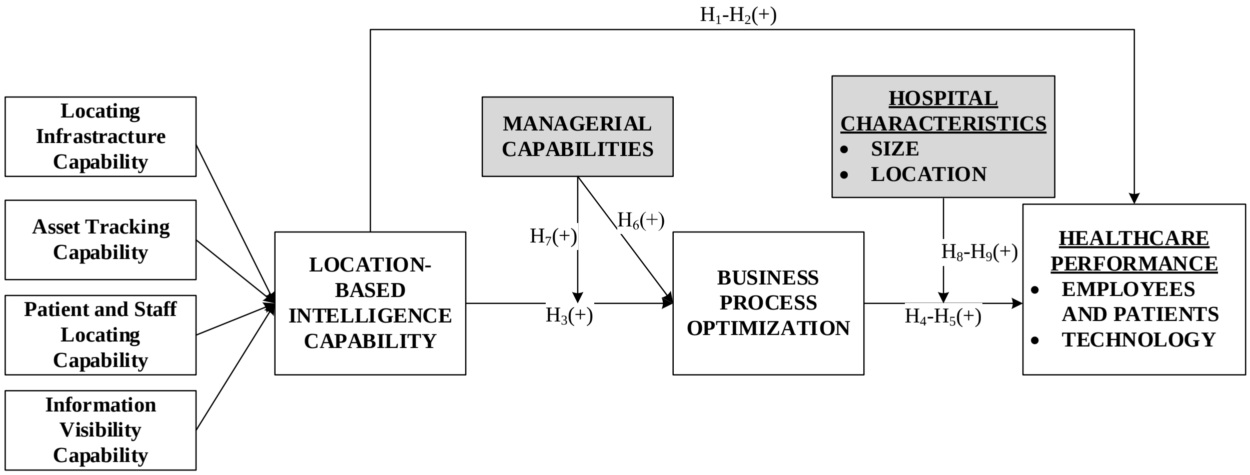
> the essence of competencies and capabilities is embedded in organizational processes of one kind or another. But the content of these processes and the opportunities they afford for developing competitive advantage at any point in time are shaped by the assets the firm possesses and by the evolutionary path it has adopted. Hence organizational processes are shaped by a firm's asset positions.

Consistent with these arguments, this study posits a positive relationship between LCTs as IT capabilities and creating and sustaining competitive advantages.

Dependent Variable: Healthcare Performance

As shown in Figure 1, this study conceptualized healthcare performance as having two sub-dimensions: performance benefits for employees and patients and improved IT capabilities in harnessing the power of LCTs. Prior studies have indicated similar performance improvements from using LCTs (i.e., Arunachalam et al., 2016, 2017; Jones & Gupta, 2015; Moatari-Kazerouni & Bendavid, 2017; Yazici, 2014). Some examples of healthcare performance include improvement in asset utilization, reduction in time searching for and inventorying equipment, reduction in time to log readings, progress in rounding staff efficiency (in terms of compliance), and improvement in staff documentation compliance (Asamoah et al., 2016; Ersol & Fescioglu-Unver, 2017; Naresh et al., 2020; Yazici, 2014).

Figure 1. Research Model



Note: + denotes a positive association

Location-Based Intelligence Capability

The extant literature has stated healthcare uses LCTs such as RFID, RTLS, Bluetooth low energy, and Wi-Fi tracking for tracking assets (i.e., medical devices and supplies) and people staff and patients (i.e., Vilamovska et al., 2009; Wamba et al., 2013). The prior literature has also contended that healthcare has struggled to deploy and use LCTs due to technological complexities, data management, and security concerns (Boulos & Berry, 2012; Gupta et al., 2015; Yazici, 2014).

While LCTs enable healthcare firms to collect large volumes of data, these organizations lack data visualization capabilities to make informed decisions on where and when to optimally deploy resources (i.e., Fosso Wamba et al., 2013; Vilamovska et al., 2009). Based on anecdotal experience in health IT, having only the data generated by LCTs would not lead to improved business processes and performance without the capability to visualize the data. While having the technology for locating and the capabilities to track people (i.e., staff and patients) and assets are essential, information visibility capability are required to make sense of the data (Dixit et al., 2020; Ristevski et al., 2020; Wang et al., 2018).

Numerous scholars have discussed the positive relationship between locating capabilities and firm performance in managing assets, patients, or staff. (Aboelmaged & Hashem, 2018; Amendola et al., 2014; Arunachalam et al., 2016, 2017; Asamoah et al., 2018; Boulos & Berry, 2012; Bradley et al., 2018; Ersol & Fescioglu-Unver, 2017; Fisher & Monahan, 2012; Jones & Gupta, 2015; Moatari-Kazerouni & Bendavid, 2017; Naresh et al., 2020; Vilamovska et al., 2009; Volland et al., 2017; Yazici, 2014). Based on this extant literature on LCTs and practitioner literature in the healthcare domain, this study posits that LBI capability is a second-order capability consisting of four dimensions, each enumerating the capability to track a particular type of asset or resource and the corresponding information visualization. The four dimensions are locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability. I elaborate on each of these dimensions in the following paragraphs.

Locating Infrastructure Capability

Locating infrastructure capability refers to technologies for locating and tracking, such as RFID, RTLS, Bluetooth low energy, and Wi-Fi. Locating infrastructure capability encompasses these factors: the healthcare firm's IT infrastructure that provides location-based services, the skill level of the IT personnel for maintaining and supporting LCTs, the ability of the firm to understand changing patient preferences using LCTs, the extent to which the firm has trained its employees in the proper use of LCTs, and the scale at which the firm deployed LCTs throughout the enterprise (Gu & Black, 2020; Ilangakoon et al., 2021; Moretti et al., 2019; Tamilvizhi et al., 2020; Wei et al., 2015; Zhu et al., 2022).

Asset Locating Capability

Asset locating capability refers to the firm's ability to find and track assets such as medical equipment and supplies, and it accounts for these factors: the ability of the healthcare firm to search for and locate medical equipment, the ability of the firm to locate mobile equipment such as ventilators and intravenous pumps in real time, the extent to which the firm is efficient in managing its asset inventory, the ability of the firm to determine which equipment is in use for patient care, and the firm's capability in identifying medical equipment due for maintenance (Abugabah et al., 2021; Haddara & Staaby, 2020, 2022; Shokouhifar, 2021; Yazici, 2014).

Patient and Staff Locating Capability

Patient and staff locating capability refers to the firm's ability to identify and track patients and staff, specifically locating and tracking patients, tracking the processing time of patient care, facilitating the admission and discharge of patients efficiently, monitoring patients' vital signs in real time, collecting and transmitting medical data from biosensors implanted in patients, associating patients with their medical treatment, matching the correct medication to the patient treatment plans, tracking medical staff in real time for scheduling and infection controls, and securing access to sensitive medical facilities (Abugabah et al., 2021; Haddara & Staaby, 2020, 2022; Yazici, 2014).

Information Visibility Capability

Information visibility capability refers to the firm's ability to collect, analyze and visualize data from LCTs (Asamoah et al., 2016; Fisher & Monahan, 2012; Liang et al., 2010). Examples of this capability in healthcare firms include investing in business operation systems such as enterprise resource planning (for human resources, finance, supply chain), LCTs, and electronic medical record systems for patient admission and discharges, as well as integrating the firms' information from enterprise resource planning and electronic medical records to track all clinical data (Abugabah et al., 2021; Haddara & Staaby, 2020, 2022; Shokouhifar, 2021; Yazici, 2014).

From the DC perspective, LBI capability can enable a healthcare firm to dynamically reconfigure its resources to generate superior healthcare performance. As argued previously, the capability to track resources (patients, staff, inventory) in real time can enable healthcare organizations to realize significant performance benefits. For example, studies have shown that real-time asset-tracking capabilities enable healthcare organizations to significantly reduce inventory loss and wastage (Ersol & Fescioglu-Unver, 2017; Jones & Gupta, 2015; Yazici, 2014). Further, real-time tracking of patients, such as remote patient monitoring, can reduce infection rates and hospital readmissions (Amendola et al., 2014; Jones & Gupta, 2015; Naresh et al., 2020). Similarly, staff tracking capability can lead to better conformance with established norms of healthcare organizations; this was evident during the COVID-19 pandemic as hospital staff were asked to follow strict hospital routines related to hygiene and quarantine (Datta et al., 2022; Kabasakal et al., 2021; Lipsitz et al., 2020). Taken together, LBI capability as an IT capability can drive healthcare performance related to employees and patients and can offer technology benefits. Thus, this study hypothesized that:

H_1: LBI is positively associated with employee and patient healthcare performance.

H_2: LBI is positively associated with healthcare performance in technology.

Business Process Optimization

In the research model (Figure 1), LBI capability refers to an IT firm resource that utilizes LCTs, providing visibility into the location information of staff, patients, and medical assets and supplies. As discussed previously, the extant literature has established a positive relationship between LCTs as IT resources and firm performance. This study posits that LCTs and data visualization capabilities form LBI capability. Organizations that do not have the information visibility capability cannot harness LCTs to drive performance.

Also shown in Figure 1, BPO refers to the ability of a healthcare firm to adapt its business processes by exploiting opportunities and avoiding threats from competitors; this represents the transformational component of DC (Torres et al., 2018). There are three ways in which BPO depends on LBI capability:

1. The support of various stakeholders leads to taking strategic action (Parmar et al., 2010; Teece, 2007).
2. From the DC perspective, the seizing capability of LBI enables a shared understanding of opportunities and the devising of a plan of action by decision-makers while overcoming resistance to change (Hammer, 2015).
3. Seizing capabilities of LBI can strengthen linkages between business process initiatives and the organization's strategic priorities, as these linkages are crucial for the success of BPO (Popovič et al., 2012; Rosemann et al., 2015).

The DC perspective posits that functional performance, realized from the firm's ordinary capabilities, mediates the relationship between DC (i.e., the LBI capability) and firm performance (Bowman & Ambrosini, 2003; Helfat et al., 2007; Protogerou et al., 2011). Ordinary capabilities involve exploiting a firm's existing resources through day-to-day operations (Ganesh & Marathe, 2019). Functional performance refers to the operational efficiency and effectiveness of business processes utilizing ordinary capabilities (Helfat et al., 2007). In this study, the transformation component of DC (BPO) enables firms to develop their ability to optimize business processes and improve their competitiveness (Schreyögg & Kliesch-Eberl, 2007). Prior studies have reported positive associations between BPO and firm performance (i.e., financial and efficiency measures; Frei & Harker, 1999; Ramirez et al., 2010). Other studies have identified mediators between IT capabilities and firm performance, including senior leadership involvement (i.e., Armstrong & Sambamurthy, 1999; Attili et al., 2021; Huntsman et al., 2022; Rehman et al., 2021), knowledge management (i.e., Kareem et al., 2021; Tanriverdi, 2005), organizational culture (i.e., Iqbal et al., 2020), and organizational learning (i.e., Rasool & Waheed, 2021). Thus, this study hypothesized, as shown in Figure 1:

H_3: LBI capability is positively associated with BPO.

H_4: BPO is positively associated with employee and patient healthcare performance.

H_5: BPO is positively associated with healthcare performance in technology.

Managerial Capabilities

In the research model (Figure 1), managerial capabilities refer to the roles of managers in decision-making, strategy planning and implementation, and managerial actions. Ganesh & Marathe (2019), in their morphological analysis of the literature on DCs, identified leadership and executive actions as endogenous factors moderating the effects of DCs on firm performance. Prior studies have reported direct and positive effects of managerial capabilities on business process improvements and their moderating impacts on DCs, such as the selection of product architecture and business models (Teece, 2007), entrepreneurial mindset (Savolainen, 1999; Teece, 2007), DC configuration and orchestration (Kor & Mesko, 2013; Sirmon & Hitt, 2009), strategy formulation, planning, and budgeting, setting direction, environmental scanning (Bititci et al., 2011; Rosenbloom, 2000), and handling success traps (Wang et al., 2015).

According to Martin (2011), managerial actions both directly impact business process improvements and moderate the effects of DCs by developing capabilities to plan and implement strategies, exerting controls over firm resources to achieve business deliverables, and satisfying their obligations to use the firm’s resources and business processes effectively. Prior studies have identified the moderating effects of managerial actions to be problem-solving and handling complexity (Fainshmidt et al., 2016; Macher & Mowery, 2009; Schreyögg & Kliesch-Eberl, 2007), market communications (Eggers, 2012), dominant managerial logic and managerial cognition (Kor & Mesko, 2013), performance measurement and reporting, resource allocation, staff management, infrastructure building, stakeholder communications (Davenport, 1993), managing strategy, managing performance, resource planning and assignment, alliancing and networking, managing change, strategic decision-making, competence building, organizational learning, and knowledge management (Bititci et al., 2011). Based on prior studies' findings, this study posited that managers could enhance the performance impact of LCTs by developing implementation plans, promoting the use of LCTs, developing policies that address adoption challenges, facilitating communication among departments, and providing staff training. Thus, this study hypothesized, as shown in Figure 1:

H_6: Managerial capabilities are positively associated with BPO.

H_7: Managerial capabilities positively moderate the relationship between LBI capability and BPO.

Hospital Size

Prior studies have found the size of hospitals measured by staffed beds to influence healthcare performance, patient satisfaction (i.e., McFarland et al., 2017), and hospital quality comparison (Geweke et al., 2003; Gowrisankaran & Town, 2003). The underlying theoretical rationale is that hospital size plays a role in economies of scale due to the availability of additional technology and human resources; this suggests a moderating influence of hospital size, as the translation of BPO to healthcare performance would be enhanced due to resource availability. Arguably, larger hospitals have a substantial amount of economic, human, and technological resources at their disposal. Therefore, larger hospitals can convert their process improvements to performance benefits as they can more effectively deploy the technology and human resources needed (McFarland et al., 2017; Murphy & Wilson, 2021; Spaulding et al., 2021). In contrast, smaller hospitals might find it difficult to realize all performance benefits from process improvement due to a lack of human and technological resources at their disposal

(Agwunobi & Osborne, 2016; Murphy & Wilson, 2021; Spaulding et al., 2021;). Thus, the study hypothesized, as shown in Figure 1:

H_8: Hospital size positively moderates the relationship between BPO and employee and patient healthcare performance.

Hospital Location

Hospital location in this study refers to whether a hospital's location is urban or rural. Prior studies have indicated different outcomes based on location, including impacts of Medicaid expansion (Kaufman et al., 2016), hospital performance (Garcia-Lacalle & Martin, 2010), and Medicaid expansion and hospital closures (Lindrooth et al., 2018). Extant literature has stated that urban hospitals tend to perform better due to factors such as a diverse population made up of younger, healthier, and more affluent residents who possess private insurance coverage, allowing hospitals to charge higher rates for their services (Garcia-Lacalle & Martin, 2010; Giancotti et al., 2017; Lindrooth et al., 2018).

Rural hospitals tend to be smaller, with a higher payer mix and less-profitable Medicare and Medicaid patients (Patel et al., 2020; Segel et al., 2021; Slonim et al., 2020;). Consequently, these hospitals have limited technology and human resources to optimize their business processes and enhance technology performance (Dang et al., 2022; Pick et al., 2022; Slonim et al., 2020). For instance, optimized processes such as real-time tracking in electronic medical records could exist in rural hospitals. However, due to a lack of resources, rural hospitals might find it difficult to fully utilize the features of electronic medical records to make effective healthcare decisions. This could lead to less than optimal healthcare performance. In other words, the benefits that accrue from process optimization could be limited for rural hospitals when compared with urban hospitals. Thus, this study hypothesized, as shown in Figure 1:

H_9: Hospital location positively moderates the relationship between BPO and healthcare performance in technology.

Methodology

Sample Design

Previous researchers have used survey data to study the organizational impact of LCTs on performance. For example, Yazici (2014) investigated the relationship between hospital information requirements and perceived efficiency, surveying hospital operation directors. Aboelmaged and Hashem (2018) surveyed hospital’' managers, technicians, and clinicians to determine the enablers and impediments of RFID adoption.

I developed this stud’'s survey instrument (Appendix B) by adapting scales from earlier studies. While the population in this study was composed of all healthcare staff worldwide, the sample frame aimed to cover only healthcare staff in the United States, focusing on the healthcare staff’s perception of LCTs’ impact on performance. Using an online statistical power calculator from Soper (2022), the minimum required sample size for this study was 135 (effect size 0.15, desired statistical power level 0.8, 14 predictors from the research model, probability level of 0.05). This study collected data from 256 participants.

This study expected a high participation rate as the participants received compensation after providing valid responses. The survey required respondents to possess attributes such as 18 years or older, previous job titles related to delivering or supporting patient care, managing hospital operations, and consenting to respond to the survey. Moreover, the study performed screening to exclude responses containing flaws such as straight-lining (usually caused by respondents rushing through the survey and providing the same answers). The study did not include incomplete surveys in the analysis. Survey instructions clearly stated that respondents were participating voluntarily and anonymously.

Research Design and Methods of Data Collection

As this study aimed to perform theory testing instead of theory building, a survey instrument was applicable (Yin, 2013). In this endeavor, theories from previous studies guided the analysis rather than constructing new theories. This study utilized SmartPLS version 3.3.9 to perform exploratory factor analysis, confirmatory factor analysis CFA, and hypotheses testing. This study performed the activities noted in Table 10 to evaluate the reliability and validity of the responses.

Since this study measured all variables simultaneously, using the same survey platform (Qualtrics), common-method bias is a concern (Podsakoff et al., 2003). This bias can adversely influence constructs and beta-weights, questioning the validity of studies (Jarvis et al., 2003; Podsakoff et al., 2003). Therefore, this study evaluated common-method bias by isolating factor loading of dimensions and performing a single-factor test (Podsakoff et al., 2003).

Conceptual and Operational Definitions of Variables

Table 11 shows variable definitions, measures, and sources of survey scales. The measures of the second-order construct LBI came from measuring its four first-order dimensions, as shown in Appendix A: locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability. The control variables in this study were hospital type (i.e., adult, pediatric, or both), number of employees, and annual hospital revenue.

Table 10. Activities for Performing Reliability and Validity Analysis

Issue Addressed	Function Performed
Content Validity	Adopting validated survey scales from prior studies when possible
Reliability of Constructs	Calculating Cronbach's alpha and average variance extracted
Convergent Validity	Performing item-to-total correlation (correlation of each item by the sum of the remaining items)
Discriminant Validity	Conducting principal component analysis with varimax rotation

Table 11. Conceptual and Operational Definitions of Variables

Variable	Variable Type	Conceptual Definition	Operational Definition	Code	Source
Location-Based Intelligence (LBI) Capability	Independent	Visibility into the movement and management of assets, supplies, patients, and staff in real time; a second-order construct represented by its four first-order dimensions			
		Locating Infrastructure Capability: Refers to technologies for locating and tracking such as RFID, RTLS, BLE, and Wi-Fi	The extent toIch healthcare staff believe how their organization uses LCTs such as RFID, RTLS, BLE, and Wi-Fi	LIC	Wei et al. (2015)
		Asset Locating Capability: Refers to the ability to find and track assets such as medical equipment and supplies	The extent to which healthcare staff believe how their organization uses LCTs to track medical equipment and supplies	ALC	Yazici (2014)
		Patient and Staff Locating Capability: Refers to an organization’s ability to identify and track patients and staff	The extent to which healthcare staff believe how their organization uses LCTs to identify and track patients and staff	PSLC	Yazici (2014)
		Information Visibility Capability: Refers to the ability to collect, analyze, and visualize data from LCTs	The extent to which healthcare staff believe how their organization uses LCTs to collect, analyze, and visualize data from locating systems	IVC	Yazici (2014)

Variable	Variable Type	Conceptual Definition	Operational Definition	Code	Source
Business Process Optimization	Mediator	Refers to the ability of a healthcare firm to adapt its business processes by exploiting opportunities and avoiding threats from competitors	The extent to which healthcare staff believe how their organization optimizes its business processes to align with LBI capability	BPO	Aboelmaged & Hashem (2018); Wei et al. (2015); Yazici (2014)
Managerial Capabilities	Moderator	Refers to the roles of managers in decision-making, strategy planning and implementation, and managerial actions	The extent to which healthcare staff believe the impact of management in the application of LBI capability in optimizing business processes	MC	Reyes et al. (2016)
Hospital Size	Moderator	Refers to the hospital size based on the number of beds	The number of hospital beds as reported by healthcare staff	Hosp_size	
Hospital Location	Moderator	Refers to the geographical location of the hospital (urban vs. rural)	Whether the hospital location is urban or rural, as reported by healthcare staff	Hosp_loc	
Healthcare Performance	Dependent	Refers to what extent the use of LCTs impacts two aspects of healthcare performance: employee and patients, and technology	The extent to which the healthcare professionals believe the LBI capability's impact on healthcare performance	HCP	Aboelmaged & Hashem (2018); Yazici (2014)

Note. *LCTs = Locating Capabilities Technologies; RFID=Radio Frequency Identification; RTLS=Real-time Location Systems; BLE = Bluetooth Low Energy; WiFi = Wireless Fidelity.*

Procedures

The study utilized the Qualtrics survey tool to administer the survey, using the CloudResearch (formerly MTurk Prime) survey panel platform to recruit respondents who received compensation after providing valid responses. The survey instructions stated that respondents could complete the questionnaire in single or multiple sessions.

The study took measures to address potential issues with non-response bias: keeping the survey questions short and simple to understand, setting expectations on the purpose of the survey to encourage participation, offering both desktop and mobile options to participate in the study, making personal connections with the participants to motivate participation, and sending reminder emails to ensure improved participation.

The study also took measures to address social-desirability bias by highlighting the anonymous aspect of participating in the study, assuring participants that personal information would not be shared with others, and communicating to respondents that all responses would be kept confidential.

Analysis and Results

This section of the paper presents the survey data analysis, measurement, and structural models. This study used SmartPls 3.3.9 for analysis. The measurement model evaluated reliability, convergent, and discriminant validity, and the structural model was used for hypotheses testing.

Measurement Model

Based on the perceptions of healthcare staff, this study aimed to explore the performance impacts of LCTs. The presentation of the results begins with the respondent's demographics in Table 12.

Table 12. Sample Respondent Characteristics

Demographics	Count	%
Age		
18–25	32	13
26–30	29	11
31–35	42	16
36–40	38	15
41–45	48	19
46–50	20	8
51–55	15	6
56–60	8	3
61–65	9	4
More than 65	15	6
Gender		
Male	100	39
Female	155	61
Undisclosed	1	0
Highest level of education		
8th grade or less	0	0
Some High School	3	1
High School Diploma or GED	38	15
Some College	92	36
4-Year College	67	26
More than 4 Years of College	55	21
Undisclosed	1	0
Role in Organization		
Staff	79	31
Manager	70	27
Director	40	16
C-level or higher	35	14
Other	29	11
Undisclosed	3	1
Years in Organization		
0–2 years	41	16
3–5 years	86	34
6–10 years	74	29
More than 10 years	55	21

The study followed the guidelines for conducting confirmatory factor analysis in PLS to establish the model as well as the reliability and validity of the constructs (Gefen & Straub, 2005). Single-item constructs were excluded from discriminant and convergent reliability analysis, understanding that the indicator captured the item of measure with an average variance extracted (AVE) of 1.000. Reliabilities of the constructs and the item loadings were above the recommended threshold of 0.70 (Nunnally, 1978). Table 13 depicts the *t* values of the outer model loadings. The first validation criteria required *t* values equal to or greater than 1.96 to ensure convergent validity (Gefen & Straub, 2005). Thus, all the *t* values in Table 13 are significant ($t > 1.96$), establishing convergent validity. The study also verified the AVE values were equal to or greater than 0.5 (Fornell & Larcker, 1981). Table 14 shows the AVE values of the constructs; all values were above 0.5, indicating the convergent validity of the constructs.

Factor loadings refer to“the "extent to which each item in the correlation matrix correlates with the given principal component. Factor loadings can range from -1.0 to +1.0, with higher absolute values indicating a higher correlation of the item with the underlying factor" (Pett et al., 2003, p. 299). The study removed items with factor loadings less than the recommended value of .50 (Hair et al., 2018). Factor loadings of the remaining items are presented in Table 13. Table 15 depicts the item-to-construct correlation.

Table 13. Outer Model Loadings

Construct	Item	Question	*t* values
Locating Infrastructure Capability (LIC)	LIC_1	The hospital has the necessary information technology (IT) infrastructure, which provides location-based services (e.g., radio-frequency identification, real-time location systems, Bluetooth tracking).	41.500
	LIC_2	The hospital has personnel who have the necessary IT skills for managing locating technologies.	56.288
	LIC_3	The hospital is able to understand changing patient preferences using locating technologies.	31.839
	LIC_4	The hospital has embedded the technical knowledge of its employees to use locating technologies in our organiz'tion's process, policies, and information repositories.	35.243
	LIC_5	The hospital can share resources and capabilities about locating technologies across organizational divisions.	40.570
Asset Locating Capability (ALC)	ALC_5	The hospital has a need to know when equipment requires preventative maintenance in real time.	26.519
	ALC_6	The hospital has a need to know when equipment no longer belongs to the hospital in real time.	23.739
	ALC_7	The hospital has a need to track equipment for regulatory purposes in real time.	28.291
	ALC_8	The hospital has a need to manage laboratory samples in real time.	32.343
	ALC_9	The hospital has a need to monitor therapeutic devices in the hospital in real time.	53.516
	ALC_10	The hospital has a need to track materials (intravenous pumps, implants, biologicals) that come in contact with patients in real time.	46.487
	ALC_11	The hospital has a need to check the drugs to see if they are counterfeited.	28.677
Patient & Staff Locating Capability (PSLC)	PSLC_1	The hospital can locate and track patients in real time.	30.681
	PSLC_2	The hospital can track the processing time of each exam performed for the patient in real time.	34.832
	PSLC_3	The hospital can facilitate patient admission and discharge efficiently in real time.	28.585
	PSLC_4	The hospital can locate the movements of patients with impaired cognitive function in real time.	19.370
	PSLC_5	The hospital can automatically monitor patients' vital signs and exigencies in real-time.	26.330

Construct	Item	Question	*t* values
Patient & Staff Locating Capability	PSLC_7	The hospital can associate the patient to his or her medical treatment.	33.745

(cont.)

Construct	Item	Question	*t* values
	PSLC_8	The hospital can associate the correct medication with the therapy of the patient.	26.291
	PSLC_9	The hospital can track the movements of medical staff, patients, and visitors to check which people have been in contact with people affected by infectious diseases such as Covid-19.	19.127
Information Visibility Capability (IVC)	IVC_1	The hospital has invested in accounting/financial information systems.	41.708
	IVC_2	The hospital has invested in patient admission, discharges, and transfers of information systems.	31.948
	IVC_3	The hospital has invested in computerized patient clinical records.	39.137
	IVC_4	The hospital has invested in integrating information systems for tracking all clinical information.	30.238
	IVC_5	The hospital has invested in ancillary (laboratory, radiology, pharmacy, dietary) information systems.	31.903
Business Process Optimization (BPO)	BPO_1	The hospital has the ability to effectively use auto-identification and real-time data capture systems.	29.746
	BPO_2	The hospital assigns employees a broader range of tasks.	19.968
	BPO_3	The hos’ital's employees have quality control responsibilities.	31.855
	BPO_4	The hos’ital's employees participate in employee empowerment programs.	32.090
	BPO_5	The hos’ital's employees participate in job-sharing programs.	25.034
Managerial Capabilties (MC)	MC_1	The hos’ital's top management develops locating technologies implementation plan.	39.086
	MC_2	The hos’ital's top management communicates the locating technologies implementation plan.	48.679
	MC_3	The hos’ital's top management sets priorities for locating technologies implementation.	41.162
	MC_4	The hos’ital's top management participates in developing and implementing the policies and methods of the locating technologies implementation.	41.142
	MC_5	The hos’ital's top management fosters communication among different departments concerning the locating technologies implementation.	31.644
	MC_6	The hos’ital's top management assures the organization’s staff is trained to implement locating technologies.	32.590

Healthcare Performance: Employees (HCP_Emp)	HCP_3	The hospital can help to comply with regulatory requirements.	48.351
	HCP_4	The hospital can shorten response time to critical events.	38.158
	HCP_8	The hospital can help maintain high capacity utilization (hospital bed capacity/equipment utilization).	34.244
	HCP_11	The hospital can improve employee job satisfaction.	29.251
Healthcare Performance: Patients (HCP_Pat)	HCP_1	The hospital can make equipment and patient tracking easier.	41.984
	HCP_9	The hospital can use locating technologies to improve patient satisfaction.	41.362
	HCP_12	The hospital can respond better to patient requests.	31.006
Healthcare Performance: Technology (HCP_Tech)	HCP_5	The hospital can help to integrate medical information systems.	33.181
	HCP_6	The hospital can help to improve patient accounting/finance information systems.	26.715
	HCP_14	The hospital can improve communication across the organization.	43.594
	HCP_15	The hospital can improve the preventive maintenance of medical and non-medical assets.	24.661

Table 14. Measurement Model Validation: Average Variance Extracted

Construct	Average Variance Extracted
LIC	0.741
ALC	0.674
PSLC	0.625
IVC	0.681
BPO	0.608
MC	0.715
HCP_Emp	0.692
HCP_Pat	0.732
HCP_Tech	0.680

Note. *LIC = locating infrastructure capability; ALC = asset locating capability; PSLC = patient and staff locating capability; IVC = information visibility capability; BPO = business process optimization; MC = managerial capabilities; HCP = employee healthcare performance; HCP_Pat = patient healthcare performance; HCP_Tech = healthcare performance in technology.*

Table 15. Item-to-Construct Correlation

	Constructs								
Items	LIC	ALC	PSLC	IVC	BPO	MC	HCP_Emp	HCP_Pat	HCP_Tech
LIC_1	0.862	0.490	0.576	0.559	0.598	0.569	0.426	0.492	0.387
LIC_2	0.887	0.556	0.586	0.605	0.617	0.547	0.464	0.479	0.442
LIC_3	0.843	0.449	0.592	0.556	0.577	0.541	0.403	0.402	0.367
LIC_4	0.839	0.493	0.558	0.539	0.571	0.540	0.443	0.414	0.398
LIC_5	0.871	0.516	0.607	0.552	0.618	0.523	0.450	0.402	0.407
ALC_5	0.444	0.786	0.585	0.512	0.537	0.502	0.465	0.450	0.426
ALC_6	0.403	0.791	0.582	0.562	0.499	0.472	0.488	0.463	0.471
ALC_7	0.474	0.811	0.584	0.561	0.510	0.526	0.479	0.480	0.483
ALC_8	0.512	0.831	0.580	0.585	0.530	0.491	0.536	0.503	0.514
ALC_9	0.571	0.872	0.627	0.592	0.559	0.514	0.539	0.531	0.555
ALC_10	0.525	0.856	0.596	0.613	0.546	0.485	0.537	0.530	0.566
ALC_11	0.411	0.795	0.578	0.508	0.509	0.458	0.506	0.546	0.501
PSLC_1	0.561	0.573	0.811	0.599	0.680	0.677	0.439	0.543	0.444
PSLC_2	0.539	0.590	0.834	0.614	0.680	0.665	0.432	0.503	0.465
PSLC_3	0.504	0.551	0.807	0.626	0.639	0.622	0.459	0.515	0.456
PSLC_4	0.455	0.530	0.746	0.522	0.555	0.602	0.441	0.441	0.426
PSLC_5	0.479	0.540	0.777	0.582	0.555	0.580	0.506	0.531	0.464
PSLC_7	0.627	0.594	0.829	0.663	0.638	0.636	0.487	0.541	0.435
PSLC_8	0.599	0.641	0.777	0.691	0.606	0.599	0.571	0.557	0.554
PSLC_9	0.507	0.513	0.735	0.514	0.579	0.604	0.406	0.467	0.419
IVC_1	0.584	0.568	0.665	0.827	0.652	0.663	0.614	0.640	0.594
IVC_2	0.523	0.560	0.642	0.824	0.642	0.564	0.492	0.487	0.495
IVC_3	0.514	0.572	0.637	0.842	0.578	0.579	0.569	0.570	0.553
IVC_4	0.524	0.517	0.588	0.799	0.522	0.532	0.550	0.531	0.484
IVC_5	0.547	0.607	0.618	0.835	0.611	0.566	0.544	0.560	0.549
BPO_1	0.577	0.544	0.709	0.638	0.791	0.722	0.469	0.577	0.457
BPO_2	0.447	0.486	0.539	0.522	0.735	0.549	0.500	0.571	0.488
BPO_3	0.587	0.546	0.616	0.660	0.802	0.590	0.530	0.518	0.543
BPO_4	0.569	0.462	0.585	0.561	0.805	0.672	0.467	0.427	0.460
BPO_5	0.515	0.455	0.587	0.441	0.763	0.618	0.389	0.432	0.420
MC_1	0.592	0.528	0.663	0.605	0.701	0.836	0.483	0.576	0.449
MC_2	0.524	0.470	0.677	0.611	0.705	0.870	0.511	0.553	0.478
MC_3	0.505	0.504	0.687	0.632	0.695	0.869	0.475	0.523	0.454
MC_4	0.535	0.492	0.667	0.600	0.676	0.862	0.464	0.498	0.481
MC_5	0.521	0.517	0.657	0.576	0.644	0.828	0.490	0.480	0.490
MC_6	0.529	0.531	0.646	0.559	0.680	0.807	0.436	0.497	0.447
	Constructs								
Items	LIC	ALC	PSLC	IVC	BPO	MC	HCP_Emp	HCP_Pat	HCP_Tech
HCP_3	0.479	0.518	0.501	0.606	0.537	0.466	0.871	0.679	0.723

HCP_4	0.382	0.462	0.466	0.535	0.497	0.423	0.838	0.686	0.764
HCP_8	0.446	0.572	0.553	0.593	0.524	0.531	0.822	0.693	0.713
HCP_11	0.377	0.502	0.448	0.496	0.457	0.450	0.795	0.663	0.666
HCP_1	0.457	0.509	0.593	0.600	0.647	0.592	0.658	0.861	0.627
HCP_9	0.472	0.575	0.593	0.630	0.550	0.556	0.717	0.871	0.686
HCP_12	0.368	0.477	0.469	0.499	0.460	0.419	0.733	0.833	0.673
HCP_5	0.393	0.570	0.505	0.567	0.552	0.519	0.724	0.663	0.829
HCP_6	0.405	0.470	0.454	0.507	0.502	0.420	0.699	0.643	0.836
HCP_14	0.342	0.465	0.448	0.520	0.428	0.385	0.709	0.640	0.783
HCP_15	0.396	0.511	0.506	0.548	0.521	0.483	0.709	0.600	0.849

Note. *The shaded columns are the constructs corresponding to the items in each row. LIC = locating infrastructure capability; ALC = asset locating capability; PSLC = patient and staff locating capability; IVC = information visibility capability; BPO = business process optimization; MC = managerial capabilities; HCP = employee healthcare performance; HCP_Pat = patient healthcare performance; HCP_Tech = healthcare performance in technology.*

Reliability Analysis

Mark (1996, p.285) defines reliability as "the extent to which a measuring instrument is stable and consistent. The essence of reliability is repeatability. If an instrument is administered over and over again, will it yield the same results?". Cronbach's alpha and composite reliability are the two most used methods for establishing reliability (Hair et al., 2011). Table 16 depicts the results of the two methods for this study. While Cronbach's alpha values ranged from .817 to .920, composite reliability values ranged from .886 to .938. Both reliability indicators exceed the required threshold of .70 (Hair et al., 2011). Hence, construct reliability is established.

Table 16. Construct Reliability Analysis

Construct	Cronbach's Alpha	Composite Reliability
LIC	0.912	0.935
ALC	0.919	0.935
PSLC	0.914	0.930
IVC	0.883	0.914
BPO	0.839	0.886
MC	0.920	0.938
HCP_Emp	0.851	0.900
HCP_Pat	0.817	0.891
HCP_Tech	0.843	0.895

Note. LIC = locating infrastructure capability; ALC = asset locating capability; PSLC = patient and staff locating capability; IVC = information visibility capability; BPO = business process optimization; MC = managerial capabilities; HCP = employee healthcare performance; HCP_Pat = patient healthcare performance; HCP_Tech = healthcare performance in technology.

Measures of Validity

Construct validity is established in PLS-SEM through convergent and discriminant valid“ty. "Convergent validity is the degree to which multiple attempts to measure the same concept agree. The idea is that two or more measures of the same thing should highly covary if they are valid measures of the concept" (Bagozzi et al., 1991, p. 425). When the AVE value is greater than or equal to the recommended value of .5, items converge to measure the underlying construct, establishing convergent validity (Fornell & Larcker, 1981). As shown in Table 13, the AVE values were above the recommended threshold of .5. Hence, convergent validity is established. Discriminant validity refers to "the degree to which measures of different concepts are distinct. The notion is that if two or more concepts are unique, then valid measures of each should not correlate too highly" (Bagozzi et al., 1991, p. 425).

Fornell and Larcker Criterion

According to Fornell and Larcker (1981), discriminant validity is established when the square root of AVE for a construct exceeds its correlation with all other constructs. As shown in Table 17, the square of AVE for a given construct was greater than its correlation with other constructs, supporting the establishment of discriminant validity.

Table 17. Discriminant Validity: Fornell and Larcker Criterion

Construct	ALC	BPO	HCP_Emp	HCP_Pat	HCP_Tech	IVC	LIC	MC	PSLC
ALC	*0.821*								
BPO	0.642	*0.780*							
HCP_Emp	0.619	0.607	*0.832*						
HCP_Pat	0.611	0.652	0.818	*0.855*					
HCP_Tech	0.614	0.610	0.861	0.772	*0.825*				
IVC	0.685	0.730	0.673	0.679	0.651	*0.825*			
LIC	0.583	0.693	0.509	0.510	0.466	0.654	*0.861*		
MC	0.599	0.809	0.564	0.618	0.552	0.707	0.632	*0.846*	
PSLC	0.719	0.781	0.594	0.651	0.581	0.765	0.678	0.788	*0.790*

Note. LIC = Locating Infrastructure Capability; ALC = asset locating capability; PSLC = patient and staff locating capability; IVC = information visibility capability; BPO = business process optimization; MC = Managerial Capabilities; HCP_Emp = employee healthcare performance; HCP_Pat = patient healthcare performance; HCP_Tech = healthcare performance in technology.

Validating Higher Order Constructs

This study considered two higher-order constructs: LBI (based on the four lower-order constructs of locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability) and employee and patient healthcare performance (HCP_EmpPat; based on the employee healthcare performance [HCP_Emp] and patient healthcare performance [HCP_Pat] constructs). The study evaluated outer weights, outer loadings, and variance inflation factors in establishing higher-order construct validity, as shown in Table 18. All the outer weights and outer loadings were significant, validating both higher-order constructs.

Table 18. Higher Order Construct Validity

HOC	LOC	Outer Weights	Outer Loadings
LBI Capability	LIC	0.128+	0.768***
	ALC	0.272**	0.854***
	PSLC	0.270**	0.901***
	IVC	0.457***	0.933***
HCP_EmpPat	HCP_Emp	0.464***	0.942***
	HCP_Pat	0.584***	0.964***

Note. *HOC = higher-order construct; LOC = lower-order construct; LBI = location-based intelligence; LIC = locating infrastructure capability; ALC = asset locating capability; PSLC = patient and staff locating capability; IVC = information visibility capability; HCP_EmpPat = employee and patient healthcare performance; HCP_Emp = employee healthcare performance; HCP_Pat = patient healthcare performance.*
*+p < 0.01, *p < 0.05, **p < 0.01, ***p < 0.001.*

Structural Model

This study tested the proposed hypothesized relationships via the structural equation modeling statistical technique. The results of this testing are detailed in the following paragraphs.

Hypotheses Testing

First, H_1 evaluates whether LBI capability is positively associated with employee and patient healthcare performance (*HCP_EmpPat*). The results revealed that LBI capability significantly affects *HCP_EmpPat* ($\beta = .628$, $p < 0.001$, $t = 7.815$). Hence, H_1 was supported.

The second hypothesis, H_2, evaluates whether LBI capability is positively associated with healthcare performance in technology (*HCP_Tech*). The results revealed that LBI capability significantly affects *HCP_Tech* ($\beta = .464$, $p < 0.001$, $t = 5.566$). Hence, H_2 was supported.

Third, H_3 evaluates whether LBI capability is positively associated with BPO. The results revealed that LBI capability significantly affects BPO ($\beta = .477$, $p < 0.001$, $t = 6.430$). Hence, H_3 was supported.

The fourth hypothesis, H_4, evaluates whether BPO is positively associated with employee and patient healthcare performance (*HCP_EmpPat*). The results revealed that BPO significantly affects *HCP_EmpPat* ($\beta = .165$, $p < 0.05$, $t = 2.097$). Hence, H_4 was supported.

The fifth hypothesis, H_5, evaluates whether BPO is positively associated with healthcare performance in technology (*HCP_Tech*). The results revealed that BPO significantly affects *HCP_Tech* ($\beta = .268$, $p < 0.01$, $t = 3.090$). Hence, H_5 was supported.

Sixth, H_6 evaluates whether managerial capabilities are positively associated with BPO. The results revealed that managerial capabilities significantly affect BPO ($\beta = .381$, $p < 0.001$, $t = 5.196$). Hence, H_6 was supported.

Next, H_7 evaluates whether managerial capabilities positively moderate the relationship between LBI capability and BPO. The results revealed that managerial capabilities do not moderate the relationship between LBI capability and BPO ($\beta = .042$, $p > 0.10$, $t = 1.426$). Hence, H_7 was not supported.

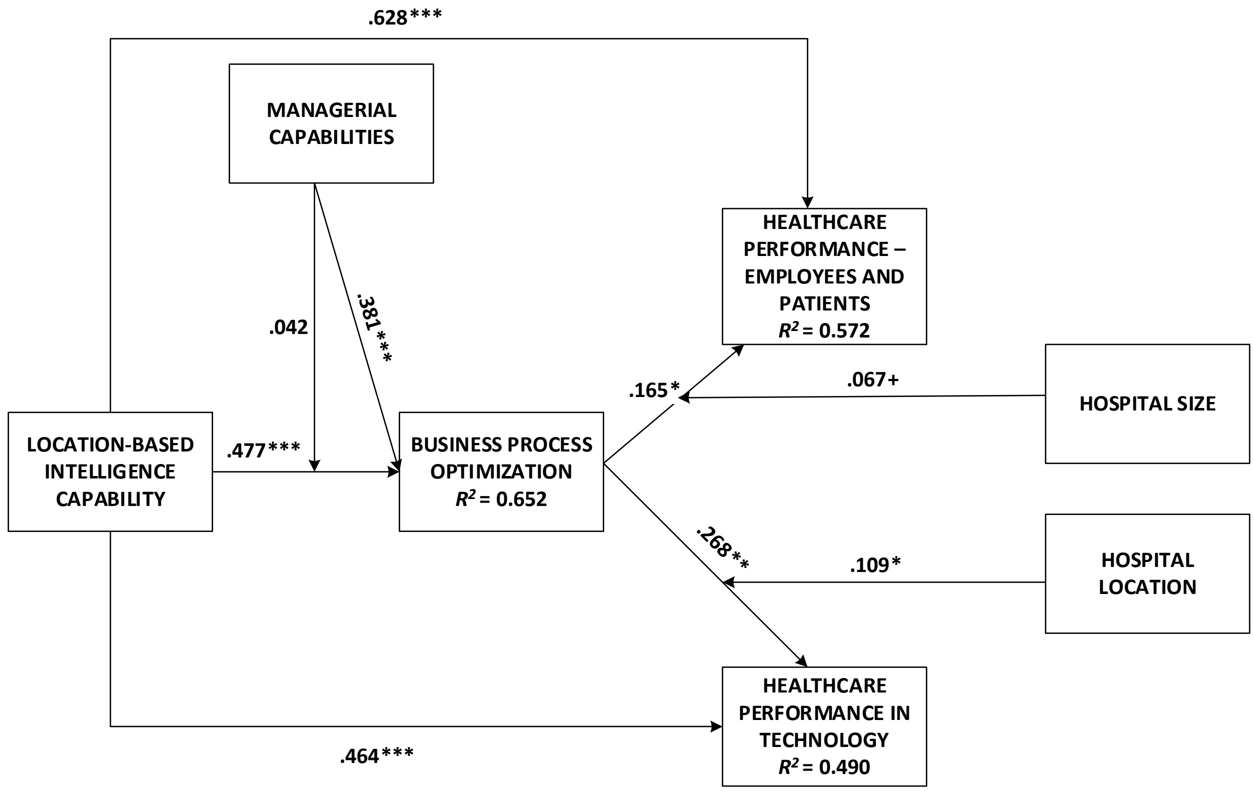
The eighth hypothesis, H_8, evaluates whether hospital size (*Hosp_Size*) positively moderates the relationship between BPO and employee and patient healthcare performance (*HCP_EmpPat*). The results revealed that *Hosp_Size* moderates the relationship between BPO and *HCP_EmpPat* ($\beta = .067$, $p < 0.05$, $t = 1.793$). Hence, H_8 was supported.

Finally, H_9 evaluates whether hospital location (*Hosp_loc*; urban vs. rural) positively moderates the relationship between BPO and healthcare performance in technology (*HCP_Tech*). The results revealed that *Hosp_Loc* moderates the relationship between BPO and *HCP_Tech* ($\beta = .109$, $p < 0.05$, $t = 2.042$). Hence, H_9 was supported. Figure 2 depicts the structural model for the main effects.

Mediation and Common Method Bias Analysis

In addition to the PLS mediation analysis, this study also performed the Sobel test, obtaining the same results as presented in Appendix B. Moreover, the study conducted Harmon's single-factor test by performing an exploratory factor analysis of all principle components in the study (Podsakoff & Organ, 1986). Results indicated that all items loaded on more than one factor, which provided reassurance that method bias should not be a serious concern. Addressing recent concerns regarding the adequacy of Harmon's single-factor test (Podsakoff et al., 2003), the constructs were compared using Pearson's correlations to ensure none were over 0.90; this confirmed that common method bias was not an issue in this study (Pavlou et al., 2007). Table 20 depicts the results summary for the main effects.

Figure 2. Structural Model for the Main Effects



Note. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20. Summary of Results (Main Effects)

Hypotheses	Result	Standard β	*t* value
H_1: LBI → HCP_EmpPat	Supported	.628***	7.815
H_2: LBI → HCP_Tech	Supported	.464***	5.566
H_3: LBI → BPO	Supported	.477***	6.430
H_4: BPO → HCP_EmpPat	Supported	.165*	2.097
H_5: BPO → HCP_Tech	Supported	.268**	3.090
H_6: Managerial Capabilities → BPO	Supported	.381***	5.196
H_7: Managerial Capabilities → moderate the relationship between LBI and BPO	Not Supported	0.042	1.426
H_8: Hospital Size → positively moderates the relationship between BPO and HCP_EmpPat	Supported	.067+	1.793
H_9: Hospital Location → positively moderates the relationship between BPO and HCP_Tech	Supported	.109*	2.042

Note. LBI = Location-Based Intelligence; BPO = Business Process Optimization, HCP_EmpPat = employee and patient healthcare performance, HCP_Tech = healthcare performance in technology.
$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Discussion

This study answered the call by Fosso Wamba et al. (2013) in their literature review on RFID-enabled healthcare applications for future empirical studies to explore the performance impacts of LCTs. To the best of my knowledge, this is the first study that has examined the effects of LCTs based on the performance perceptions of healthcare staff. This paper discusses the essential contributions of this study to the extant literature next.

First, this study addressed the overarching research question, what impacts do LCTs have on healthcare performance? The results revealed that based on the perceptions of healthcare staff, LCTs indeed impact healthcare performance in two areas: employee and patient performance and performance in technology.

Second, to the best of my knowledge, this is the first study that has developed a higher-order construct called LBI capability. This capability is comprised of four lower-order constructs: locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability. The results established LBI capability as a formative construct.

Third, to the best of my knowledge, this is also the first study that has developed a higher-order construct called Employee and Patient Healthcare Performance. This formative construct comprises two lower-order constructs: employee healthcare performance and healthcare performance in technology. The results established that healthcare performance can be conceptualized as containing the two dimensions.

Fourth, the study's results revealed that the construct of BPO mediates the relationship between LBI capability and the two healthcare performance dimensions: employee healthcare performance and healthcare performance in technology. The results underscored the importance of adapting or optimizing business processes to harness the powers of LCTs. The results also revealed that LCTs (i.e., LBI capability) have a positive and direct effect on healthcare performance.

Fifth, the study did not find evidence that supported the moderating effects of managerial capabilities in the relationship between LBI capability and BPO. The results revealed that according to the perceptions of healthcare staff, managerial capabilities do not enhance the significant relationship between the two constructs; this finding was the opposite of what was expected, as prior studies have reported the moderating impacts of managerial capabilities in the relationship between IT capabilities and BPO (adaptation; i.e., Davenport, 1993; Eggers, 2012; Fainshmidt et al., 2016; Gao et al., 2020; Kor & Mesko, 2013; Macher & Mowery, 2009; Schreyögg & Kliesch-Eberl, 2007). One possible explanation for this finding could be the role of healthcare managers in the healthcare context. Prior studies have suggested that healthcare practitioners (doctors, nursing staff) have significantly more bargaining power over technology decisions compared to managers in healthcare organizations (i.e., Aborujiah et al., 2022; Kumar et al., 2020, 2022; Van de Wetering & Versendaal, 2021). Process changes through technology are conducted only after the buy-in and consent of healthcare practitioners (Alrahbi et al., 2021; Laukka et al., 2020; Tasri & Tasri, 2020;). Therefore, the interaction between managerial capabilities and IT capabilities may bear no relevance in this context in the absence of the explicit support of healthcare practitioners and the presence of associated capabilities. In other words, the main effects of the influences of managerial capabilities were significant, while the moderating influences of MC in the relationship between LCTs and BPO did not prove to be significant. In light of these findings, future studies should further explore the role of healthcare practitioners, such as doctors and nurses, in such healthcare technology decisions and the corresponding process changes.

Finally, this paper also explored the impacts of hospital characteristics such as size and location on their moderating implications in the relationship between BPO and healthcare performance (employee and patient healthcare performance and healthcare performance in technology). The results revealed that hospital size positively moderates the relationship between BPO and employee and patient healthcare performance. This finding suggests that larger hospitals can enjoy enhanced benefits from LCTs concerning employee and patient performance. Moreover, the results revealed that hospital location positively moderates the relationship between BPO and healthcare performance in technology. This study suggests that rural hospitals can enjoy enhanced benefits from LCTs in technology-related performance.

Limitations of This Study

This study does have some limitations. First, this paper advises caution in applying the findings of this study in other countries, as this study examined only the perceptions of United States-based healthcare staff.

Second, this study only explored the performance impacts of LCTs in healthcare. Future studies may find differing results in other industries. Thus, this study advises caution in the interpretation of the findings.

Third, this study does not claim to have explored all factors that impact the relationship between LCTs and healthcare performance. Future studies may discover additional constructs.

Fourth, as this study only explored the perceptions of healthcare staff, healthcare firms may experience different results during the adoption phase of LCTs.

Finally, as this study employed the survey research method rather than the qualitative research method, it could not explore in-depth the factors impacting the relationship between LCTs and healthcare performance.

Implications for Research

While extant literature has suggested the potential performance benefits of locating LCTs, empirical studies that have explored the performance impacts of the technology in the healthcare context are lacking. As a result, prior studies have called for future research to address this gap (i.e., Fosso Wamba et al., 2013; Vilamovska et al., 2009;). The research contributions of this study are as follows.

First, to the best of my knowledge, this study is the first to empirically explore the performance impacts of LCTs in the healthcare context. Prior studies have suggested that healthcare staff are critical to the successful adoption of LCTs (i.e., Boulos & Berry, 2012; Fosso Wamba et al., 2013; Vilamovska et al., 2009). The survey research method in this study used primary data from healthcare staff related to their perceptions of LCTs' impact on firm performance.

Second, this study is also the first to conceptualize LBI capability as a higher-order or formative construct, consisting of locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability. The establishment of this construct has the potential to advance future research on how to best harness the power of LCTs to drive healthcare firm performance.

Third, this is the first study (to the best of my knowledge) to conceptualize healthcare performance in two dimensions: employee and patient healthcare performance and healthcare performance in technology. Moreover, this paper established that employee and patient healthcare performance is a higher-order or formative construct consisting of employee and patient performance benefits.

Finally, the research model in this paper investigated BPO as a mediator between LBI capability and healthcare performance (employee, patient, and technology benefits). Future research has the potential to explore other mediators further. While Brynjolfsson (1993) discussed the productivity paradox of IT, where increased investments in IT do not lead to improved performance in firms, Brynjolfsson and Hitt (1998) stated the importance of optimizing business processes to exploit improved capabilities in IT. The findings of this study support results from prior studies that have indicated that investments in IT without business process improvements do not lead to enhanced performance (i.e., Brynjolfsson & Hitt, 1998; Malinova et al., 2022). Moreover, the findings of this study highlight the role of managerial capabilities in BPO. The direct effects of managerial capabilities on business process improvements emphasize investments in managerial talents, in addition to IT investments that are critical to enhancing firm performance.

Implications for Practice

As healthcare firms are winding down their modernizations of electronic health records systems and ICD-10 conversions, they are looking at future IT investments to drive performance (“RFID: What's the frequency”, 2019). Healthcare leaders are looking to invest in LCTs to improve performance (i.e., financial and improved efficiency). As deploying LCTs can cost millions of dollars, decision-makers are eyeing research findings such as this study to make informed decisions on how to use their limited resources on IT projects. The essential contributions of this study on practice are as follows.

First, the findings of this study shed light on the perceptions of healthcare staff on the performance impacts of LCTs. Prior studies have indicated that staff play a crucial role in technology adoption (i.e., Boulos & Berry, 2012; Fosso Wamba et al., 2013; Vilamovska et al., 2009). Healthcare leaders can use insights from this paper to understand the factors with the potential to impact adoption.

Second, healthcare leaders may use the findings of this study for comparison with the results from Essay 1, where healthcare firms that deployed LCTs are compared with those without LCTs in regard to the financial measures of return on assets, net operating profit margin, and net income margin. Firms exploring LCT investment opportunities could use the insights from this study to learn from their peers that have successfully harnessed LCTs.

Third, the conceptualization of LBI capability could empower healthcare firms to identify the essential ingredients for implementing LCTs. For example, only having the asset and people capabilities without the information visibility capability will not lead to the successful use of LCTs.

Finally, the findings of this study underscore the importance of optimizing business processes to harness LCTs for enhanced performance. Healthcare firms should critically examine their existing business processes and adapt them for LCTs. In addition, developing managerial talent is critical for these firms, as the findings of this study indicate that managerial capabilities regarding the management of technology and resources have a direct effect on BPO.

Conclusion

Prior studies have suggested that healthcare firms face adoption challenges in using LCTs due to staff resistance related to privacy and security concerns. As most healthcare organizations complete the modernization of their electronic health record systems and ICD-10 conversions, they are exploring future IT investments for enhancing firm performance. However, healthcare leaders struggle to make optimal investment decisions due to a lack of understanding of whether investments in projects such as deploying costly locating capabilities technologies will positively impact performance. The findings of this study help healthcare decision-makers understand the pathways in how LCTs impact firm performance.

Although Essay 1 indicates that healthcare firms using LCTs perform worse than those that do not, this study sheds light on factors such as harnessing LCTs as LBI capability, optimizing business processes, and enhancing managerial capabilities. This paper recommends that future studies employ the case-study method for a more profound or richer exploration of healthcare firms using LCTs.

Finally, LCTs can positively impact healthcare firms' performance. This paper calls for future empirical studies to explore the interaction between LCTs and other IT capabilities, such as artificial intelligence and the Internet of things, to drive healthcare performance.

References

Aboelmaged, M., & Hashem, G. (2018). RFID application in patient and medical asset operations management: A technology, organizational and environmental (TOE) perspective into key enablers and impediments. *International Journal of Medical Informatics*, *118*, 58–64. https://doi.org/10.1016/j.ijmedinf.2018.07.009

Abugabah, A., Sanzogni, L., Houghton, L., AlZubi, A. A., & Abuqabbeh, A. (2021). RFID adaption in healthcare organizations: An integrative framework. *Computers, Materials and Continua*, *70*, 1335–1348. http://dx.doi.org/10.32604/cmc.2022.019097

Aborujiah, A., Elsebaie, A. E. F. M., Mokhtar, S. A., Long, Z. A., Shariff, S. M., Hussien, N. S., & Husen, M. N. (2022, January). A conceptual framework for an integrated healthcare information systems from an organizational perspective. In *2022 16th International Conference on Ubiquitous Information Management and Communication* (pp. 1–8). IEEE. https://doi.org/10.1109/IMCOM53663.2022.9721767

Agwunobi, A., & Osborne, P. (2016). Dynamic capabilities and healthcare: A framework for enhancing the competitive advantage of hospitals. *California Management Review*, *58*(4), 141–161. https://doi.org/10.1525/cmr.2016.58.4.141

Alrahbi, D., Khan, M., & Hussain, M. (2021). Exploring the motivators of technology adoption in healthcare. *International Journal of Healthcare Management*, *14*(1), 50–63. https://doi.org/10.1080/20479700.2019.1607451

Álvarez López, Y., Franssen, J., Álvarez Narciandi, G., Pagnozzi, J., González-Pinto Arrillaga, I., & Las-Heras Andrés, F. (2018). RFID technology for management and tracking: E-health applications. *Sensors, 18*(8), Article 2663. https://doi.org/10.3390/s18082663

Amendola, S., Lodato, R., Manzari, S., Occhiuzzi, C., & Marrocco, G. (2014). RFID technology for IoT-based personal healthcare in smart spaces. *IEEE Internet of Things Journal*, *1*(2), 144–152. https://doi.org/10.1109/JIOT.2014.2313981

Armstrong, C. P., & Sambamurthy, V. (1999). Information technology assimilation in firms: The influence of senior leadership and IT infrastructures. *Information Systems Research*, *10*(4), 304–327. https://doi.org/10.1287/isre.10.4.304

Arunachalam, S. P., Marisamy, G., Sir, M., Nestler, D., Hellmich, T., & Pasupathy, K. (2016). Linking patient alone time and provider time to staffing levels and LOS at the emergency department: a RFID based study. In W.-T. Fu, L. Hodges, K. Zheng, G. Stiglic, & A. Blandford (Eds.), *2016 IEEE International Conference on Healthcare Informatics* (pp. 102–105). IEEE. https://doi.org/10.1109/ichi.2016.17

Arunachalam, S. P., Sir, M., Marisamy, G., Sadosty, A., Nestler, D., Hellmich, T., & Pasupathy, K. (2017). Identifying factors influencing patient alone time at the emergency department using RFID data: What is next? In S. T. C. Wong, M. D. Wang, & A. F. Laine (Eds.), *2017 IEEE EMBS International Conference on Biomedical & Health Informatics* (pp. 225–228). IEEE. https://doi.org/10.1109/bhi.2017.7897246

Asamoah, D. A., Sharda, R., Rude, H. N., & Doran, D. (2018). RFID-based information visibility for hospital operations: Exploring its positive effects using discrete event simulation. *Health Care Management Science*, *21*(3), 305–316. https://doi.org/10.1007/s10729-016-9386-y

Attili, V. S., Mathew, S. K., & Sugumaran, V. (2021). Information privacy assimilation in IT organizations. *Information Systems Frontiers*, 1–17. https://doi.org/10.1007/s10796-021-10158-0

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, *36*(3), 421–458. https://doi.org/10.2307/2393203

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, *24*(1), 169–196. https://doi.org/10.2307/3250983

Bititci, U. S., Ackermann, F., Ates, A., Davies, J., Garengo, P., Gibb, S., MacBryde, J., Mackay, D., Maguire, C., van der Meer, R., Shafti, F., Bourne, M., & Firat, S. U. (2011). Managerial processes: Business process that sustain performance. *International Journal of Operations & Production Management*, *31*(8), 851–891. https://doi.org/10.1108/01443571111153076

Boulos, M. N., & Berry, G. (2012). Real-time locating systems (RTLS) in healthcare: A condensed primer. *International Journal of Health Geographics*, *11*(1), 1–8. https://doi.org/10.1186/1476-072X-11-25

Bowman, C., & Ambrosini, V. (2003). How the resource-based and the dynamic capability views of the firm inform corporate-level strategy. *British Journal of Management*, *14*(4), 289-303. https://doi.org/10.1111/j.1467-8551.2003.00380.x

Bradley, R. V., Esper, T. L., In, J., Lee, K. B., Bichescu, B. C., & Byrd, T. A. (2018). The joint use of RFID and EDI: Implications for hospital performance. *Production and Operations Management*, *27*(11), 2071–2090. https://doi.org/10.1111/poms.12955

Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM*, *36*(12), 66–77. https://doi.org/10.1145/163298.163309

Brynjolfsson, E., & Hitt, L. M. (1998). Beyond the productivity paradox. *Communications of the ACM*, *41*(8), 49–55. https://doi.org/10.1145/280324.280332

Budak, A., & Ustundag, A. (2015). Fuzzy decision making model for selection of real time location systems. *Applied Soft Computing*, *36*, 177–184. https://doi.org/10.1016/j.asoc.2015.05.057

Carr, N. G. (2004). *Does IT matter? Information technology and the corrosion of competitive advantage*. Harvard Business Press.

Dang, A., Thakker, R., Li, S., Hommel, E., Mehta, H. B., & Goodwin, J. S. (2022). Hospitalizations and mortality from non–SARS-CoV-2 causes among Medicare beneficiaries at US hospitals during the SARS-CoV-2 pandemic. *JAMA Network Open*, *5*(3), Article 221754.

Datta, R., Glenn, K., Pellegrino, A., Tuan, J., Linde, B., Kayani, J., Patel, K., Calo, L., Dembry, L. M., & Fisher, A. (2022). Increasing face-mask compliance among healthcare personnel during the coronavirus disease 2019 (COVID-19) pandemic. *Infection Control & Hospital Epidemiology*, *43*(5), 616–622. https://doi.org/10.1017%2Fice.2021.205

Davenport, T. H. (1993). *Process innovation: Reengineering work through information technology*. Harvard Business Press.

Dixit, R. A., Hurst, S., Adams, K. T., Boxley, C., Lysen-Hendershot, K., Bennett, S. S., Booker, E., & Ratwani, R. M. (2020). Rapid development of visualization dashboards to enhance situation awareness of COVID-19 telehealth initiatives at a multihospital healthcare system. *Journal of the American Medical Informatics Association, 27*(9), 1456–1461. https://doi.org/10.1093/jamia/ocaa161

Eggers, J. P. (2012). All experience is not created equal: Learning, adapting, and focusing in product portfolio management. *Strategic Management Journal*, *33*(3), 315–335. https://doi.org/10.1002/smj.956

Ersol, D., & Fescioglu-Unver, N. (2017). Heuristic policies for mobile asset sharing within hospitals. *Computers & Industrial Engineering*, *111*, 352–363. https://doi.org/10.1016/j.cie.2017.07.038

Frei, F. X., & Harker, P. T. (1999). Measuring aggregate process performance using AHP. *European Journal of Operational Research*, *116*(2), 436–442. https://doi.org/10.1016/S0377-2217(98)00134-9

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. *Journal of Management Studies*, *53*(8), 1348–1380. https://doi.org/10.1111/joms.12213

Fisher, J. A., & Monahan, T. (2012). Evaluation of real-time location systems in their hospital contexts. *International Journal of Medical Informatics*, *81*(10), 705–712. https://doi.org/10.1016/j.ijmedinf.2012.07.001

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.2307/3150980

Fosso Wamba, S. (2012). RFID-enabled healthcare applications, issues and benefits: An archival analysis (1997–2011). *Journal of Medical Systems*, *36*(6), 3393–3398. https://doi.org/10.1007/s10916-011-9807-x

Fosso Wamba, S., Anand, A., & Carter, L. (2013). A literature review of RFID-enabled healthcare applications and issues. *International Journal of Information Management*, *33*(5), 875–891. https://doi.org/10.1016/j.ijinfomgt.2013.07.005

Ganesh, L. S., & Marathe, R. R. (2019). Dynamic capabilities: A morphological analysis framework and agenda for future research. *European Business Review*.

Gao, P., Zhang, J., Gong, Y., & Li, H. (2020). Effects of technical IT capabilities on organizational agility: The moderating role of IT business spanning capability. *Industrial Management & Data Systems*, *120*(5), 941–961. https://doi.org/10.1108/IMDS-08-2019-0433

Garcia-Lacalle, J., & Martin, E. (2010). Rural vs urban hospital performance in a 'competitive'public health service. *Social Science & Medicine*, *71*(6), 1131–1140. https://doi.org/10.1016/j.socscimed.2010.05.043

Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information systems*, *16*, Article 5. https://doi.org/10.17705/1CAIS.01605

Geweke, J., Gowrisankaran, G., & Town, R. J. (2003). Bayesian inference for hospital quality in a selection model. *Econometrica*, *71*(4), 1215–1238. https://doi.org/10.1111/1468-0262.00444

Giancotti, M., Guglielmo, A., & Mauro, M. (2017). Efficiency and optimal size of hospitals: Results of a systematic search. *PloS One*, *12*(3), Article e0174533. https://doi.org/10.1371/journal.pone.0174533

Gowrisankaran, G., & Town, R. J. (2003). Competition, payers, and hospital quality. *Health Services Research*, *38*(6 Pt. 1), 1403–1422. https://doi.org/10.1111%2Fj.1475-6773.2003.00185.x

Gu, V. C., & Black, K. (2020). Integration of TTF and network externalities for RFID adoption in healthcare industry. *International Journal of Productivity and Performance Management*, *70*(1), 109–129. https://doi.org/10.1108/IJPPM-11-2018-0418

Gupta, G., Kundu, T., & Codanda, A. A. (2015). An integrated conceptual framework for RFID enabled healthcare. *Independent Journal of Management & Production*, *6*(4), 946–961. https://doi.org/10.14807/ijmp.v6i4.356

Haddara, M., & Staaby, A. (2020). Enhancing patient safety: A focus on RFID applications in healthcare. *International Journal of Reliable and Quality E-Healthcare*, *9*(2), 1–17. https://doi.org/10.4018/IJRQEH.2020040101

Haddara, M., & Staaby, A. (2022). RFID applications for patient safety in the healthcare sector. In A. Moumtzoglou (Ed.), *Quality of healthcare in the aftermath of the COVID-19 pandemic* (pp. 155–179). IGI Global. https://doi.org/10.4018/978-1-7998-9198-7.ch009

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Babin, B., Black, W., & Anderson, R. (2018). *Multivariate Data Analysis* (8th ed.). CENGAGE INDIA.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M. A., Singh, H., Teece, D. J., & Winter, S. G. (2007). Dynamic capabilities: foundations. *Dynamic capabilities: Understanding strategic change in organizations*, 30-45.

Hammer, M. (2015). What is business process management?. In *Handbook on business process management 1* (pp. 3-16). Springer, Berlin, Heidelberg.

Hossain, M. M., & Prybutok, V. R. (2008). Consumer acceptance of RFID technology: An exploratory study. *IEEE Transactions on Engineering Management*, *55*(2), 316–328. https://doi.org/10.1109/TEM.2008.919728

Huntsman, D., Greer, A., Murphy, H., & Li, X. D. (2022). The effects of empowerment at multiple leadership levels in the fire service: A moderated mediation model. *International Journal of Emergency Services*, *11*(2), 338–360. https://doi.org/10.1108/IJES-07-2021-0042

Ilangakoon, T. S., Weerabahu, S. K., Samaranayake, P., & Wickramarachchi, R. (2021). Adoption of Industry 4.0 and lean concepts in hospitals for healthcare operational performance improvement. *International Journal of Productivity and Performance Management*, *71*(6), 2188–2213. https://doi.org/10.1108/IJPPM-12-2020-0654

Iqbal, M., Siti Astuti, E., Trialih, R., Arifin, Z., & Alief Aprilian, Y. (2020). The influences of information technology resources on knowledge management capabilities: Organizational culture as mediator variable. *Human Systems Management*, *39*(2), 129–139. https://doi.org/10.3233/HSM-190562

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of consumer research*, *30*(2), 199-218.

Jones, E. C., & Gupta, S. (2015). Hospital supply chain management by implementing RFID. *International Journal of Supply Chain Management*, *4*(3), 1–6.

Kabasakal, E., Özpulat, F., Akca, A., & Özcebe, L. H. (2021). COVID-19 fear and compliance in preventive measures precautions in workers during the COVID-19 pandemic. *International Archives of Occupational and Environmental Health*, *94*(6), 1239–1247. https://doi.org/10.1007/s00420-021-01682-2

Kareem, H. M., Dauwed, M., Meri, A., Jarrar, M. T., Al-Bsheish, M., & Aldujaili, A. A. (2021). The role of accounting information system and knowledge management to enhancing organizational performance in Iraqi SMEs. *Sustainability*, *13*(22), Article 12706. https://doi.org/10.3390/su132212706

Katz, J. E., & Rice, R. E. (2009). Public views of mobile medical devices and services: A US national survey of consumer sentiments towards RFID healthcare technology. *International Journal of Medical Informatics, 78*(2), 104–114. https://doi.org/10.1016/j.ijmedinf.2008.06.001

Kaufman, B. G., Reiter, K. L., Pink, G. H., & Holmes, G. M. (2016). Medicaid expansion affects rural and urban hospitals differently. *Health Affairs*, *35*(9), 1665–1672. https://doi.org/10.1377/hlthaff.2016.0357

Kor, Y. Y., & Mesko, A. (2013). Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic Management Journal*, *34*(2), 233–244. https://doi.org/10.1002/smj.2000

Kumar, M., Singh, J. B., Chandwani, R., & Gupta, A. (2020). “Context” in healthcare information technology resistance: A systematic review of extant literature and agenda for future research. *International Journal of Information Management*, *51*, Article 102044. https://doi.org/10.1016/j.ijinfomgt.2019.102044

Kumar, M., Singh, J. B., Chandwani, R., & Gupta, A. (2022). Locating resistance to healthcare information technology: A Bourdieusian analysis of doctors' symbolic capital conservation. *Information Systems Journal*, *32*(2), 377–413. https://doi.org/10.1111/isj.12357

Laukka, E., Huhtakangas, M., Heponiemi, T., & Kanste, O. (2020). Identifying the roles of healthcare leaders in HIT implementation: A scoping review of the quantitative and qualitative evidence. *International Journal of Environmental Research and Public Health*, *17*(8), Article 2865. https://doi.org/10.3390%2Fijerph17082865

Liang, T. P., You, J. J., & Liu, C. C. (2010). A resource-based perspective on information technology and firm performance: A meta analysis. *Industrial Management & Data Systems*, *110*(8), 1138–1158. https://doi.org/10.1108/02635571011077807

Lindrooth, R. C., Perraillon, M. C., Hardy, R. Y., & Tung, G. J. (2018). Understanding the relationship between Medicaid expansions and hospital closures. *Health Affairs*, *37*(1), 111–120. https://doi.org/10.1377/hlthaff.2017.0976

Lipsitz, L. A., Lujan, A. M., Dufour, A., Abrahams, G., Magliozzi, H., Herndon, L., & Dar, M. (2020). Stemming the tide of COVID-19 infections in Massachusetts nursing homes. *Journal of the American Geriatrics Society*, *68*(11), 2447–2453. https://doi.org/10.1111/jgs.16832

Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, *54*(3), 1452–1462. https://doi.org/10.1016/j.dss.2012.12.016

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication*, *57*(2), 123–146. https://doi.org/10.1109/TPC.2014.2312452

Macher, J. T., & Mowery, D. C. (2009). Measuring dynamic capabilities: practices and performance in semiconductor manufacturing. *British Journal of Management*, *20*, S41–S62. https://doi.org/10.1111/j.1467-8551.2008.00612.x

Malinova, M., Gross, S., & Mendling, J. (2022). A study into the contingencies of process improvement methods. *Information Systems*, *104*, Article 101880. https://doi.org/10.1016/j.is.2021.101880

Mark, R. (1996). *Research made simple: A handbook for social workers*. Sage.

Martin, J. A. (2011). Dynamic managerial capabilities and the multibusiness team: The role of episodic teams in executive leadership groups. *Organization science*, *22*(1), 118-140.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, *19*(4), 487–505. https://doi.org/10.2307/249630

McFarland, D. C., Shen, M. J., Parker, P., Meyerson, S., & Holcombe, R. F. (2017). Does hospital size affect patient satisfaction? *Quality Management in Health Care*, *26*(4), 205–209. https://doi.org/10.1097/QMH.0000000000000149

Moatari-Kazerouni, A., & Bendavid, Y. (2017). Improving logistics processes of surgical instruments: Case of RFID technology. *Business Process Management Journal*, *23*(2), 448–466. https://doi.org/10.1108/BPMJ-06-2016-0127

Moretti, E. D. A., Anholon, R., Rampasso, I. S., Silva, D., Santa-Eulalia, L. A., & Ignácio, P. S. D. A. (2019). Main difficulties during RFID implementation: An exploratory factor analysis approach. *Technology Analysis & Strategic Management*, *31*(8), 943–956. https://doi.org/10.1080/09537325.2019.1575351

Murphy, W. H., & Wilson, G. A. (2021). Dynamic capabilities and stakeholder theory explanation of superior performance among award-winning hospitals. *International Journal of Healthcare Management*, *15*(3), 211–219. https://doi.org/10.1080/20479700.2020.1870356

Naresh, V. S., Reddi, S., & Murthy, N. V. (2020). Secure lightweight IoT integrated RFID mobile healthcare system. *Wireless Communications and Mobile Computing, 2020,* Article 1468281. https://doi.org/10.1155/2020/1468281

Nunnally, J. C. (1978). An overview of psychological measurement. In B. B. Wolman (Ed.), *Clinical diagnosis of mental disorders*, (pp. 97–146). Springer. https://doi.org/10.1007/978-1-4684-2490-4_4

Parmar, B. L., Freeman, R. E., Harrison, J. S., Wicks, A. C., Purnell, L., & De Colle, S. (2010). Stakeholder Theory:*The state of the Art*. *Academy of Management Annals*, *4*(1), 403-445. https://doi.org/10.5465/19416520.2010.495581

Patel, L., Elliott, A., Storlie, E., Kethireddy, R., Goodman, K., & Dickey, W. (2020). Ethical and legal challenges during the COVID-19 pandemic: Are we thinking about rural hospitals. *The Journal of Rural Health*, *37*(1), 175–178. https://doi.org/10.1111/jrh.12447

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198–227. https://doi.org/10.1287/isre.1060.0094

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly*, *31*(1), 105–136.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*. Sage.

Pick, M., Lahr, M., Charania, S., & Moscovice, I. (2022, June). *Supporting critical access hospital staff during COVID-19*. Flex Monitoring Team. https://www.flexmonitoring.org/sites/flexmonitoring.umn.edu/files/media/Supporting_CAH_Staff_during_COVID-19.pdf

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531–544. https://doi.org/10.1177/014920638601200408

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, *54*(1), 729-739. https://doi.org/10.1016/j.dss.2012.08.017

Protogerou, A., Caloghirou, Y., & Lioukas, S. (2011). Dynamic capabilities and their indirect impact on firm performance. *Industrial and Corporate Change*, *21*(3), 615-647. https://doi.org/10.1093/icc/dtr049

Ramirez, R., Melville, N., & Lawler, E. (2010). Information technology infrastructure, organizational process redesign, and business value: An empirical analysis. *Decision Support Systems*, *49*(4), 417–429. https://doi.org/10.1016/j.dss.2010.05.003

Rasool, W., & Waheed, A. (2021). Improving organizational performance through knowledge management capabilities: Mediating role of organizational learning and organizational innovation. *Paradigms*, *15*(1), 1–11.

Ravichandran, T., Lertwongsatien, C., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of Management Information Systems*, *21*(4), 237–276. https://doi.org/10.1080/07421222.2005.11045820

Rehman, N., Mahmood, A., Ikram, A., & Ahmad, A. (2021). Firing on all cylinders: Configuring information technology around the constituents of corporate entrepreneurship to outperform in SME sector. *Plos One*, *16*(9), Article e0256539. https://doi.org/10.1371/journal.pone.0256539

Reyes, P. M., Li, S., & Visich, J. K. (2016). Determinants of RFID adoption stage and perceived benefits. *European Journal of Operational Research*, *254*(3), 801–812. https://doi.org/10.1016/j.ejor.2016.03.051

RFID: What's the frequency, healthcare? (2019, August 23). Healthcare Purchasing News. https://www.hpnonline.com/sourcing-logistics/article/21092222/rfid-whats-the-frequency-healthcare

Ristevski, B., Savoska, S., & Blazheska-Tabakovska, N. (2020). Opportunities for big data analytics in healthcare information systems development for decision support. In V. Dimitrov & V. Georgiev (Eds.), *ISGT 2020: The 13th conference on information systems and grid technologies* (pp. 38–50). CEUR-WS.org. https://ceur-ws.org/Vol-2656/paper4.pdf

Rosemann, M., & Brocke, J. V. (2015). The six core elements of business process management. In *Handbook on business process management 1* (pp. 105-122). Springer, Berlin, Heidelberg.

Rosenbloom, R. S. (2000). Leadership, capabilities, and technological change: The transformation of NCR in the electronic era. *Strategic management journal*, *21*(10-11), 1083-1103.

Ross, J. W., Beath, C. M., & Goodhue, D. L. (1996). Develop long-term competitiveness through IT assets. *Sloan Management Review*, *38*(1), 31–42.

Savolainen, T. I. (1999). Cycles of continuous improvement: realizing competitive advantages through quality. *International Journal of Operations & Production Management*.

Schreyögg, G., & Kliesch-Eberl, M. (2007). How dynamic can organizational capabilities be? Towards a dual-process model of capability dynamization. *Strategic Management Journal*, *28*(9), 913–933. https://doi.org/10.1002/smj.613

Segel, J. E., Ross, H. I., Edwards, J. L., Braun, K. A., & Davis, L. A. (2021). The unique challenges facing rural providers in the COVID-19 pandemic. *Population Health Management*, *24*(3), 304–306. https://doi.org/10.1089/pop.2020.0151

Shokouhifar, M. (2021). Swarm intelligence RFID network planning using multi-antenna readers for asset tracking in hospital environments. *Computer Networks*, *198*, Article 108427. https://doi.org/10.1016/j.comnet.2021.108427

Slonim, A. D., See, H., & Slonim, S. (2020). Challenges confronting rural hospitals accentuated during COVID-19. *Journal of Biomedical Research*, *34*(6), 397–409. https://doi.org/10.7555%2FJBR.34.20200112

Sirmon, D. G., & Hitt, M. A. (2009). Contingencies within dynamic managerial capabilities: Interdependent effects of resource investment and deployment on firm performance. *Strategic management journal*, *30*(13), 1375-1394.

Soper, D.S. (2022). A-priori Sample Size Calculator for Multiple Regression [Software]. https://www.danielsoper.com/statcalc

Spaulding, A. C., Hamadi, H., Osagiede, O., Lemini, R., Cochuyt, J. J., Watson, J., Naessens, J. M., & Colibaseanu, D. T. (2021). Hospital robotic use for colorectal cancer care. *Journal of Robotic Surgery*, *15*(4), 561–569. https://doi.org/10.1007/s11701-020-01142-y

Tamilvizhi, T., Surendran, R., & Bommi, R. M. (2020, December). Radio frequency identification (RFID) based ubiquitous health care data handling. In K. Tanaka, R. Mervin, & R. Menaka (Eds.), *IOP Conference Series: Materials Science and Engineering* (Vol. 994, Article 012021). IOP Publishing. https://doi.org/10.1088/1757-899X/994/1/012021

Tanriverdi, H. (2005). Information technology relatedness, knowledge management capability, and performance of multibusiness firms. *MIS Quarterly*, *29*(2), 311–334. https://doi.org/10.2307/25148681

Tasri, Y. D., & Tasri, E. S. (2020). Improving clinical records: Their role in decision-making and healthcare management–COVID-19 perspectives. *International Journal of Healthcare Management*, *13*(4), 325–336. https://doi.org/10.1080/20479700.2020.1803623

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319-1350. https://doi.org/10.1002/smj.640

Ting, S. L., Kwok, S. K., Tsang, A. H., & Lee, W. B. (2011). Critical elements and lessons learnt from the implementation of an RFID-enabled healthcare management system in a medical organization. *Journal of Medical Systems*, *35*(4), 657–669. https://doi.org/10.1007/s10916-009-9403-5

Torres, R., Sidorova, A., & Jones, M. C. (2018). Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Information & Management*, *55*(7), 822-839. https://doi.org/10.1016/j.im.2018.03.010

Van de Wetering, R., & Versendaal, J. (2021). Information technology ambidexterity, digital dynamic capability, and knowledge processes as enablers of patient agility: Empirical study. *JMIRx Med*, *2*(4), Article e32336. https://doi.org/10.2196/32336

Vilamovska, A. M., Hatziandreu, E., Schindler, H. R., van Oranje-Nassau, C., De Vries, H., & Krapels, J. (2009). Study on the requirements and options for RFID application in healthcare Identifying areas for radio frequency identification deployment in healthcare delivery: A review of relevant literature. *Directorate General Information Society and Media*, *13*(1), 223–238.

Volland, J., Fügener, A., Schoenfelder, J., & Brunner, J. O. (2017). Material logistics in hospitals: A literature review. *Omega*, *69*, 82–101. https://doi.org/10.1016/j.omega.2016.08.004

Wang, C. L., Senaratne, C., & Rafiq, M. (2015). Success traps, dynamic capabilities and firm performance. *British Journal of Management*, *26*(1), 26-44.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3–13. https://doi.org/10.1016/j.techfore.2015.12.019

Wei, J., Lowry, P. B., & Seedorf, S. (2015). The assimilation of RFID technology by Chinese companies: A technology diffusion perspective. *Information & Management*, *52*(6), 628-642.

Yazici, H. J. (2014). An exploratory analysis of hospital perspectives on real time information requirements and perceived benefits of RFID technology for future adoption. *International Journal of Information Management*, *34*(5), 603–621. https://doi.org/10.1016/j.ijinfomgt.2014.04.010

Yeoh, C. B., Van Rooyen, C., Tan, K. S., Mascarenhas, J., Yang, G., Kerpelev, M., & Tollinche, L. E. (2019). Real Time Locating Systems and sustainability of Perioperative Efficiency of Anesthesiologists. *EC anaesthesia*, *5*(8), 233–238.

Yin, R. K. (2013). Validity and generalization in future case study evaluations. *Evaluation*, *19*(3), 321-332.

Zhu, X., Tao, Y., Zhu, R., Wu, D., & Ming, W. K. (2022). Impact of hospital characteristics and governance structure on the adoption of tracking technologies for clinical and supply chain use: Longitudinal study of US hospitals. *Journal of Medical Internet Research*, *24*(5), Article e33742.

Concluding Remarks

This dissertation aimed to explore the performance impacts of locating capabilities technologies (LCTs) on healthcare performance. To the best of my knowledge, this is the first empirical study that employed both secondary data and survey data analysis to explore the impact of LCTs. While Essay 1 compared the financial performance (return on assets, net operating profit margin, and net income margin) of healthcare firms with LCTs and those without, Essay 2 explored LCTs' impacts through the performance perceptions of healthcare staff.

While extant literature has widely established the positive link between information technology and firm performance (i.e., Teece et al., 1997), the two essays produced opposite results. In Essay 1, contrary to what this study expected, the secondary data analysis indicated that healthcare firms using LCTs significantly performed worse. Interestingly, Essay 2's results were the opposite, where LCTs had a positive and significant relationship with healthcare performance (employee, patient, and technology benefits). Moreover, Essay 2 identified that business process optimization (BPO) mediates the relationship between LCTs (location-based intelligence capability) and performance, and hospital characteristics such as size and location positively moderate the relationship between BPO and performance.

What might explain the discrepancy between the results from the two essays? First, the secondary data set did not include any information on whether the firms using LCTs had all four formative dimensions of location-based intelligence capability (locating infrastructure capability, asset locating capability, patient and staff locating capability, and information visibility capability), whether the firms optimized their business processes to harness LCTs, whether the firms had the managerial capabilities to exploits LCTs, and whether firms used LCTs throughout the enterprise.

Second, the secondary data set contained some firms that achieved improved financial performance after deploying LCTs. This study recommends that future researchers employ qualitative research methods (i.e., case studies) to realize a much richer understanding of how LCTs impact healthcare.

Third, Essay 2 indicated that healthcare firms that optimize their business processes potentially improve performance; BPO mediated the relationship between LCTs (location-based intelligence capability) and healthcare performance. Thus, this study recommends that healthcare firms expend serious efforts in adapting their existing business processes to exploit LCTs.

Fourth, Essay 2 also indicated that managerial capabilities directly and positively impact BPO. Managers play critical roles in organizations' decision-making, strategy planning, and implementation (Ganesh & Marathe, 2019). Thus, this study recommends that healthcare firms take the initiative to develop their managerial talent for adaptive business processes for LCTs.

Finally, the secondary data set indicates that the adoption of LCTs in healthcare has slowed down significantly—most of the firms in the treatment group (using LCTs) deployed the technology between 2011 and 2013. There appeared to be a sharp drop after 2013. Seeing this in the data did not surprise me. From my professional experience selling business software such as LCTs in healthcare, I know that firms have been struggling with the complexity of using LCTs. Moreover, decision-makers have had difficulties understanding the cost-benefit equation of their investments in LCTs. My hope is that the two essays' findings illuminate the factors linking LCTs with healthcare performance.

Appendix A

t Test Results

While the treatment group, Group 1, contained healthcare firms using Locating Capabilities Technologies (LCTs), Group 2 contained firms that were not.

Table A1. Descriptive Statistics – Treatment Group (Group 1)

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Skewness	
Variable	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error
Group	92	0	1	1	1.00	0.000	0.000		
Urban or Rural	92	1	0	1	.51	.052	.503	-.044	.251
Size	92	2	1	3	1.91	.096	.922	.175	.251
ROA Year 0	91	1.3134	-.6519	.6615	.035592	.0150966	.1440125	-.479	.253
ROA Year 1	92	1.7539	-.9392	.8147	.008807	.0211535	.2028972	-1.373	.251
ROA Year 2	92	8.3595	-1.9068	6.4526	.096624	.0816784	.7834319	6.224	.251
ROA Year 3	92	2.1537	-1.7173	.4364	-.016966	.0252850	.2425249	-4.268	.251
ROA Year 4	92	1.2734	-.8332	.4402	-.001309	.0191638	.1838126	-1.463	.251
ROA Year 5	92	1.6963	-1.0685	.6278	.037461	.0190539	.1827582	-2.377	.251
NOPM Year 0	91	.8290	-.5810	.2480	-.039549	.0111658	.1065153	-1.241	.253
NOPM Year 1	92	1.2900	-1.0320	.2580	-.062348	.0166983	.1601641	-2.915	.251
NOPM Year 2	91	.9430	-.4420	.5010	-.029495	.0124824	.1190749	.643	.253
NOPM Year 3	92	1.3030	-.9930	.3100	-.072120	.0186914	.1792815	-2.149	.251
NOPM Year 4	92	.9120	-.5860	.3260	-.069543	.0157123	.1507068	-.454	.251
NOPM Year 5	92	1.5930	-1.0640	.5290	-.045435	.0178596	.1713032	-1.999	.251
NIM Year 0	91	.3920	-.1380	.2540	.038242	.0079810	.0761334	.107	.253
NIM Year 1	92	1.1720	-.9080	.2640	.025848	.0143320	.1374677	-3.497	.251
NIM Year 2	91	.8730	-.5900	.2830	.033088	.0114389	.1091199	-2.095	.253

NIM Year 3	92	1.2220	-.9060	.3160	-.002848	.0162063	.1554456	-3.030	.251
NIM Year 4	92	.7280	-.3970	.3310	.015598	.0134328	.1288432	-.537	.251
NIM Year 5	92	.9760	-.4280	.5480	.044587	.0122099	.1171136	.291	.251

Note. ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin.

Table A2. Descriptive Statistics – Control Group (Group 2)

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Skewness	
Variable	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error
Group	92	0	2	2	2.00	0.000	0.000		
Urban or Rural	91	1	0	1	.52	.053	.502	-.067	.253
Size	92	2	1	3	1.91	.096	.922	.175	.251
ROA Year 0	92	.5022	-.2188	.2834	.046920	.0092529	.0887503	.104	.251
ROA Year 1	90	1.1353	-.5596	.5757	.053043	.0127096	.1205737	-.405	.254
ROA Year 2	91	1.6038	-.9611	.6426	.046189	.0171091	.1632102	-1.846	.253
ROA Year 3	92	.7684	-.3230	.4453	.050455	.0124758	.1196635	-.084	.251
ROA Year 4	92	1.4744	-.4739	1.0005	.060140	.0182201	.1747613	2.063	.251
ROA Year 5	92	9.3498	-2.3537	6.9961	.109125	.0818638	.7852099	7.244	.251
NOPM Year 0	92	1.6420	-1.4340	.2080	-.042511	.0184616	.1770777	-5.517	.251
NOPM Year 1	90	.6100	-.3920	.2180	-.030544	.0115946	.1099964	-.465	.254
NOPM Year 2	91	.5990	-.3830	.2160	-.022857	.0129422	.1234606	-.688	.253
NOPM Year 3	92	1.1300	-.8520	.2780	-.032663	.0164020	.1573221	-2.074	.251
NOPM Year 4	92	1.4300	-1.0190	.4110	-.027098	.0172705	.1656524	-2.150	.251
NOPM Year 5	91	2.1130	-.6520	1.4610	-.024209	.0227711	.2172221	3.191	.253
NIM Year 0	92	.3920	-.1630	.2290	.037120	.0069896	.0670417	.038	.251
NIM Year 1	90	.4480	-.2070	.2410	.041244	.0083214	.0789433	-.259	.254
NIM Year 2	91	.7070	-.3810	.3260	.040165	.0096961	.0924946	-.717	.253
NIM Year 3	92	.6290	-.3440	.2850	.040859	.0092439	.0886646	-.889	.251

NIM Year 4	92	.5700	-.1810	.3890	.044804	.0098472	.0944508	.536	.251
NIM Year 5	91	1.7650	-.2790	1.4860	.045857	.0189864	.1811189	5.567	.253

Note. ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin.

Table A3. Group Statistics

Financial Measure	Group	N	M	SD	SE Mean
ROA Year 1	1	92	.008807	.2028972	.0211535
	2	90	.053043	.1205737	.0127096
ROA Year 2	1	92	.096624	.7834319	.0816784
	2	91	.046189	.1632102	.0171091
ROA Year 3	1	92	-.016966	.2425249	.0252850
	2	92	.050455	.1196635	.0124758
ROA Year 4	1	92	-.001309	.1838126	.0191638
	2	92	.060140	.1747613	.0182201
ROA Year 5	1	92	.037461	.1827582	.0190539
	2	92	.109125	.7852099	.0818638
NOPM Year 1	1	92	-.062348	.1601641	.0166983
	2	90	-.030544	.1099964	.0115946
NOPM Year 2	1	91	-.029495	.1190749	.0124824
	2	91	-.022857	.1234606	.0129422
NOPM Year 3	1	92	-.072120	.1792815	.0186914
	2	92	-.032663	.1573221	.0164020
NOPM Year 4	1	92	-.069543	.1507068	.0157123
	2	92	-.027098	.1656524	.0172705
NOPM Year 5	1	92	-.045435	.1713032	.0178596
	2	91	-.024209	.2172221	.0227711
NIM Year 1	1	92	.025848	.1374677	.0143320
	2	90	.041244	.0789433	.0083214
NIM Year 2	1	91	.033088	.1091199	.0114389
	2	91	.040165	.0924946	.0096961
NIM Year 3	1	92	-.002848	.1554456	.0162063
	2	92	.040859	.0886646	.0092439
NIM Year 4	1	92	.015598	.1288432	.0134328
	2	92	.044804	.0944508	.0098472
NIM Year 5	1	92	.044587	.1171136	.0122099
	2	91	.045857	.1811189	.0189864

Note. ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin.

Table A4. Independent Samples t-Tests

Financial Measures and Variance Assumptions		Levene's Test for Equality of Variances *F*	Sig.	t-test for Equality of Means *t*	*df*	Sig. (2-tailed)	*M* Difference	*SE* Difference	95% Confidence Interval of the Difference Lower	Upper
ROA Year 1	Equal variances assumed	3.034	.083	-1.783	180	.076	-.0442354	.0248087	-.0931887	.0047179
	Equal variances not assumed			-1.793	148.741	.075	-.0442354	.0246780	-.0930001	.0045294
ROA Year 2	Equal variances assumed	2.918	.089	.601	181	.548	.0504352	.0838725	-.1150585	.2159289
	Equal variances not assumed			.604	98.968	.547	.0504352	.0834511	-.1151505	.2160210
ROA Year 3	Equal variances assumed	3.378	.068	-2.391	182	.018	-.0674208	.0281953	-.1230525	-.0117891
	Equal variances not assumed			-2.391	132.829	.018	-.0674208	.0281953	-.1231906	-.0116509
ROA Year 4	Equal variances assumed	.556	.457	-2.324	182	.021	-.0614489	.0264428	-.1136228	-.0092749
	Equal variances not assumed			-2.324	181.538	.021	-.0614489	.0264428	-.1136237	-.0092740
ROA Year 5	Equal variances assumed	2.342	.128	-.853	182	.395	-.0716646	.0840519	-.2375061	.0941770
	Equal variances not assumed			-.853	100.831	.396	-.0716646	.0840519	-.2384044	.0950753

NOPM Year 1	Equal variances assumed	.734	.393	-1.558	180	.121	-.0318034	.0204098	-.0720766	.0084698
	Equal variances not assumed			-1.564	161.514	.120	-.0318034	.0203290	-.0719483	.0083415
NOPM Year 2	Equal variances assumed	.983	.323	-.369	180	.712	-.0066374	.0179809	-.0421178	.0288430
	Equal variances not assumed			-.369	179.765	.712	-.0066374	.0179809	-.0421181	.0288434

Financial Measures and Variance Assumptions		Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Sig.	*t*	*df*	Sig. (2-tailed)	*M* Difference	*SE* Difference	Upper	Lower
NOPM Year 3	Equal variances assumed	.150	.699	-1.587	182	.114	-.0394565	.0248675	-.0885222	.0096091
	Equal variances not assumed			-1.587	178.979	.114	-.0394565	.0248675	-.0885277	.0096147
NOPM Year 4	Equal variances assumed	.015	.903	-1.818	182	.071	-.0424457	.0233483	-.0885139	.0036226
	Equal variances not assumed			-1.818	180.397	.071	-.0424457	.0233483	-.0885166	.0036253
NOPM Year 5	Equal variances assumed	.958	.329	-.734	181	.464	-.0212260	.0289023	-.0782548	.0358028
	Equal variances not assumed			-.733	170.845	.464	-.0212260	.0289394	-.0783507	.0358988

NIM Year 1	Equal variances assumed	3.741	.055	-.924	180	.357	-.0153966	.0166652	-.0482808	.0174876
	Equal variances not assumed			-.929	145.759	.354	-.0153966	.0165726	-.0481503	.0173570
NIM Year 2	Equal variances assumed	.412	.522	-.472	180	.638	-.0070769	.0149954	-.0366663	.0225124
	Equal variances not assumed			-.472	175.296	.638	-.0070769	.0149954	-.0366716	.0225178
NIM Year 3	Equal variances assumed	3.905	.050	-2.343	182	.020	-.0437065	.0186573	-.0805190	-.0068941
	Equal variances not assumed			-2.343	144.545	.021	-.0437065	.0186573	-.0805829	-.0068301
NIM Year 4	Equal variances assumed	3.745	.055	-1.754	182	.081	-.0292065	.0166556	-.0620694	.0036563
	Equal variances not assumed			-1.754	166.889	.081	-.0292065	.0166556	-.0620893	.0036762
NIM Year 5	Equal variances assumed	.240	.625	-.056	181	.955	-.0012702	.0225227	-.0457111	.0431707
	Equal variances not assumed			-.056	153.816	.955	-.0012702	.0225736	-.0458645	.0433241

Note. ROA = return on assets; NOPM = net operating profit margin; NIM = net income margin.

In Years 3 and 4, ROA for the control group was higher than the treatment group ($p < 0.05$). Thus, the control group performed better than the treatment group in years 3 and 4. While the results showed no difference between the two groups on NOPM at the 0.05 significance level, the NIM for the control group was higher than the treatment group in year 3 ($p < 0.05$). The treatment group did not perform better than the control group during years 1 through 5.

Appendix B

Mediation Analysis

This study examined the mediation effects of business process optimization (BPO) on location-based intelligence (LBI) capability and healthcare performance (employee, patient, and technology) using the steps outlined in Lowry and Gaskin (2014) as follows.

1. Measure direct effect betas with mediators and without mediators to ensure a reduction was evident with mediation.
2. Measure betas and standard errors from the independent variable, LBI capability BPO.
3. Measure betas and standard errors from the mediating variable (BPO) to the dependent variables (employee and patient healthcare performance and healthcare performance in technology)

The study then conducted a Sobel test for the mediating variable (BPO) to validate that the Sobel test statistic was greater than 1.96 ($p < 0.05$). Table B1 depicts the analysis results. The manner of the mediation was determined by checking for the decrease in strength on the direct effects of LBI capability on the dependent variables and evaluating if the relationship was significant. If the direct effects and mediated relationship were found to be significant, the effects were both direct and indirect, and if only the mediated relationships were significant, only the indirect effects were attained. The results in Table B1 indicate that BPO indirectly affects the relationship between the independent variable (LBI capability) and the dependent variables.

Table B1. Mediation and Sobel Test Values

Relationship	LBI → BPO → HCP_EmpPat	LBI → BPO → HCP_Tech
Direct, No Mediators	0.744	0.666
Direct, Mediator	0.622	0.481
IV→ Mediator Beta	0.767	0.767
Mediator → DV Beta	0.159	0.241
IV → Mediator SE	0.032	0.032
Mediator → DV SE	0.078	0.087
Mediation BPO	Indirect	Indirect
Sobel Test Stat	2.03112926	2.75179819
One-tailed probability	0.02112094	0.00296345
Two-tailed probability	0.04224188	0.0059269

Note. *IV = Independent Variable; DV = Dependent Variable; LBI = location-based intelligence; BPO = business process optimization; HCP_EmpPat = employee and patient healthcare performance; HCP_Tech = healthcare performance in technology.*

VITA

Harun R. Musa was born on November 28, 1975, in Awassa, Ethiopia. He completed his undergraduate work at McMaster University, receiving a Bachelor of Computer Engineering degree (1999). He holds a Master of Business Administration degree from the University of Texas at Dallas (2008). Harun is currently an Enterprise Cloud Architect working in software sales.