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Professional Certifications

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Professional Experience

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TECHNOLOGY'S IMPACT ON WHOLESALE DISTRIBUTION BRANCH OPERATIONS

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ABSTRACT

The primary role of a warehouse is to decouple supply from demand, minimize cost, maintain a high degree of inventory control, and assure customer service. To these ends, organizational capabilities, technology, and business practices will determine an operation's effectiveness. This research investigated the impact of technology and warehousing practices on key performance indicators for wholesale distribution branch operations.

An on-line questionnaire gathered objective data from distribution branches on types of technologies utilized, warehouse best practices employed, and inventory control or customer service metrics used to monitor performance. Correlation analysis, multiple linear regression, analysis of variance, and stepwise regression were utilized to determine the impact of the individual technologies, as well as interactions between technology and practices.

A salient insight of this research was that technology adoption alone did not produce a discernible difference in performance, and appeared to require industry best practices to generate improvements. Also, when information technology was adopted, there seemed to be approximately one year of implementation required before positive operational results materialized and/or stabilized.

The research pointed to warehouse management systems as the predominant information and communication technology (ICT) for discernible differences in inventory related performance, with improved performance realized when combined with ABC inventory stock analysis and/or physical inventory practices. The use of automatic identification and data

capture (AIDC) technologies did not show any effect on inventory or customer service metrics, indicating that they are a support tool rather than an impact technology.

Neither ICT nor AIDC technologies demonstrated a predictive value for inventory accuracy or on-time shipping performance. Predictive models were created for fill rate and inventory accuracy, but the veracity of the models is somewhat limited by the sample size and study population.

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CHAPTER 1

INTRODUCTION

Warehousing and distribution technologies are critical to managing over $515 billion in wholesale inventory in the US, which is around 3.2% of Gross Domestic Product (Bureau of Economic Analysis, 2013). In studying the impacts of technology on inventory management in the supply chain, research has pointed to a need for focusing on "the operational management of warehousing systems, where different processes in a warehouse are considered jointly" and "multiple objectives are considered simultaneously" (J. Gu, Goetschalckx, & McGinnis, 2007).

A supply chain may have many different distribution channels, defined as "the route, from raw materials through consumption, along which products travel" (APICS, 2013). Within the various types of distribution channels, there may be different types of warehouse operations, and warehouse types are generally "defined by the customers they serve" (Bartholdi III, 2011). This study begins by defining three types of supply chain warehouse operations: 1) fulfillment centers, 2) distribution centers, and 3) wholesale distribution branch warehouses. In general terms, all three have the same mission, that being to hold inventory to decouple upstream suppliers and/or manufacturing operations from downstream customers, within a supply chain. It is the third categorization, wholesale distribution branches, that is the subject of this research.

The primary difference between fulfillment and distribution centers lay in the customers they serve, with fulfillment centers servicing an end user and/or consumer, and distribution centers servicing another downstream link in the supply chain. A fulfillment center is typically described as a catalog or e-commerce distribution center, with a primary mission of receiving material from a variety of manufacturers and shipping small orders to individual end users or customers (Bartholdi III, 2011; Frazelle, 2002). In contrast, a distribution center's primary customer is a downstream link in a supply chain, i.e. another location within the same company that will sell to either a business (B2B) or a consumer (B2C). Bartholdi, 2011, defines central distribution centers as "retail distribution centers," while Frazelle, 2002, makes a differentiation between distribution warehouses and distribution centers. For this research, the distribution center and retail distribution center are analogous terms, defining an operation that typically supplies "big box" retail stores (Bartholdi III, 2011; Frazelle, 2002).

The third type of warehouse category is the wholesale distribution branch warehouse, whose primary mission is industrial or B2B sales, with a small B2C presence for show room and customer convenience. The distinction in the branch operation is that it is supplied by the company's own central distribution center (CDC) for all product's stored in the branch, rather than being supplied by multiple external suppliers. The primary role of the wholesale distribution branch warehouse is to maintain inventory in close customer proximity to satisfy B2B and/or B2C sales demand. The wholesale distribution channel is depicted in Figure 1. The intent of this study is focused on the nodes denoted as "Branch Warehouse".

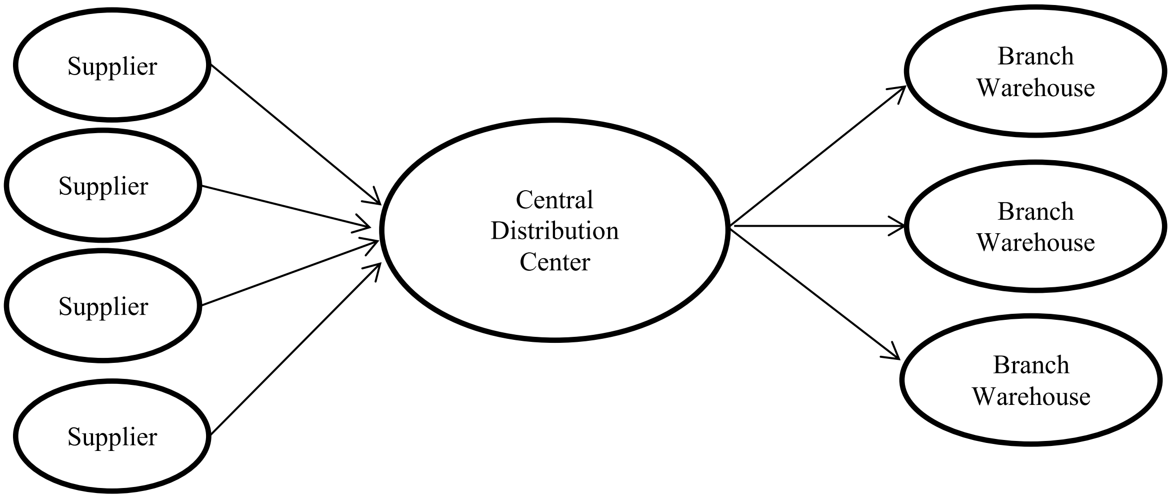


Figure 1. Wholesale Distribution Model

A high level overview of the intent of the dissertation may be characterized using the Supplier-Input-Process-Output-Customer (SIPOC) methodology (popularized by the six-sigma movement) to explain the wholesale distribution supply chain (APICS, 2013). In Figure 2 below, the "process" box is considered the wholesale branch operation that is the focus of this research.

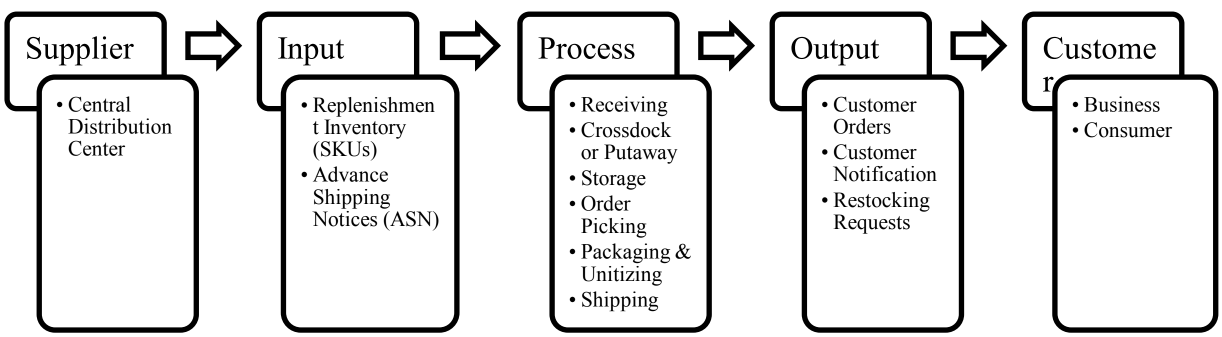


Figure 2. Supplier-Input-Process-Output-Customer Wholesale Branch Model

In summary, the goal is to determine the impact of technologies on the performance metrics related to inventory management used to monitor the "last link" in the wholesale distribution channel. This dissertation will study the impact of technology on the operations performed within the branch warehouse by evaluating the use and interaction of technologies and business practices employed to achieve the warehouse mission. Technology will be classified into two general categories: information and communication technologies (ICT), and automatic identification and data capture (AIDC).

Theoretical Framework

A theoretical framework utilizing a resource based perspective is used to guide the study. Resource based theory is generally used to explain performance differences between enterprises within an industry. The Resource Based View (RBV) argues that "firms which possess unique resources achieve competitive advantage and have superior long term performance" (Hwang, 2011). RBV posits that an organization's performance is attributed to its strategic resources, which include core competence (Prahalad and Hamel 1990), dynamic capability (Teece et al. 1997), and absorptive capacity (Cohen and Levinthal 1990) (Cao, Vonderembse, Zhang, & Ragu-Nathan, 2010). The underlying theory is that the different resources of an organization are exploited in different manners based on the firm's unique internal characteristics, allowing for marketplace differentiation (Autry, Griffis, Goldsby, & Bobbitt, 2005). As stated by Dyer and Singh, 1998, "firms that combine resources in a unique way may achieve an advantage over competing firms" that do not employ the same degree of innovation in utilizing their resources (Cao et al., 2010).

Within RBV, resources are defined as "all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive and implement strategies that improve its efficiency and effectiveness" (Barney, 2012; Hwang, 2011). RBV assets considered in this study are those that support data input and exchange for information technology and information systems, which are considered the most valuable of technologies allowing for a competitive advantage (Hwang, 2011; Teece, 1998). The competitive advantage arises from the deployment of the assets in conjunction with capabilities in the systems and processes utilized by an operation (Hwang, 2011). In turn, the organizational capabilities create an organization's competitive advantage, providing effectiveness and efficiency, which allows for improved customer service (Hwang, 2011).

For this dissertation, resources will be defined as the technologies used within wholesale distributor branch warehouses to manage the flow of materials into and out of the facility. Technologies considered in this study include information and communication technologies (ICT) and automatic identification and data capture (AIDC) technologies. ICT will encompass enterprise resource planning (ERP) software and supporting modules, such as warehouse management systems (WMS), including transactional and managerial functions.

One interpretation of RBV by Teece (1998) is that enterprises that best utilize IT resources will be more effective at developing business process capabilities by leveraging information management to gain positive outcomes (Autry et al., 2005; Teece, 1998). Therefore, this research also considers the fundamental warehouse processes of receiving, putaway, storage, order picking, sortation, packaging, unitizing, and shipping. This study evaluates the interaction of technology and the business practices employed and/or modified by technology adoption.

In summary, the RBV is useful to define information technology and other general technology as a source of competitive advantage, and a method to measure performance or benchmark key performance indicators for the distribution industry. This theory, and its derivatives and interpretations found in the review of literature, is used as the foundation for studying the investment in technology and its interaction with business practices to determine how technology adoption impacts key performance indicators (KPI) as depicted in Figure 3.

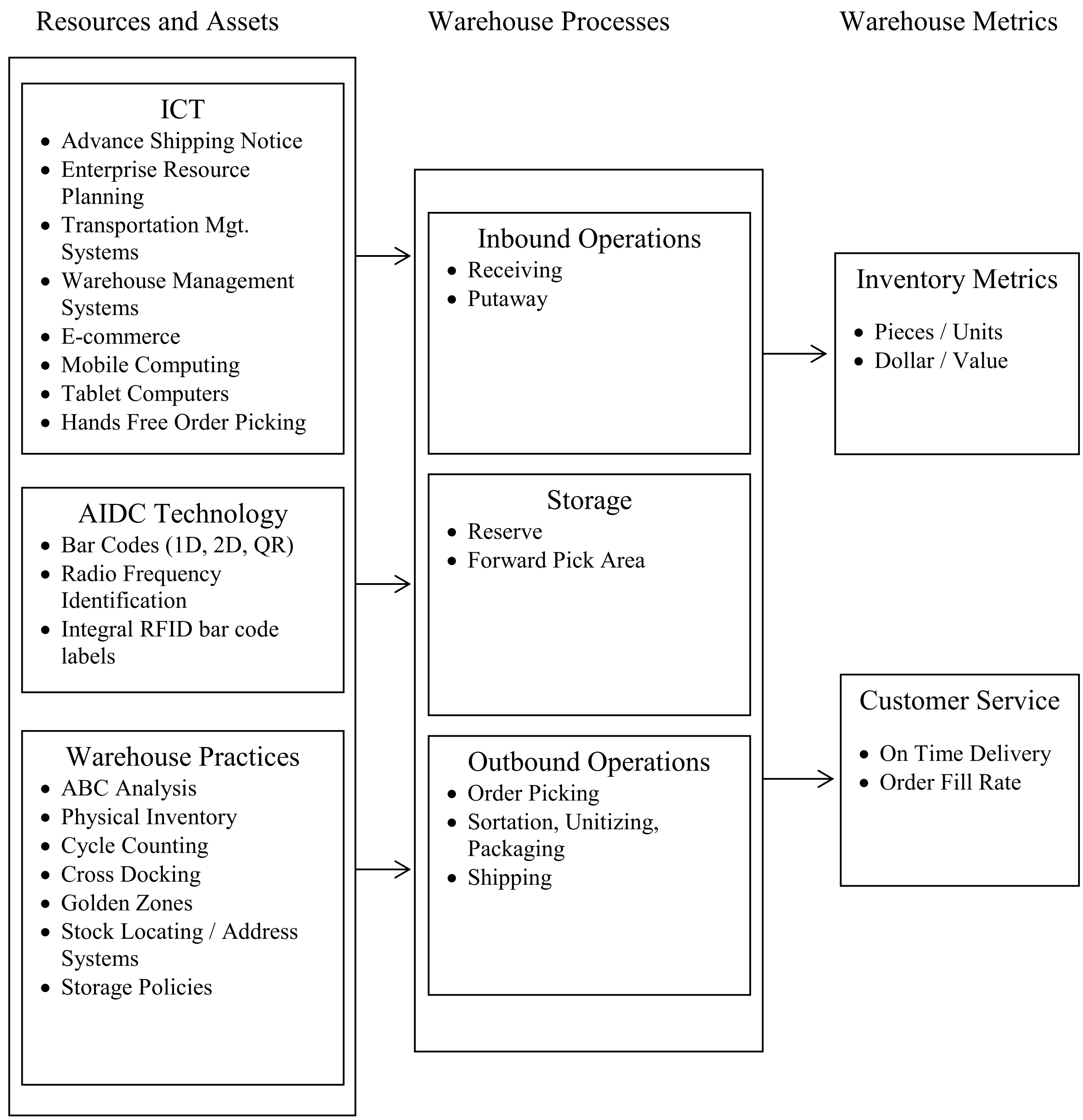


Figure 3. Resource Based View of Technology Adoption

Statement of Problem

The role of a warehouse in the supply chain is to support the temporary storage and subsequent movement of inventory. As such, warehouses are generally considered cost centers rather than profit centers (Johnson & McGinnis, 2010). There is little a warehouse or distribution operation can do to improve revenue; however, a warehouse can negatively impact the revenue side of the profit equation by poor inventory management and/or poor performance. Thus, the primary role of warehouse management is to minimize cost while maintaining a high degree of inventory control to insure customer service. To that end, organizational capabilities, technology, and methods will determine warehouse effectiveness, efficiency, and customer service, thereby providing a means of competitive advantage (Hwang, 2011).

This study's goal is to assess the inventory performance and customer service outcomes realized through technology adoption and business practices utilized within a wholesale distribution branch operation. Specifically, this dissertation answers the following questions:

Q1: Do branch operations that invest in information and communication technology (ICT) have better performance than those that do not?

Q2: Do branch operations that invest in automatic identification and data capture (AIDC) technology have better performance than those that do not?

Q3: Do branch operations that utilize "best warehousing practices" have better performance than those that invest only in technology?

Q4: What are the contributions of different technologies and best practices to inventory and customer service metrics in a distribution branch operation?

Statement of Purpose

Research points to a need for focusing on "the operational management of warehousing systems, where the different processes in a warehouse are considered jointly" and "multiple objectives are considered simultaneously" (J. Gu et al., 2007). The purpose of this study is to determine the extent to which technology improves key performance indicators (KPI) for wholesale distribution branch warehouse organizations. This research will contribute to the field by exploring the relationships between types of technologies available to the distribution industry, and how implementation impacts business practices and performance metrics. Specifically, this research will measure the impact on performance metrics for inventory accuracy and customer service, which are fundamental priorities of a branch distribution operation in supporting the wholesale distribution channel.

In an extensive and comprehensive review of literature on warehouse operations, J. Gu et al., 2007, concluded that operational decisions for distribution centers need to be supported by heuristic processes to find good solutions rapidly (J. Gu et al., 2007). From a practitioner standpoint, this study will identify the beneficial interactions of technology, operational policies, and warehouse processes. The research is guided by the conceptual model in Figure 4 to correlate relationships among independent (predictor) variables of technology applications, automatic identification and data capture, and best warehousing practices, and the dependent (outcome) variables as measured by performance metrics.

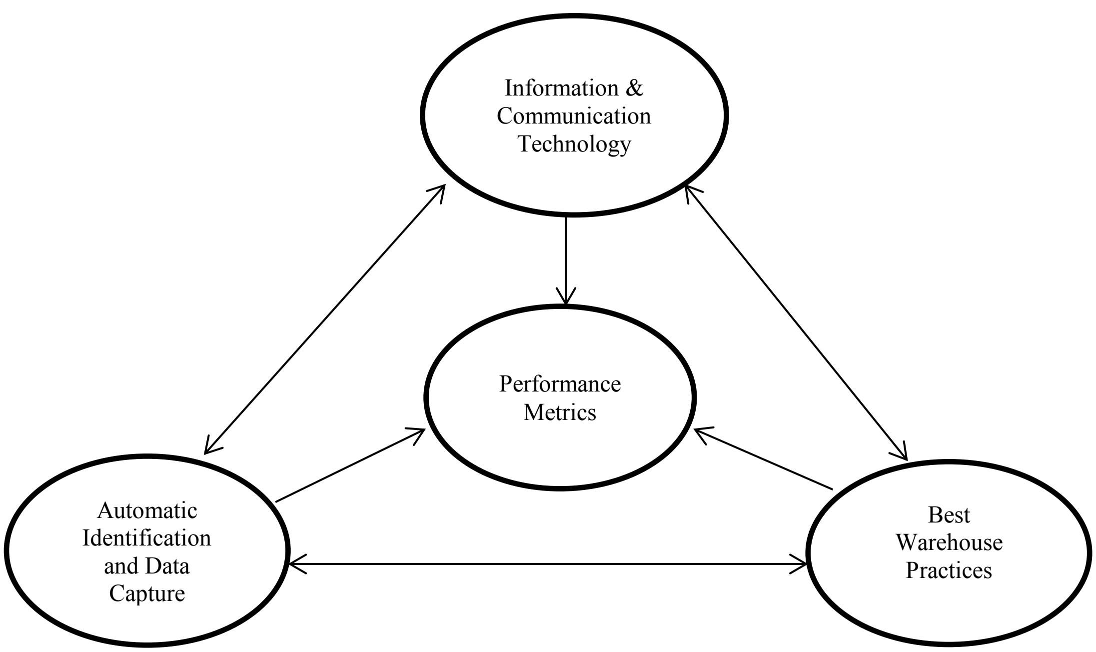


Figure 4. Conceptual Research Model

Significance of the Study

The complexity and sophistication of warehouse operations has increased markedly with the rise of a global economy managing an environment of high product diversification and short product life cycle (Chow, 2008). The preponderance of literature on technology supporting and impacting warehousing operations primarily focuses on the extended supply chain and central distribution centers. The most relevant research was by Koster & Balk, 2008, in their analysis of European distribution centers. In their comparison study between European, Asian and American distribution operations, Koster and Balk found that overall European distribution center efficiency did not benefit from an increase in technology and that where efficiency did improve through technology, it was not uniform (Koster & Balk, 2008). However, their study specifically excluded inventory management measures, which is an integral part of this research.

The review of literature also determined that warehousing design and management methods impact customer service level and cost, but “there is not an integrated framework that explains how companies leverage them to improve the logistical effectiveness and efficiency” (Gallmann & Belvedere, 2011). In addition, there is no existing framework to explain how warehouse management together with inventory management can affect customer service performance (Gallmann & Belvedere, 2011).

Finally, the review of literature determined that there is a gap in merging research and industry applications for warehousing facilities dedicated to storage and distribution. As stated by J. Gu et al., 2007, there is “an enormous gap between the published warehouse research and the practice of warehouse design and operations” (J. Gu, Goetschalckx, & McGinnis, 2010). This study will focus on the final link in the wholesale distribution supply chain, which has primary interaction with end users, to establish an associative model using technology and inventory control constructs.

Statement of Assumptions

As the review of literature demonstrates, research into warehouse related technology primarily does not differentiate the various types of warehouse operations. The underlying assumption of this dissertation is that all warehouses in supply chains are not equal, and their different missions have diverse needs and applications for technology.

Statement of Limitations

A primary limitation in the scope of this research is that the focus is solely on the wholesale distribution model utilizing a concept of central distribution centers shipping to local branch operations. This research does not consider warehouse and/or distribution operations for catalog or e-commerce fulfillment centers, retail distribution centers servicing retail stores, raw material, or private warehouses. In addition, the physical warehouse design, storage modes, and layout will not be considered, nor will the physical aspects of materials and the commercial sector serviced.

Additionally, this study does not involve storage operations for logistics companies involved in third party logistics (3PL). These types of companies typically employ the warehouse technologies studied herein, but their organizational mission is not the same as the distribution branch. Hence, 3PL operations do not drive off of the same performance metrics studied and were excluded from the population.

The products for this study are goods that are transferred or bought from an upstream source in the supply chain, stored, and then transferred or sold downstream. Within the context of "trading goods", the materials studied herein may undergo kitting operations but will not be subject to any additional value added manufacturing processes.

Finally, the technologies for this study center on information technologies and information systems. Automation technology for material handling is not considered as it is more of a strategic investment undertaken based upon the mission of a distribution center rather than a wholesale branch operation.

Statement of Methodology

Warehouse performance depends on the strategic and tactical decisions involving storage systems, storage location assignments, order picking strategies, and order picking heuristics (Chow, 2008). Inherent to cost effective execution of warehouse practices is the ability to manage and control the inventory, which is the subject of all the processes. Research points to a need for focusing on "the operational management of warehousing systems, where the different processes in a warehouse are considered jointly" and "multiple objectives are considered simultaneously" (J. Gu et al., 2007). Thus, this dissertation considers information and communication technology, automatic identification and data capture technology assets, and warehouse "best practices" as independent (predictor) variables having influence on performance metrics, i.e. outcomes (dependent) variables as measured by key performance indicators.

A survey of managers of wholesale distribution branch warehouses from a cross section of industrial products was utilized to obtain objective data on the types of technology utilized within the warehouse environment, the warehousing practices employed, and the performance metrics measured. Given that this research is exploratory in nature; physical attributes of the warehouse are included in the survey instrument as potential controlling factors.

Once data was collected, Pearson correlation coefficients were calculated to establish if any of the outcome (dependent) variables demonstrated a high degree of association to facilitate the statistical analysis. The data for the predictor (independent) variables was collected as nominal or ordinal data to assess the research questions. The use of continuous outcome variables with dichotomous predictor variables supported the statistical techniques of multiple linear regression and analysis of variance (ANOVA) to determine relationships and contributing factors between ICT, AIDC, and business practices to the specific warehouse metrics studied.

To analyze the interactions between the predictor variables and the outcome variables, multiple linear regression analysis was the first statistical technique applied to allow for assessing the contributions of the variables to the performance metrics. Given the exploratory nature of the data collection, the initial set of predictors would over-fit the model and require reduction techniques, again facilitated through the multiple regression procedures for analysis of research questions. Stepwise regression was utilized second to develop predictive models to address each of the outcome KPI with respect to all of the predictor variables in the study.

Statement of Terminology

Advance Shipping Notice (ASN) – ASN is an information technology that is used between two supply chain partners to electronically provide information on a product shipment in advance of the product receipt at its destination. The technology allows for coordination of resources at the destination and more efficient data entry for inventory.

E-Commerce – An information technology facilitating the exchange of information between an end user (consumer) and a supplier. Typical e-commerce applications are found in product catalogs, customer entered order placement, on-line payment functionality, and account management. E-commerce systems are typically linked to a supplier's ERP or business management software for data integrity and efficiency.

Enterprise Resource Planning (ERP) – ERP is a transaction management system that integrates several types of information utilizing a centralized database, enabling access to common information through an entire organization, i.e. enterprise (Barbosa & Musetti, 2010).

Extended Supply Chain – A series of linked enterprises from different companies that work together to bring materials from raw components to the end user. This differs from a "supply chain" based on inter-company interactions.

Fill rate – the fraction of demand that is satisfied directly from stock on hand (Teunter, Babai, & Syntetos, 2010).

Information and Communication Technology (ICT) – ICT is an "electronic means of capturing, processing, storing, and disseminating information," including the telecommunication technologies and computer networking systems that support this function (Cheng-Min & Chien-Yun, 2006).

Information Systems (IS) – "A combination of complementary tangible and intangible resources (including IT) that support business operations" to achieve competitive advantage (Lai, Li, Wang, & Zhao, 2008).

Information Technology (IT) – Hardware, software, computer networking and databases (Lai et al., 2008).

Putaway – An industry standard term to define the activity of taking stock from the receiving dock and "putting it away" into a warehouse storage location.

Sortation – An industry term describing high speed automation used to distribute, i.e. sort, packages to designated conveyor lanes to transport product to the appropriate location.

Stock Keeping Unit (SKU) – The smallest measurement of a material tracked by an information technology system within an enterprise.

Transportation Management System (TMS) – An information technology that is used to track and control the logistics and carriers moving materials within a supply chain.

Warehouse Management System (WMS) – A WMS is an information system to provide support to inbound and outbound logistics processes for a warehouse storage operation. This may be accomplished through a stand-alone software package, or an integrated module within an ERP system. The purpose of the WMS is to "manage and optimize operational and administrative" business processes within a warehouse or distribution center (Barbosa & Musetti, 2010). WMS are used to "plan, optimize, and execute warehouse operations", as well as track inventory in real time and measure or report on warehouse productivity metrics (Autry et al., 2005).

CHAPTER 2

REVIEW OF LITERATURE

Warehouse Operations

Regardless of the type of customer it is intended to support, the role of the warehouse is to hold inventory in order to decouple supply and demand within a supply chain. There are seven fundamental warehouse processes utilized within a warehouse operation, each interacting with the technology applications that are part of the warehouse resources. In general, warehouse resources, such as labor, space, and capital are also allocated among the various warehouse processes (J. Gu et al., 2007; Hackman, Frazelle, Griffin, Griffin, & Vlasta, 2001). Warehouse operations depicted in Figure 5 include: 1) inbound operations of receiving and putaway, 2) storage, 3) outbound operations of order picking, sortation, unitizing, value add, and shipping. Cross docking is a hybrid operation encompassing parts of inbound and outbound while omitting the storage process completely.

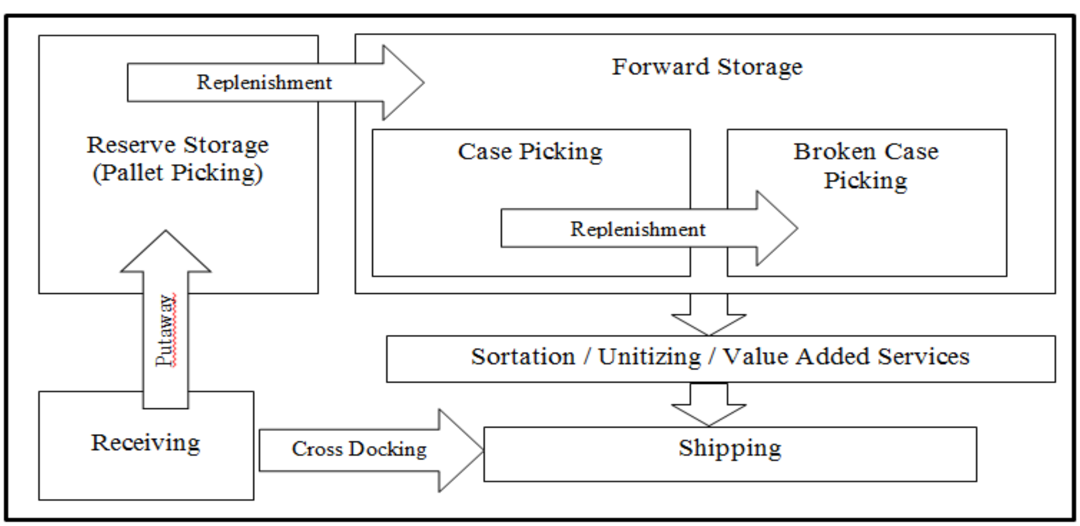


Figure 5. Basic Warehouse Operation Process Flow

For this research, inbound materials are considered to be any "trading goods" inventories that arrive from a central or regional distribution center that is "upstream" in the flow of a company's supply chain. The inventory will physically reside in warehouse storage as an intermediate holding point before being sold to a downstream customer, which is primarily a business. Inbound operations include receiving activities and the "putaway" function. Receiving operations encompass all activities that are required to physically and electronically (virtually) introduce inventory into the warehouse. Typically, this requires interface with the warehouse information and communication technology (ICT) and the computer information systems managing the inventory. ICT related receiving activities typically include transactional data recording, i.e. entry of specific activities tied to material movement, and may include application of automatic identification and data capture (AIDC) technology applications.

The transactional data is compiled by the information technology, which may include the warehouse management systems (WMS) and/or the enterprise resource planning (ERP) systems. Transactional data may be recorded either manually, or by AIDC technology such as bar coding and/or radio frequency identification tags (RFID). In the receiving process, the IT system may facilitate the receiving function through external technology communications via a business practice of advance shipping notices (ASN). The ASN process will electronically transmit information on an inbound shipment provided by the consignor to the warehouse to facilitate the receiving function. One of the first functions of the ASN may be assignment of a receiving dock door for the inbound transportation itself, depending on the physical size of the facility (J. Gu et al., 2007). The common practice is to use a "random" assignment of inbound doors, along with a fixed door assignment for outbound materials. "Random" in this sense means assigning a door that best suits the putaway operation based on the intended storage locations for the inbound material. ASNs can also facilitate the cross docking operation for more sophisticated warehouse operations, as well as planning of labor and the putaway operations (J. Gu et al., 2007).

The putaway function is the transfer, both physical and virtual, of material from the receiving department to the assigned mode of storage within the confines of the warehouse. This warehouse function consumes approximately fifteen percent of warehouse operational cost (Bartholdi III, 2011; Frazelle, 2002; Gong & de Koster, 2011). The technology involved in managing these operations is primarily a WMS, which is generally a module within a more comprehensive ERP technology application. The use of a WMS will allow for a business practice referred to as "directed putaway," which will assign a specific storage location for inventory to improve storage location efficiency and/or utilization, as well as accommodate retrieval labor costs in the order picking processes (Gong & de Koster, 2011). The WMS accomplishes this by keeping track of storage locations, i.e. warehouse addresses, via a "stock locator" module. This warehouse practice requires the use of AIDC technology to scan a warehouse address to record that material has been physically located into a specific bin location. This module allows the WMS to know where available storage locations are and if they are candidates for inventory to be moved, i.e. "put away," into a specific storage location (Bartholdi III, 2011).

The role of warehousing is temporary storage of material to decouple supply from demand since the two will never be in balance. The storage system within a warehouse is a characteristic of several factors, including warehouse size, physical profile of the product, capital investments, return on investment, etc. (J. Gu et al., 2010). Materials in storage are organized based on a variety of factors, including: 1) physical characteristics of the goods, 2) packaging and/or containerization, and 3) material handling unit. These variables, in turn, are either influenced by, or drive, the material storage mode, i.e. type of hardware and equipment utilized for the materials to reside upon (Bartholdi III, 2011; Frazelle, 2002).

Storage mode is defined as the physical method used to hold inventory, and can include floor (block) storage, shelving units, cabinets, carousels, or various types of rack systems to hold pallets, cases, or individual units of materials. There is no specific storage mode, although there are common storage strategies, which are intended to promote one of two managerial priorities: 1) storage space utilization, or 2) stock extraction, i.e. order picking and labor efficiency. To execute a storage strategy, most warehouses have inventory areas classified as "reserved" storage or "forward pick" storage areas. The reserve – forward storage system is a "two-echelon" system designed to optimize the dual warehousing goals of storage efficiency and labor productivity (Gong & de Koster, 2011). The assignment of inventory to either a reserve or forward pick storage area is a primary function of a WMS. The WMS may utilize a "best practice" of Pareto analysis, i.e. ABC analysis, which is determined from data mining of customer order data.

Further, there are inventory management considerations that include storage methodologies, i.e. location assignment policies, internal replenishment strategies, and order picking methods. Chow describes five types of storage methods: 1) dedicated, 2) random, 3) class based, 4) closest open location, and 5) full turnover storage (Chow, 2008). However, the three most popular storage methods are: 1) dedicated storage, 2) dynamic (random) storage, and 3) class based (Bartholdi III, 2011; Frazelle, 2002; J. Gu et al., 2007). These three types of storage methods dominate the professional and scholarly literature for warehousing handbooks and distribution center design. Regardless, the determination of storage policy in a warehouse is not uniform, i.e. different policies may be utilized in different geographic zones within a warehouse. In addition, storage policies are based on management objectives and warehouse design, with competing priorities of cost and space utilization influenced by the characteristics of the stock keeping unit (SKU) and the storage mode (Chow, 2008; J. Gu et al., 2007). In addition, the storage modes are influenced by three inventory management policies, including: 1) quantity of each SKU to hold in inventory, 2) replenishment strategies from suppliers, and 3) material movements within the warehouse environment (J. Gu et al., 2007).

Next in sequence after the storage process are the outbound operations, comprised of order picking, sortation and packaging, unitizing and shipping. Order picking is generally recognized as the most expensive warehouse operation, comprising fifty-five percent of warehouse operational cost, either due to being very labor intensive or very capital intensive, and is a managerial decision, based on the size of the operation, and warehouse mission (Bartholdi III, 2011; Frazelle, 2002).

Order picking and storage strategies are key business practice inputs needed by a WMS to determine stock locations for SKUs. Order picking is influenced by storage areas, which are geographically classified within a warehouse facility as “zones” or “departments”. Stock locations within a zone are referred to as “slots” or “bins” by a WMS. Zoning and slotting are key analytics performed by a WMS to optimize warehouse traffic congestion and order picking efficiency (Chow, 2008). The combination of the zoning and slotting is also impacted by the storage mode as previously defined (Bartholdi III, 2011; Frazelle, 2002; J. Gu et al., 2007). In summary, order picking methodologies are both influenced by, and influence the storage practices of a warehouse’s reserve storage and forward (fast) pick areas.

Order picking is generally classified as one of two methods: 1) stock to picker, where the labor is stationary and SKUs travel by means of automation, or 2) picker to stock, where the

SKUs are in static state and warehouse employees, i.e. labor, travels to the inventory for extraction from storage. For "stock to picker" operations, Gong, 2011, includes automated storage and retrieval systems (AS/AR) and automated guided vehicle (AGV) systems (Gong & de Koster, 2011). The picker to stock systems is divided into two categories: 1) low level picking, and 2) high level picking (Gong & de Koster, 2011). Both of these methods may be executed in either the reserve or forward pick areas. As the work by GU, et al., states, "the selection of the order picking method is a strategic decision since it has a wide impact on many other decisions in warehouse design and management" (J. Gu et al., 2007). For distributor branch operations, order picking methods are typically "picker to stock," due to capital investment and return on investment considerations.

Order picking technologies are maintained and controlled by complementary information technology driven WMS and the AIDC technology utilized within the operations. For a WMS technology enabled operation, order picking may require a scan of a warehouse location to properly record that an SKU has been removed from a specific location. This practice will allow a WMS to keep track of amount of inventory and the availability of remaining space in the storage mode. In summary, the WMS is the analytic side that controls and determines the what, when, and how of the business practices required for order picking.

The outbound operations after order picking are those that move, organize, and deliver the stock to the correct place within the warehouse to support packaging, unitizing, and shipping. If these technologies are automated, they are generally classified as "sortation" systems. The volume of the warehouse activity, customer profiles, and management strategies dictate the degree and investment into sortation systems. The role of a sortation system is to transfer and accumulate orders, picked remotely or in batches, and deliver them to an outbound staging area for shipping (Gong & de Koster, 2011). To facilitate the outbound sortation systems, outbound dock doors maintain a fixed location in a large DC (Frazelle, 2002). This provides continuity for material handling automation, and, ultimately, the technology utilized.

The shipping operation in a wholesale branch warehouse will include various aspects of packaging and palletizing of product, depending on the type of product and customer order profiles. Outbound shipments are a key interface point with the WMS for inventory management and control, and may utilize AIDC if the technology is part of the warehouse investment.

The cross docking operation of a warehouse is intended to save labor cost by matching inbound shipments and outbound requirements. If WMS technology is utilized, SKUs are identified on incoming ASNs as being needed for an immediate outbound shipment. If identified as such, material is processed for the WMS in the receiving function and then taken directly to the outbound shipping area for shipment, again interfacing with the WMS and AIDC to properly manage the inventory. The direct movement from receiving to shipping avoids warehouse cost by eliminating the putaway, storage, and order picking operations.

Benchmarking and Warehouse Performance

In a 1989 American Society of Quality Control (ASQC) article by R. C. Camp, the practice of benchmarking was first popularized by the Xerox Corporation in the 1980s (Hackman et al., 2001). The "traditional" performance benchmarks for the warehousing and distribution industry have included operation cost, operating productivity, response time, and shipping accuracy as defined within Table 1 (Hackman et al., 2001).

Table 1. Industry Standard Warehouse Performance Benchmarks

Benchmark	Definition
Operating Cost	Controllable cost as a percent of sales
Operating Productivity	Units (e.g. lines, orders, cases, pieces, pallets, etc.) per person-hour
Response Time	Varies by operation, typically order receipt until "ready to ship"
Shipping Accuracy	Varies by operation, may include on-time delivery, order fill rate, etc.

Warehouse performance depends on the strategic and tactical decisions involving storage systems, storage location assignments, order picking strategies, and order picking heuristics (Chow, 2008). J. Gu et al., 2010, stated that the vast majority of scholarly literature focuses on standard metrics such as order picking costs, and that there are many unstudied practical metrics that carry equal weight such as order cycle time and shipping performance (J. Gu et al., 2007). This research will focus on inventory accuracy and customer service.

In *World Class Warehousing and Material Handling,* Frazelle categories warehouse performance into three subsets: productivity, quality, and responsiveness (Frazelle, 2002). Productivity is the primary cost measurement, quantifying a metric of output per a quantity of input, with order lines per labor hour as the standard bearer for warehouse operations. Quality and responsiveness are both measures of customer service, with quality being considered as accuracy in order picking and shipping, and responsiveness as the cycle time to accomplish these tasks (Gallmann & Belvedere, 2011).

J. Gu et al., 2010, find that operation strategies "once selected, have important effects on the overall system and are not likely to be changed frequently" (J. Gu et al., 2010). In warehouse operations, the order picking operation is the largest controllable cost, and labor is the largest component of the order picking operation (Frazelle, 2002). Therefore, this must be a key data consideration when researching the impact of technology.

In summary, the technologies that are studied herein are primarily involved in improving warehouse performance. The opportunities for warehouse utilization of these technologies include real time control of operations, automation, and communications for supply chain partners (J. Gu et al., 2007). The focus of this dissertation is the real time control aspects of the distribution branch warehouse.

As a final note on benchmarking, although inventory storage is a primary function of a warehouse, metrics relating to inventory turnover are not useful comparison statistics, as inventory levels are frequently determined by corporate policy outside the influence of the warehouse or distribution center (Koster & Balk, 2008). As Koster and Balk (2008) determined, when measuring warehouse performance, it is justifiable to only consider cost and service aspects since warehouse and distribution operations are not responsible for sales (Koster & Balk, 2008). The goal of this dissertation is to determine the impact of technologies on performance that is controllable strictly by warehouse management, and as such, inventory turns, although a classical metric, will not be considered.

Information and Communication Technology (ICT)

In the supply chain, information technology (IT) is significantly more valuable in facilitating the physical movement of materials rather than just a tool for conveying information (Cachon & Fisher, 2000). IT, as related to supply chain operations, is defined by Cattani and Mabert as data elements, data capture systems, analysis, and reporting (Cattani & Mabert, 2009).

Autry, et al., state that transportation management systems (TMS) and WMS are the two most common technologies that exploit the processing data into “usable formats for decision making in logistics operations”, while Bowersox et al., 1999, espouse benefits in transportation management, warehouse management, and demand forecasting and planning (Autry et al., 2005;

Bowersox, Closs, & Stank, 1999). An IT system facilitates the data flow and processing of information to execute the functions of a WMS, which include the fundamental warehouse operations of receiving, putaway, order picking, and shipping. The WMS, in turn, provides the data for real time inventory management and labor productivity measures (Autry et al., 2005).

The work by Autry et al., 2005, determined that the human resource element had little to do with the effectiveness of the IT system, suggesting that the technology, not the people, are the real drivers behind the gains in the system metrics. Their findings further show that the human resource investment for training does not translate for improvements in inventory management or customer service (Autry et al., 2005). The conclusion they draw is that hardware, equipment, and software, i.e. technology adoptions, make an enterprise "informationally agile," providing benefits in internal warehouse operations and customer service, the latter through improved inventory management (Autry et al., 2005).

Warehouse Management Systems (WMS)

Utilizing the information and data facilitated by IT within a warehouse includes applications such as ERP and WMS. Autry et al., 2005, find that the ability to use and leverage information correlates to increased internal efficiencies, i.e. cost performance, and improved customer service, i.e. customer responsiveness (Autry et al., 2005). The purpose of a WMS is "to manage and optimize operational and administrative activities along the warehousing process, which involves receiving, inspecting, labeling, storing, sorting, packing, loading, shipping, issuing documents and managing inventory (Banzato, 1998)" (Barbosa & Musetti, 2010).

A WMS impacts positively on performance metrics and customer service (Barbosa & Musetti, 2010). Performance improvement results from optimization of operational resources, and customer service from management of the inventory and outbound processes, by combining improvement on the flow of information and materials (Barbosa & Musetti, 2010). The WMS will also integrate information across the supply chain through electronic data interchange (EDI) and internally via radio frequency (RF) communication methods, which enable greater operational speed and, therefore, reduced cost (Barbosa & Musetti, 2010).

The WMS provides data mining capability, i.e. the analytics to investigate the transactional data to provide information to management for strategic and tactical decisions. The WMS provide capability for continual analysis of inventory movements and other data to assist in determining storage locations for both inventory zones and inventory slots. However, the capabilities and benefits of a WMS is limited by the physical characteristics of warehouse design, which includes the physical space allocated for storage, the capital equipment in place to use for storage modes, and the technology utilized. J. Gu et al., 2007, presents a framework for warehouse operations and inputs that lead to performance measurement metrics (J. Gu et al., 2007).

Finally, while the WMS works in conjunction with an ERP system to maintain control over the quantity of stock, the WMS may also be tasked with keeping track of where inventory resides in a warehouse facility, requiring continual update of stock locations, i.e. warehouse addresses, and inventory movement into and out of each location. The WMS maintains a database of stock locations so that material may be appropriately assigned, i.e. slotted, into the most beneficial location for labor efficiency and\or space utilization. This information is captured and maintained by a WMS module knows as a stock locator system (Bartholdi III, 2011).

Storage Policies

Simultaneously being defined by and constraining the WMS, are the inventory storage policies of a warehouse. Storage areas are generally classified into one of three categories: reserve storage, forward pick areas, and staging areas. The primary function of reserve storage is to house material for support of other operations. Specifically, reserve storage is intended to facilitate large or bulk storage of material that may either replenish empty slots in a forward pick area, or reserve storage can serve as a primary order picking location for case or pallet quantities. Reserve storage area's primary metric is space utilization, thus order picking from reserve storage is generally limited to large orders for an SKU or a less popular (active) SKU so that labor efficiency and productivity are not negatively impacted (Bartholdi III, 2011; Frazelle, 2002). Forward pick areas, sometimes referred to as fast pick areas (FPA) are intended to store items that are selected more often, i.e. more popular SKUs within a warehouse. The performance metric for a FPA centers on labor efficiency. Staging areas are defined as temporary storage, or an intermediate resting place, for inventory as it is moved from one warehouse address to another location.

The determination of storage location must factor in other policies including picking strategies, storage modes, and automation (J. Gu et al., 2007). Data maintained by the stock location aspects of a WMS include the physical configuration of the storage mode, including type and dimensions, plus the availability of storage locations for stock (J. Gu et al., 2007). To interface with the storage locator system, and subsequently the order picking processes, a WMS maintains a database of stock locations which allow for execution of a directed putaway into a storage mode, and then the order picking for the extraction of SKUs from the same locations. In properly assigning SKUs to storage locations for the putaway operation, a WMS can use several criteria, but the most common are item popularity and maximum inventory storage (Frazelle, 2002; J. Gu et al., 2007). When directing putaway operations based on popularity, the WMS is working to minimize order picking and material handling costs.

A WMS input parameter for assignment of a SKU to a stock location is an operational decision to utilize dedicate (fixed), or random storage policies. Dedicated storage refers to a policy that each warehouse location will house only a specific SKU, or set of SKUs. The aisle spaces in a grocery store are an example of a dedicated storage policy, in that the merchandise is always found in the same location to facilitate the shopper (order picker). This policy is intended to optimize order picking operations, while random storage is intended to maximum space utilization (Bartholdi III, 2011; Frazelle, 2002; J. Gu et al., 2007; Hackman et al., 2001).

In a random storage policy, a WMS will keep track of all the storage locations and dynamically assign SKUs to specific locations based upon a set of criteria, algorithms, heuristics, as well as current "on hand" inventory. The goal of random storage is to maximize storage space utilization while keeping track of where SKUs are in the warehouse environment to facilitate order picking operations (Bartholdi III, 2011; Frazelle, 2002).

In addition, a third factor of "class based" storage using ABC analysis requires SKUs to be assigned to categories (classes) based on chosen characteristics, such as annual sales volume or ordering frequency (popularity). Putaway and storage is then based on the class, which in turn will interface with the picking operations. In general, storage policy is a strategic decision, affecting warehouse design, systems, and management methods (J. Gu et al., 2007).

It should be noted that in a distribution warehouse operation, there are generally multiple storage strategies that may be employed within the various warehouse zones, based on zone priorities. As such, a single storage policy is not typically considered efficient or practical, hence the need for a WMS for inventory control.

To summarize, there is an inter-relationship between facility design and operational strategies, with operational strategies including such managerial decisions as storage policy (random, dedicated, class), picking methods (single, batch, zone, hybrids, etc.), and sortation methods (progressive or downstream) (J. Gu et al., 2010). For storage policies, dedicated storage is preferred to improve order picking efficiency and yields improvements via order picker recall of SKU location, and a reduction in travel time associated with this. Class based storage with "relatively few" classes can have similar travel time characteristics as dedicated storage policies (J. Gu et al., 2010). J. Gu et al., 2010, find that performance measurement must take into consideration cost, throughput, space utilization, and service.

Automatic Identification and Data Capture (AIDC)

Automatic identification and data capture is a generic term to describe technology designed to access data contained by an information technology, such as a bar code or an RFID tag, and transfer the data to an information system without human computer keypunch operations. AIDC technologies "share the common purpose of identifying, tracking, recording, storing, and communicating essential business, personal, or product data" (Q. Gu, 2008).

AIDC for distribution operations includes many technologies such as: bar codes, RFID, magnetic stripes, smart cards, machine vision, and real time locating systems. Each technology has its own data capacities and application niche (Q. Gu, 2008). Bar coding is the dominant AIDC application in warehouse applications, having been introduced into retailing in 1974 and now the established low cost AIDC application. RFID is a technology that is becoming commercially attractive in the extended supply chain, but is still seeking a foothold inside the warehouse at an SKU level (Q. Gu, 2008).

Bar Codes

Bar codes are the most popular technology for automating data input in a warehouse environment (J. Gu et al., 2010). The physical representation of a bar code is either a one or two dimensional presentation. When a bar code is confronted with scanning technology, the information is interpreted, transferred, and converted to virtual computer entry keystrokes. Data in a bar code is static in nature, in that bar code technology is a one-time application printed to a media with information that is fixed and cannot be modified. As the data is retrieved, the information system utilizing the data must refer back to a data base or other IT source to conduct further analysis or processes.

One dimensional (1D) bar codes are a defined application of spaces and bars printed on a contrasting media for a scanner to interpret by a process of laser light reflection. The 1D bar code's most common application is the Universal Product Code (UPC), found on most every retail product in North American. A global version of this type of retail bar code is the European Article Number (EAN).

In order to hold more information, two dimensional (2D) bar codes were developed to hold information in both a horizontal and vertical symbol context. The 2D bar code requires a different scanning technology than one dimensional bar codes. The 2D technology requires an "imager" or camera type operation to capture the pattern of spaces and symbols (bars) in pixel format for proper interpretation. 2D bar codes have an advantage in the ability to hold and transfer a greater amount of data than can be stored in a comparable space for an 1D bar code.

As new communication technologies are coming on line and mobile technology application can replace traditional bar code scanners, more two dimensional bar codes may become prevalent.

Radio Frequency Identification (RFID)

Bar coding is a "line of site" technology whereby the reading technology must be able to physically see a bar code to read them one at a time. An emerging alternative to bar codes is radio frequency identification technology, which does not need line of site and can also read many items simultaneously, making it more versatile as a next generation AIDC (Walker, 2008). Karaer, 2008 concludes that RFID is an "enabler" technology in the supply chain, providing input and data for information systems to manage inventory costs in both the forward and reverse supply chain (Karaer, 2008).

From a technology standpoint, RFID offers greater data capability than bar codes, and RFID tags are generally categorized as passive or semi-passive. Passive tags wait until they receive energy from a reader, and then return the signal through a back scatter. Semi-passive tags are battery powered and are able to record information about their environment at programmed times, and then transmit the data as with a passive tag. Where bar codes are a static technology application, RFID can be considered dynamic technology with the ability to record data.

RFID may provide inventory visibility for both location and quantity, and is therefore expected to provide data to an extended supply chain and help reduce cost (Karaer, 2008). For internal warehouse operations, RFID is still primarily a pallet application. In a warehousing setting, a benefit can be found in advance information sharing (AIS). This will allow a distributor to predict and mitigate supply uncertainty by receiving AIS from manufacturers (Q. Gu, 2008).

Q. Gu concludes that companies are still in the “early adopter” phase of RFID implementation, per Roger’s Diffusion of Innovation technology adoption model, as they evaluate business process impact versus cost (Q. Gu, 2008). While, bar codes can carry a "license plate" number to reference back to a database stored in an IT system, RFID can literally carry its database with it. The biggest hurdle to RFID adoption is system integration and RFID tag cost (Q. Gu, 2008). However, Q. Gu goes on to state that much of the RFID related research is that expected benefits are really estimates, and that studies have not been able to quantify the cost benefit.

Some studies find that RFID’s greatest advantages are for complex supply chains with a large volume of material and SKUs, and therefore have high information technology demands for timely and accurate information (Chopra & Sodhi, 2007). However, RFID at the case or pallet level, as opposed to individual item, is beneficial for cross docking operations within a distribution center (Chopra & Sodhi, 2007). From a WMS viewpoint, Q. Gu’s research shows that in a central distribution center application, integrating on–hand inventory and outstanding orders can aid in replenishment decision making, benefiting in reduced back orders and lower total costs (Q. Gu, 2008). The potential at the individual SKU level has not been explored and there is a lack of research for practitioners to use RFID technology in supply chain management, and to quantify the benefits (Andhare, 2010; Wu, 2012).

Inventory Management and Control

Inventory management and control in a warehouse operation is a combination of ordering policies, storage policies, and inventory control methods (J. Gu et al., 2007). Ordering policies for inventory management are not a topic of this dissertation as these decisions are generally at the central distribution center level and outside the control of the distribution branch. Order policy is generally a function of replenishment of established inventory levels determined for customer service. The inventory control, i.e. monitoring and tracking inventory count within the branch warehouse, is of primary interest.

The information technology interaction with inventory control begins with the receiving function, as inbound material is entered into the IT database, and potentially assigned a storage location to reduce material handling cost and manage space utilization (J. Gu et al., 2007). The three primary storage policies for inventory in a distribution operation include dedicated, random, and class-based storage. Of the three, WMS technology is needed to operate in a random or class-based storage environment. Dedicated storage doesn't specifically require a WMS, but it is beneficial as the number of SKUs increases.

As distribution centers and branch warehouse operations service larger regions, assurance of accurate inventory records becomes much more significant and a more challenging task. Brooks and Wilson, 2005, state that failure to keep accurate inventory records can result in loss of product, wasted time in correcting records, product not in stock for consumers, and overstock of items. Heese, 2007, concluded that inaccurate inventory impacts optimal storage policies, and therefore, profit. In addition, Heese, 2007, finds that inventory control inefficiency is compounded in decentralized distribution systems, which is the environment for the distribution branch warehouse (Q. Gu, 2008).

The kind of IT and WMS employed by a warehouse are vital to maintain the tradeoffs between stock availability and inventory holding cost. However, having stock physically available does not always translate into order fulfillment and customer service (Gallmann & Belvedere, 2011). Technology adoption and inventory control are key factors in managing warehouse operations to improve customer service and control costs. Service level is the key performance indicator of an inventory control system (Teunter et al., 2010).

A key outcome of inventory control is inventory accuracy. Inventory accuracy is achieved through a combination of technology and warehousing best practices. Inventory accuracy, best practices of ABC analysis, data mining activities facilitated through IT, and cycle counting are discussed below.

Inventory Accuracy

The goal of inventory control is to monitor the amount of inventory held in a facility. Inventory accuracy is defined as the physical on hand inventory compared to the perpetual inventory, i.e. the inventory value stored in the IT system, and is a key outcome of inventory control activities. A critical function of a WMS and warehouse related IT is to maintain a high level of inventory accuracy in order to achieve high customer service levels.

In a 2008 study of 370,000 retail level inventory records, DeHoratius and Raman find that only 35% of records were accurate (DeHoratius & Raman, 2008). If inventory systems cannot maintain accurate counts and locations, customer promises may go unfilled. The implications for the upstream distribution center or branch warehouse activities are two-fold. First, if downstream operations cannot manage inventory properly, the interactions between supply chain members will create erroneous “true” demand and negatively impact data mining for item popularity and volume, which in turn will impact distribution center storage, slotting, and order picking methods. Second, if we translate these inventory record inaccuracies from retail to distribution, a possible loss of 10% of profits may result due to higher inventory costs and lost sales (DeHoratius & Raman, 2008).

Inventory accuracy is impacted by many sources, including transaction errors from inbound and outbound processes, incorrect product identification, incorrect storage location, and shrink due to damage or theft (Wu, 2012). The application of AIDC and storage technology combined with a WMS may be able to automate and/or improve the business process involved in inventory accuracy (Wu, 2012). Inventory accuracy is controlled through best practices of class-based ABC analysis and cycle counting.

ABC Analysis

ABC analysis is the application of the Pareto principle within the context of inventory management. The proliferation of SKUs began in the 1980s with the advent of "micro marketing" strategies, and has caused a tremendous increase in shipment frequency from distribution centers (Hackman et al., 2001). As the number of SKUs grew, so did the complexity of warehouse management and the need for technology intervention. The main purpose of classification of SKUs into categories ranked as A, B, or C is to simplify inventory management by allowing the application of differentiated management strategy based on SKU's class based value to the organization (Teunter et al., 2010).

The conventional ABC breakdown, as defined by APICS, the Association for Operations Management, is the "classification of a group of items in decreasing order of annual dollar volume, defined as the number of units sold multiplied by the purchase price" (APICS, 2013). The dollar volume stratification for ABC classification is useful for inventory control practices, typically cycle counting, to maintain inventory accuracy for a contribution to the customer service metric (Teunter et al., 2010).

Along with dollar volume stratification, ABC analysis may be based upon item popularity, which is the number of times an SKU is requested by a customer. SKU popularity will drive slotting strategies, i.e. where to place material within a storage system, which in turn directly impacts order picking in a "picker to stock" methodology (Frazelle, 2002).

An independent factor sometimes considered in ABC analysis is that of "criticality," i.e. the impact of a stock out regardless of sales volume or item popularity. It is sometimes considered for slow moving SKUs that have an inverse relationship between order frequency and cost, compared to the impact on the business (Teunter et al., 2010). The "cost criterion" relates SKU criticality, shortage cost, demand volume, holding cost, and order size, and is expressed by

$$\frac{bD}{hQ}$$

Where:

b = criticality measured by the shortage cost

D = demand volume

h = unit holding cost (piece price x carrying cost percent)

Q = order size

The analysis of warehousing technology adoption on service level requires a different approach to the conventional inventory theory that is dominated by a cost approach. A proposed multi-SKU approach developed by Teunter, et al., 2010, created a service level analysis of inventory classification. In a multi-SKU inventory system, the average fill rate over all SKUs is calculated as the weighted average of the individual SKUs, with weight being determined by the percentage of overall demand (Teunter et al., 2010). Teunter et al., 2010, conclude that cost criterion in combination with fixed service levels for each class will provide the optimum method to minimize inventory costs while maximizing customer service (Teunter et al., 2010).

Cycle Counting

Cycle counting is the practice of counting subsets of the SKUs within an operation rather than stopping all material movement and counting everything, the latter being referred to as a physical inventory. Physical inventories are generally considered the bane of a warehouse's existence due to the labor intensive requirement and customer service disruption required to stop all material movement to conduct a "physical inventory."

Cycle counting is an industry standard practice for inventory control and maintaining inventory accuracy, and therefore a critical part of any inventory management policy in a warehousing environment. Cycle counting is currently the most common and established method used by companies to keep inventory record accuracy (DeHoratius & Raman, 2008). The benefits to cycle counting generally include higher inventory accuracy levels which, in turn, lead to lower costs in realizing improved order fill rates (Koster & Balk, 2008).

The primary benefit of cycle counting is to maintain inventory accuracy by correcting discrepancies between the physical count taken by a person doing the cycle count and the value maintained by the computerized inventory, i.e. the perpetual count (Young & Nie, 1992). If there are differences between the cycle count and the perpetual count, further analysis is undertaken to: 1) enter the correct count into the computer system, and 2) find the root cause of recurring discrepancies. Brooks and Wilson, 2005, explain that with the correct execution of cycle counting, a company can have "95% or better accuracy." The dilemma for a large company is that it takes a large amount of resources, labor hours, and money to ensure that cycle counting is implemented correctly.

Cycle counting cost is dependent upon the labor involved and the frequency of the counting cycle (Young & Nie, 1992). Warehouse management's objective is to minimize cost while achieving maximum benefit, where cost is defined as:

Total Cost = stockout cost + cycle count cost + ordering cost + carrying cost
+ annual cost of SKU purchase

The counting frequency is determined by cycle count cost and the cost of a stock out (Young & Nie, 1992). Other factors impacting the cost of a cycle count program include ABC stratification and related inventory management policies.

The combination of cycle counting strategy and technology allow for organizations to improve efficiencies and reduce cost in the cycle counting process itself (DeHoratius & Raman, 2008). Other than the inventory accuracy, the benefits of cycle counting on the performance metrics within the warehouse are not easily discernible. One of the major challenges in justifying technology for a cycle counting program is the benefit to the organization in financial terms. In order to define value for an enterprise, rationalization of the investment in both labor and technology must be shown to positively impact performance metrics such as inventory accuracy, customer service, and order fill rates. Additionally, the value of improvement and performance metrics must offset the cost of the technology investment (Bowersox et al., 1999).

RFID is a potential breakthrough technology for cycle counting in that storage modes that could "self-report" inventory values could dynamically trigger cycle counting at pre-set inventory levels, thus eliminating the labor required to confirm "good" counts (Walker, 2008). A sub-goal of this research is to investigate any current application to this end.

CHAPTER 3

METHOD

Introduction

This study's goal was to determine the benefits of technology resource adoption and explore the interrelationships between technology adoption and warehousing practices. These types of measurements are useful for internal performance benchmarking and rely on multiple inputs (Hackman et al., 2001; Koster & Balk, 2008). Data for the research was collected using an on-line instrument to obtain information from primary sources, i.e. the distribution branch managers in charge of the participant branch operations that are the subject of the research. The analysis evaluated information and communication technology (ICT), automatic identification and data capture (AIDC) technology, and warehousing best practices to determine if specific factors are more meaningful than others when considering distribution branch key performance indicators (KPI).

Analytical Methods

Analysis of the data consisted of correlation analysis of the outcome (dependent) variables and multiple linear regression analysis of dichotomous predictor (independent) variables representing technologies and best practices utilized. Analysis of variance (ANOVA) is utilized as part of the multiple regression analysis by way of an overall regression *F* test, and the fundamental principle that both ANOVA and multiple regression account for variance in outcomes (Brace, Kemp, & Snelgar, 2012). In ANOVA, variance, relative to the percentage that cannot be accounted for, is accounted for by direct manipulation of an independent variable (Brace et al., 2012). Restated, ANOVA should be used when the researcher can directly manipulate factors and measure the result of a change in the dependent variable (Brace et al., 2012). Multiple regression is more applicable for naturally occurring change due to a set of predictor variables (Brace et al., 2012). In summary, both are applicable techniques but multiple linear regression is preferred for this research.

The predictor (independent) variables were analyzed within two functional technology groupings, ICT and AIDC, representing “front office” type administrative or planning technologies, and warehouse floor support technologies, respectively. Research Question 1 and 2 utilized multiple linear regression and ANOVA to investigate ICT predictor variables and AIDC predictor variables as separate technology subsets against the outcome variables, individually and separately. Research Question 3 used multiple linear regression to first determine predictor variables that were significant business practices for the KPI, and then utilized ANOVA to compare the business practices against the ICT and AIDC factors. All outcome variables were considered independently and separately, as KPI are generally unique and company specific. The fourth and final research question used the results from the first three questions to build a multiple linear regression model to establish a predictive formula on the KPI of the wholesale distribution branches. The data analysis was conducted using SAS software JMP 10pro.

In general, simple regression is used to determine a relationship between two variables and is based on a linear correlation of variables as defined by Pearson’s bivariate *r* (Hayden, 2008). The bivariate, or two variable, Pearson *r* is shorthand for the Pearson product-moment coefficient of correlation. Mathematically, Pearson *r* is defined as the covariance (of the dependent and independent variables) divided by the product of the dependent and independent variable's standard deviation. The result of the Pearson r formula is that the algebraic sign denotes the direction of the relationship, and the absolute value (between 0 and 1) reflects the magnitude (Minium, Clarke, & Coladarci, 1999). No relationship exists if $r = 0$, and a perfect correlation exists at $r = 1$. Simply stated, Pearson r is a measure of how well the data fits the model (Norusis, 2012a). Regardless of the value, regression analysis will evaluate association of variables but does not infer causation.

In simple regression, as long as there is some covariance, i.e. $r \neq 0$, then calculating the coefficient of determination, r^2, will allow the researcher to determine the amount of variance shared by two variables. The larger the r^2 value, the more direct influence is evidenced between the two variables, i.e. the r^2 value defines the "proportion of variance in one variable that is accounted for by the variation in the other" (Minium et al., 1999).

As the research goal is to investigate the impact and interaction of multiple predictor (independent) variables on single performance, outcome (dependent) variables, multiple linear regression is required for analytical purposes. Multiple regression seeks to determine the influence of more than one predictor (independent) variable and a given outcome (dependent) variable, as well as consider the effect of the interaction between the predictors (Brace et al., 2012; Norusis, 2012a). Although multiple regression analysis is best suited to predictor (independent) variables that are interval or continuous, it may be used with ordinal or nominal (dichotomous) predictor variables (Creswell, 2003; Norusis, 2012a), and was thus an acceptable statistical technique.

Multiple regression analysis was primarily utilized rather than ANOVA for two reasons. First, ANOVA is best suited for data that seeks to find if there is a difference, while regression seeks to determine if prediction is possible (Hayden, 2008). Second, the number of predictor (independent) variables used in the data collection instrument would make ANOVA an unwieldy methodology based on the number of potential interactions. The number of combinations of pairwise interactions in an ANOVA is defined as follows (Hayden, 2008):

$$C = \frac{n(n-1)}{2}$$

Where:

C = total pairs

n = levels of predictor (independent) variables

Multiple regression was selected rather than ANOVA since the number of predictors was established at a maximum of nine, yielding thirty-six interactions plus nine original factors, which would make the ANOVA difficult if not meaningless to interpret.

ANOVA and multiple linear regression are essentially the same technique and share assumptions, goals, and distributions. Whereas ANOVA calculates statistics for each interaction, multiple regression will pool the interactions into a single error value. Both models are useful for interpreting continuous outcome (dependent) variables, and both may utilize categorical variables. One difference is that nominal variables must be dichotomous for regression and do not need to be so for ANOVA.

Both regression and ANOVA use the sum of squares methodology to partition variation (Norusis, 2012a). Where ANOVA partitions variation as “within groups” and “between groups”, regression utilizes analogous parameters as variation due to “unexplained error” and “model error,” respectively (Klimberg & McCullough, 2013; Simon, 2010). The “within group”, unexplained variation, is evaluated using plots of the residuals to compare the best fit sum of squares line to the actual data points.

A review of literature was used to determine the principal wholesale distribution branch operation KPI to use as outcome (dependent) variables and the predictor (independent) variables. The investigative nature of the research required gathering data on significantly more predictor (independent) variables than could be supported under the principle of parsimony, i.e. "the smaller the number of variables the better" (Klimberg & McCullough, 2013). Therefore, the intended multiple linear regression analysis was well suited to an iterative data review which is typical for multivariate real world statistical studies (Klimberg & McCullough, 2013).

As the purpose of the multiple linear regression is to "predict" a value for the outcome (dependent) variable, it was also necessary to gauge how well the model functions. This is accomplished by considering the following steps (Klimberg & McCullough, 2013) and the output tables from JMP 10pro:

1. Evaluate (run) a set of predictor (independent) variables using the least squares regression analysis and review the overall regression *F* test ANOVA table output
2. Review and evaluate the parameter estimates (partial regression coefficients) generated for each predictor
3. Conduct a test of assumptions using the predictor residuals if a successful model is developed.
4. Estimate usefulness of the model based on the summary of fit (R^2 and adjusted R^2)

The first step in utilizing multiple regression is a review of the overall regression *F* test ANOVA that represent several equivalent null hypotheses regarding the regression (Norusis, 2012a):

1. There is no linear relation in the population between the dependent variable and the independent variables.
2. All of the parameter estimates (population partial regression coefficients) are 0
3. The population value for multiple R^2 is 0.

The evaluation of the ANOVA table determined the direction for the review of the second table, the parameter estimates (partial regression coefficients.) Given the set of null hypotheses, if the overall regression ANOVA *F* test provided a probability *F* small enough to reject the null hypothesis, the interpretation was at least one of the population parameter estimates was not zero (0) and thus influenced the outcome variable (Norusis, 2012a). This then allowed the next table of parameter estimates to be used to determine a final regression model if any of the partial regression coefficients (parameter estimates) were statistically significant based on the *t* statistic.

If the probability of *F* was too large to reject the null hypotheses, the same parameter table would be evaluated for variable screening and exclusion for a subsequent regression analysis on a different subset of variables using the “step-wise” or standard beta method.

There are automatic procedures for variable reduction; the most common is the “step-wise” method. Step-wise allows the software to remove predictor variables that are no longer significant, as new variables are introduced. This is accomplished by entering all variables in sequence and assessing their R^2 value. If the algorithm determines that a value is gained, the variable is kept and all other existing variables are re-evaluated. If there is no longer a statistical significance for a variable during re-evaluation, it is discarded from the model. The step-wise method is designed to place the smallest number of predictor variables in the model (Brace et al., 2012).

However, for discussion purposes, a “manual” approach was undertaken. In the “manual” approach, the researcher has maximum control of the analysis by determining which variables to screen out or include, and can investigate combinations based on understanding of the variables as opposed to pure mathematical review. Screening implies removing predictor variables with the least contribution to the outcome and least interactions contributing to the outcome. When there is more than one predictor (independent) variable for an outcome (dependent) variable, as is the case with multiple linear regression, it is not feasible to “compare the contribution of each predictor by simply comparing correlation coefficients” (Brace et al., 2012). Norusis states that “a common mistake in regression analysis is equating the magnitude of the partial regression coefficients to the relative importance of the variables” (Norusis, 2012a). The mistake is in assuming that the variables are all measured on the same scale or unit of measure.

Thus, there is a standardized regression coefficient (β) to measure the strength of a predictor variable’s influence on the outcome variable; the larger the value of β, the greater the impact (Brace et al., 2012). Standard Beta is the absolute value of the statistic, which is a unit-less measure since it is the partial regression coefficient standardized to its z score (Norusis, 2012a). The larger the absolute value, the more important the variable (Klimberg & McCullough, 2013; Norusis, 2012a). Note that when utilizing dichotomous variables with a level of zero (0) and one (1), the parameter estimates may be utilized as they are all based on the same sample scale. Strictly speaking, if all the predictors are dichotomous the standardized β

value is not required as all predictors have a common magnitude. However, for reproducibility of methodology, the standard β value was used for this analysis. In summary, the analytical technique for evaluating Research Questions 1 – 3 involved an iterative multiple regression analysis to determine predictor variables.

Question 4 was then a construction of a predictive model based on the variable screening conducted during Questions 1 – 3. The predictive multiple regression model is of form:

Outcome (dependent) Variable = constant + $\beta_1\, IV_1 + \beta_2\, IV_2 + \ldots\beta_n\, IV_n$

Where:

IV_n represents the independent (predictor) variables

β_n represents the partial regression coefficients

constant is analogous to the intercept of the univariate regression model (Norusis, 2012a)

The partial regression coefficients, referred to as “parameter estimates” in the JMP 10pro output, tell how much the outcome (dependent) variable will change when the value of the predictor (independent) increases by one (1), or in the case of dichotomous variables, by the presence or absence of the treatment.

Steps 1 and 2 (page 41) were run iteratively until a suitable subset of predictor variables were determined. Before the final step to evaluate the model for its usefulness, i.e. how well would the model predict, the assumptions needed to be tested via the residuals. A discussion on assumption testing is provided in the next section.

If the assumptions did not reject the multiple rejection model, the final step was a review of the “summary of fit” table which provided information on the “goodness of fit” with values for R^2, adjusted R^2, and the root mean square error (RMSE). R^2, the square of multiple correlation coefficient R is a measure to determine the proportion of the variance in the outcome variable accounted for, i.e. explained by, the model (Brace et al., 2012; Norusis, 2012a). For example, if $R^2 = 0.827$, then 82.7% of the observed variability in the model would be explained by the predictors and their interactions incorporated in the analysis (Norusis, 2012a); larger is better.

However, to improve the accuracy for "real world" predictive value, an "adjusted R^2" is calculated to factor in the number of variables in the model and the number of observations used for the analysis. The adjusted R^2 is the most valid success measure of the model, i.e. how well it would fit another set of data from the same population (Brace et al., 2012; Norusis, 2012a). An acceptable adjusted R^2 for a regression model would indicate that the parameter estimates, or partial correlation coefficients, can have predictive value.

The RMSE statistic would be useful at the end of the analysis to determine which model is better if a comparison of models is appropriate. RMSE is the amount of unexplained error in the model, therefore the one with the lower RMSE is better (Carver, 2010). Similarly, the model with the higher adjusted R^2 is better as the data is more likely to be representative of other data sets.

Multiple Linear Regression Assumptions

In order to employ multiple linear regression analysis, outcome (dependent) variables must be measured on a continuous scale; and predictor (independent) variables may be measured on either a continuous or nominal scale, with dichotomy preferred for simplicity of coding and data analysis. Given suitable variables, several assumptions need to be met to utilize the statistical analysis, including (Hayden, 2008; Norusis, 2012a):

1. All of the observations must be independent, i.e. inclusion of observations may not influence each other.

2. For each value of the predictor variable, the distribution of the values of the outcome variables must be normal. This was evaluated using histograms for each value of the predictor, i.e. the two dichotomous levels selected during the analysis.
3. The variance of the distribution of the dependent variable must be the same for all values of the predictor. In this case, histograms were evaluated for normality at each of the dichotomous levels.
4. The relationship between the predictor (independent) and the outcome (dependent) variable must be linear in the population. This is measured with the overall regression *F* test ANOVA, evaluating if the probability of *F* is significant which would reject the null hypothesis that the population slope equals zero.

Of note is that multiple linear regression is relatively robust to the normality assumption since in practice it can rarely be confirmed (Hayden, 2008; Norusis, 2012a). As the number of cases was relatively small with some of the predictors, additional analysis and interpretation was required to validate results. After the regression analysis was run, two additional hypotheses on the results were required to establish validity of the results (Carver, 2010; Norusis, 2012a):

1. Prediction errors must be random for all values of the independent variable. This was evaluated by examining a histogram and Q-Q (quantile) plot of the residuals. In JMP 10pro, this was a two-step process to first save the residuals as a new variable, and then conduct the analysis.
2. Predictor variables must vary independently with each other (Carver, 2010). If any of the predictors are highly correlated to any or all of the others, a condition of collinearity (sometimes referred to as multi-collinearity) exists (Carver, 2010). Violation of this assumption will lead to erroneous parameter estimates and potentially incorrect

interpretation of the data. From the linear regression output, if the ANOVA *F* statistic and the parameter *t* statistics are both small (significant), then no collinearity exists (Carver, 2010).

In summary, multiple regression analysis was selected for this research because it is "more or less robust" to some data requirements and/or assumptions (Hayden, 2008). Robust is further defined to mean that the technique is still valid and may be used, but "extra care should be taken" in interpreting the results as the statistical significance may be affected (Hayden, 2008).

Selection of Variables

Selection of variables required two analytical steps: 1) selection of potential variables for data collection and model inclusion, and 2) selection of variables for the predictive model, i.e. variables that remain in the model after analysis (Hayden, 2008). This section discusses the former, whereas the data analysis section of this research discusses the latter. For potential predictor (independent) variable selection, as depicted in Figure 6 below, a triangulation approach was used by conducting a review of scholarly literature, industry and professional surveys, and field visits to distribution branch operations in Eastern North Carolina.

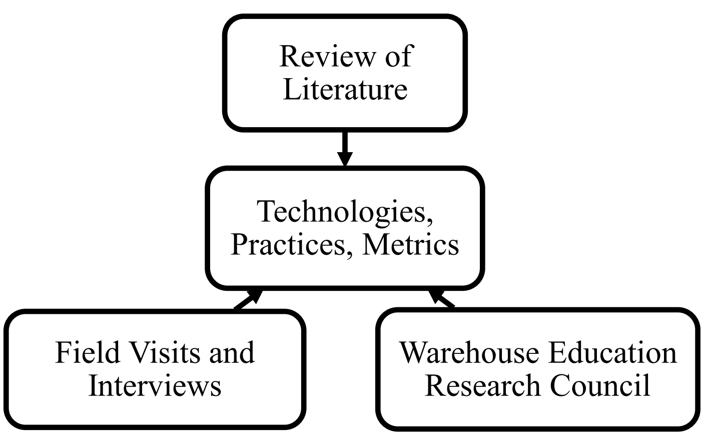


Figure 6. Triangulation of Sources for Criterion (Dependent) Variables

Predictor (independent) variables for this study were based on technologies utilized by companies in the Warehouse Education Research Council (WERC) report (Manrodt, Vitasek, & Tillman, 2013), and the review of literature conducted for this research. The WERC report is an annual survey of the wholesale distribution industry and warehouse practices, and is published through DC Velocity, a leading industry trade publication. Dr. Karl B. Manrodt, Ph.D., Professor at Georgia Southern University, collaborates with DC Velocity to conduct an annual survey of the distribution industry, and has been doing so since 2004. The 2012 report referenced by this research was based on two hundred and twenty five industry responses and provided critical information for technologies, best practices, and KPIs. In addition, warehouse practices were extracted from the review of literature, with primary contribution considerations given to Hackman et al., 2001, Frazelle, 2002, and Bartholdi, 2011.

The predictor variables obtained were categorized as dichotomous, representing utilization or non-utilization, with duration of utilization effects if applicable. Further, the predictors were classified as fixed variables, rather than random or covariate. Using a fixed approach allowed for generalization and analysis to further explore significant results from the demographic data collected as part of this research.

The establishment of outcome (dependent) variables was based on performance metrics from the WERC report, the review of literature, and field visits to distribution branch operations.

The data collection method used a “closed form” type of questionnaire and therefore it was considered necessary to provide for unanticipated responses by providing an “other” category (Best & Kahn, 2006). The “other” variable was included for each category of data collection in conjunction with an open ended response opportunity to enhance potential for future research and to compensate for any new technology on the industry horizon. The selected variables are described in Tables 2, 3, and 4.

The variables in Table 2, labeled as "Data Demographics," include the descriptive information for the individual distribution branch operations that are cases from the survey. Numeric data was collected and classified as nominal, ordinal, or continuous. Summary and descriptive statistics were generated in the data analysis section for each of the variables and cross-tabulations generated as initial data review. The data was subsequently utilized in the conclusion and discussion section of this research.

Table 3 represents the predictor (independent) variables, grouped by three categories further refined in the data analysis: 1) Information and Communication Technology, 2) Automatic Identification and Data Capture, and 3) Best (Warehousing) Practices. As the research goal was investigative, there was an abundance of potential predictor (independent) variables included in the questionnaire although the use of too many independent variables in a regression analysis allows for small contributors to artificially reduce the contribution of the meaningful ones, referred to as over-fitting the model (Hayden, 2008; Norusis, 2012a). However, the intentional over collection of predictors came with little or no expectation of an initial useable model due to the large number of predictors, and therefore lent itself to multiple linear regression analysis for a screening (reduction) of variables based on individual variable contributions and interactions. The analytical methods selected facilitated the ultimate goal to ascertain the smallest subset of predictor variables since "prediction is not practical or meaningful when there are too many variables" (Hayden, 2008).

The research questions directed data collection toward "yes" or "no" dichotomous responses, but the questionnaire was designed to collect further information by asking for three possible distinct “years of utilization” responses to allow additional investigation. The data analysis and predictive models were limited to the type of technologies and best practices extracted by the triangulation approach as shown in Figure 6.

The outcome (dependent) variables, shown in Table 4, are the measurements of the KPI that were determined by the triangulation approach to variable selection.

In considering the WERC report and the review of literature, it was apparent that different companies may have different, yet related, definitions for key measurements such as order fill rate and inventory accuracy. As the research goal was to obtain as much useful information as possible, two alternatives were presented in the questionnaire to encompass various definitions and interpretations for two of the outcome variables, shown in Table 4.

Similar to the predictor (independent) variable data collection, an “other” variable was included to capture information outside the proposed alternatives presented. The primary goal was collecting information for spotting industry trends and supporting possible future research topics. A correlation analysis was initially performed on the five outcome variables to determine if any of the outcome (dependent) variable alternatives could be eliminated from consideration for modeling to simplify the analysis while providing meaningful results.

Table 2. Data Demographics

Description	Variable	Data Type	Comments
Branch Operation Demographics	Industry	Nominal	6 types
	Warehouse ft^2	Ordinal	5,000 ft^2 increments
	Customer Base	Nominal	5 types
	Number of SKUs Stocked	Continuous	n/a
	Number of SKUs Shipped	Continuous	n/a
	Estimated Stock Locations	Continuous	n/a
	On-Site Warehouse Employees	Continuous	n/a
	Average Inbound Daily Deliveries	Continuous	n/a
	Average Outbound Daily Shipments	Continuous	n/a

Table 3. Predictor (Independent) Variables

Description	Variable	Statistic Sought: Years of Utilizations
Information & Communication Technology (ICT)	ASN – Inbound Delivery	Ordinal
	ASN – Outbound Shipment	Ordinal
	ERP – Enterprise Resource Planning	Ordinal
	TMS – Transportation Management System	Ordinal
	WMS – Warehouse Management System	Ordinal
	E-commerce Portal	Ordinal
	Mobile Computing	Ordinal
	Tablet Computers	Ordinal
	Hands Free Picking Technology	Ordinal
AIDC Technology	1D Bar Codes	Ordinal
	2D Bar Codes	Ordinal
	QR Codes	Ordinal
	RFID	Ordinal
	Integral RFID – Bar Code	Ordinal
Best (Warehousing) Practices	ABC Stock Analysis	Ordinal
	Annual Physical Inventory	Ordinal
	Cycle Counting	Ordinal
	Cross Docking	Ordinal
	Golden Zones	Ordinal
	Pick Path Routing	Ordinal
	Stock Locations / Addresses	Ordinal
	Type of Storage Policy	Nominal

Table 4. Outcome (Dependent) Variables

Description	Variable	Data Type
Key Performance Indicators (KPI)	Fill Rate (lines)	Continuous
	Fill Rate (order)	Continuous
	Inventory Accuracy – Dollars	Continuous
	Inventory Accuracy – Units	Continuous
	On-Time Shipments	Continuous
	Other – TBD	Continuous

Research Questions and Hypotheses

The research questions and their related null hypotheses, as shown in the conceptual model found in Figure 7, are detailed below:

Q1: Do branch operations that invest in information and communication technology have better performance than those that do not?

H_{O1}: Branch operations that invest in ICT have the same performance as those that do not.

Q2: Do branch operations that invest in automatic identification and data capture have better performance than those that do not?

H_{O2}: Branch operations that use AIDC have the same performance as those that do not.

Q3: Do branch operations that utilize "best warehousing practices" have better performance than those that invest only in technology?

H_{O3}: Branch operations that employ "best practices" have the same performance as those that rely solely on technology.

Q4: What are the contributions of different technologies and best practices to inventory and customer service metrics in a distribution branch operation?

For Questions 1 and 2, the individual hypotheses were further subdivided into three distinct null hypotheses based on the correlation analysis of the five outcome variables. The individual hypotheses are detailed in the data analysis section of this report. Question 3 tested the significant predictors from Questions 1 and 2 against each of the business practices to determine if the technology application created a significant difference in performance. The specific null hypotheses were established from a review of Question 1 and 2 conclusions. The analysis of Research Questions 1, 2 and 3 became the inputs to a multiple regression prediction formula to assess research Question 4.

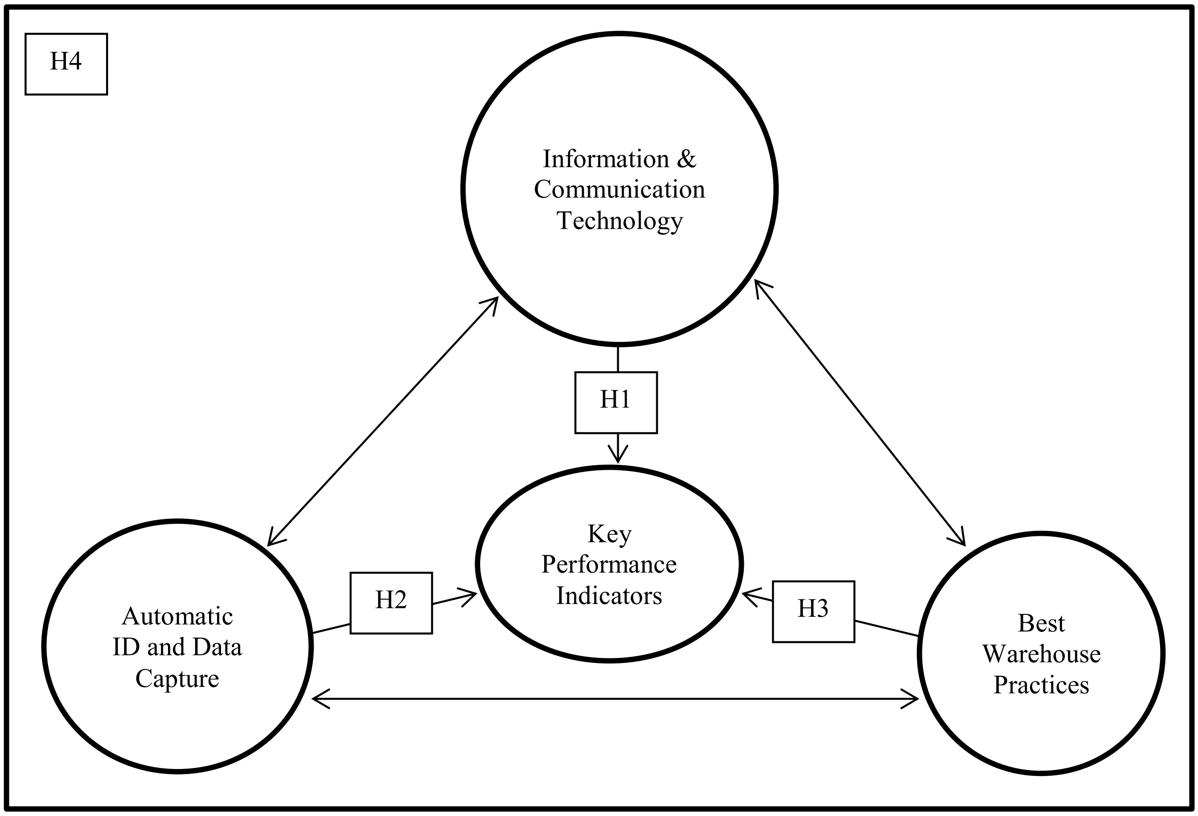


Figure 7. Conceptual Research Model and Proposed Hypotheses

Population and Sample

Figure 1 detailed the placement of distribution branch operations in a supply chain employing a wholesale distribution channel. The population for this study was the distribution branch warehouse operations for wholesale distribution companies that have a relationship with East Carolina University's (ECU) distribution and logistics degree program in the Department of Technology Systems in the College of Technology and Computer Science. Distribution companies recruiting at ECU are generally represented by one or two individuals with administrative rather than operational job functions, and recruiting tends to be for multiple company locations rather than for specific branch operations. Therefore, a relatively small group of individual contacts, i.e. the recruiters, were initially contacted to develop a much larger population for the study, consisting of branch managers of their respective distribution operations.

The sample group is defined as a non-random "sample of convenience" (Creswell, 2003) consisting of all distribution companies that had expressed an interest in hiring students for either full or part time employment during the academic year 2012-2013 and were known to East Carolina University. Although not a true random sample, the sample is considered independent in that the responding branches were not individually selected, nor did they have any interaction with each other that would influence the data. Statistically, the sample was considered independent for the test of assumptions. Additionally, the sample represents a cross section of several industries, including general industrial maintenance, repair, and operations (MRO) supplies, heating, ventilating, and air conditioning (HVAC) component suppliers, plumbing and water works suppliers, and electrical suppliers. This sample includes both public and privately owned enterprises.

The sample was restricted to distribution branches that are geographically located east of the Mississippi River. Anecdotal evidence suggested that students from the program were prone to stay in the eastern part of the U.S. for post college employment, thus the geographical limitation. The geographical limitation of participant branches was desirable since one objective of the research was to guide the technology training for students at ECU, and these branches represented the primary population.

Data Collection Method

Data was collected using an on-line survey tool, Qualtrics, licensed and administered through East Carolina University. In general, collection instruments are referred to as either "surveys" or "questionnaires," with the subtle differences being on the purpose of the questions presented (Creswell, 2003). The distinction between a survey and questionnaire is discussed by Creswell and Best and Kahn in their statistical reference books. Surveys are designed to provide "quantitative or numeric description of trends, attitudes, or opinions of a population by studying a sample" with the goal to gather opinions, attitudes, or other subjective measures of data to produce generalizations about a population from a sample (Best & Kahn, 2006; Creswell, 2003). By contrast, an instrument that seeks factual information rather than attitudes and opinions is generally referred to as a questionnaire, i.e. a tool designed to collect objective data, and not subject to opinion (Best & Kahn, 2006; Creswell, 2003). The instrument used for this research is considered a questionnaire in that it gathered data and information, rather than opinions and attitudes.

Figure 8 summarizes the process used to obtain participants for the questionnaire. A multi-step approach was required to obtain contact information for individual branch managers, as the population represents companies recruiting at ECU, but the participants never actually visit the ECU campus. A total of twenty-one individual representatives from eighteen different companies, representing six different industries, were contacted to obtain the names of branch managers at the wholesale distribution level (see Figure 1) in order to send a questionnaire.

A total of one hundred and eighty questionnaires were distributed via email through a combination of the Qualtrics survey system and the researcher's email account. The initial contacts were asked permission to utilize their name in a support statement when the questionnaire was sent to the individual branch managers to achieve a larger response rate. In addition, each survey essentially had a request from the respondent's manager to complete the survey which eliminated any bias effects with personal relationships to ECU or the researcher. The email included an introductory letter providing the context of the request for data and a referral from someone from within their company. The email to the branch managers contained a web link, and generated ninety-six individual responses. The ninety-six responses yielded a net of fifty-seven cases, a net response rate of approximately thirty-two percent.

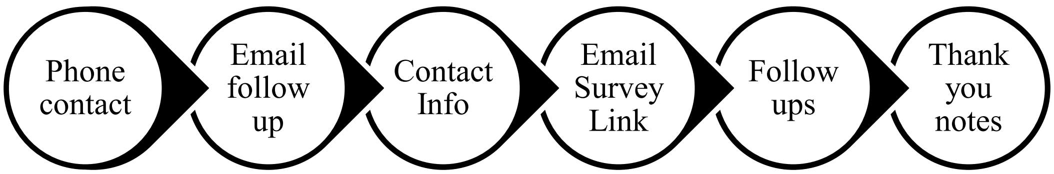


Figure 8. Data Collection Process

Data was collected over a four-week period in order to minimize impact of external business and economic forces on the performance metrics. The time window was generally segmented as follows: week one for initial representative contacts, weeks two and three for questionnaire distribution, and week four for follow up and second requests.

The first week of data collection entailed contact of company recruiters by phone to personally explain the nature of the request or leave an explanation as a voice mail. Immediately after the phone contact, regardless of live conversation or voice mail, an email with a standard script was sent to the individual to restate the verbal message just delivered. The crux of both voice and email communication was to ask company recruiters for branch manager names and email addresses. The emails served to avoid confusion or misunderstanding of the voice mail or conversation by presenting the same information in text, and providing the researcher's email to facilitate the requested information.

The second and third week of data collection was for distribution of the questionnaire through the Qualtrics system. Qualtrics provides for creating blocks of email addresses to be input for survey distribution, which allowed customized emails to the groups of branch managers working in the various companies. The email sent contained an opening referral statement so the respondent could see who provided the researcher their name. In addition, the email contained all the Institutional Review Board (IRB) requirements with regard to participant options for voluntary participation and potential negative impacts of participation.

The benefits of using the Qualtrics software were realized in the fourth week of data collection. Since the software facilitated group email, it also was capable of tracking survey responses, and differentiated between no response, started surveys, and completed surveys. Follow up emails were crafted and sent to all recipients that had not yet completed the questionnaire. The follow up email was different from the initial introductory email, but also contained the web link for the questionnaire. The fourth week of the questionnaire was utilized to send "thank you" emails to all people who had completed a questionnaire and a final follow up or second request to those who had not.

The goal of data collection to obtain a minimum of ten observations per independent (predictor) variable was established at the onset to allow for proper data analysis, even if only a limited response rate occurred. The intended multiple linear regression analysis establishes ten cases per independent variable as an acceptable minimum, with responses of twenty or over considered "best", i.e. better Type II error rate, meaning less of a chance of that we do not reject the null hypothesis when we should (Hayden, 2008).

Questionnaire Design

The questionnaire can be found in Appendix D and was reviewed by the Institutional Review Board (IRB) at Indiana State University; a copy of the IRB exemption letter is provided in Appendix A.

The research was investigative, rather than experimental in nature, hence the questionnaire was designed to cast as wide a net as possible and include numerous predictor (independent) variables. The questionnaire sought facts and objective information, and avoided financial related questions to enhance the response rate (Dillman, Smyth, & Christian, 2009). To prevent low response rate bias, the survey length was held to fourteen total questions (Dillman et al., 2009), although some of the questions had multiple component parts as shown in Table 5. In total, the fourteen questions resulted in forty two individual data points, plus "write in" responses for qualitative information on types of software, "other" metrics, and "other" technologies. The purpose of the qualitative (descriptive) information and "other" data was to provide direction for future research.

The opening page of the instrument served as an introduction of the questionnaire and to meet the guidelines as established by the IRB. The second page started with easy, lead in, questions to gather demographic information from the respondents. This question type is intended to draw the respondents into the instruments. The next cluster of questions included the predictor (independent) variables which were considered to be common knowledge for any branch manager, and included blocks on information and communication technology, automatic identification and data capture, and best practices. The final block of questions dealt with the outcome (dependent) variables, i.e. the KPIs, and potentially required some research by the participant. Thus, these were positioned last so as to "commit" the respondent to completion. A final open response question at the end was a query for technologies, practices, or metrics not listed within any prior question or response option.

Table 5. Breakdown of Survey Questions

Cluster	Number of Questions	Total Data Points	Open / Free Response?
Demographics	8	9	No
Technology – ICT	1	10	Software Type
Technology – AIDC	1	6	Software Type
Best Practices	2	9	No
Metrics	1	7	"Other"
Other Information	1	1	Open Ended
Total	14	42	n/a

Each of the predictor (independent) variable clusters, i.e. the two technology groups and best practices, were designed to obtain a response of "not utilized" or "utilized." If the branch utilized a factor, the response was directed to a time period of utilization rather than a simple "yes." Time factors were arbitrarily established at "less than one year," "one to two years," and "two or more years." The survey design intent was to capture data on technology implementation status at the same time as measuring maturity of utilization effects.

Similarly, the KPI data employed a sliding scale and a "not applicable" option. Therefore, moving the slider on the question entered the response more quickly and effectively responded "yes" without adding a question, contributing to the goal of minimizing the questionnaire form and completion time. The questionnaire response design time was ten minutes maximum, with the goal of avoiding survey fatigue and obtaining the highest possible completion rate.

Questionnaire Validity

Validity of a survey instrument refers to the ability to "draw meaningful and useful inferences" from the collected data (Creswell, 2003). Further, validity is generally subdivided into three categories: 1) content validity, i.e. the instrument measures what it is supposed to measure, 2) predictive or outcome criterion validity, i.e. the instrument predicts or correlates with a criterion, and 3) construct validity, i.e. the instrument measures concepts correctly (Creswell, 2003).

Content validity is required to insure that the questions represent the required aspects of the constructs, i.e. the data on the predictor and outcome variables. Content validity includes the number of items in the questionnaire, the format of the questions, completion time of the survey, directions to the participants, and administrative functions. For content validity, the questions must have generally accepted meanings and questions should be phrased in the least ambiguous way (Best & Kahn, 2006). Thus, there was an iterative process as questions were continually refined and modified for clarity based on feedback. Of note is that the instrument utilized was classified as a questionnaire, thus making question reliability and psychometric properties of the specific questions not as significant a factor in the instrument construction.

To obtain content validity, the instrument design was reviewed by various experts. A research consultant from the East Carolina University's Office of Faculty Excellence assessed the number of questions, format, time for completion and similar technical aspects of the Qualtrics material. To assess generally accepted meanings and potential ambiguity, the questions were reviewed with professionals in the field from distribution branches local to Greenville, NC, and faculty within the Department of Technology Systems at ECU.

The predictive (outcome) validity was evaluated by the statistical analysis completed after data collection.

Construct validity is a measure of the adequacy and relevance of the questions within the questionnaire to assess that the content being measured captures the intent of the question. For psychometric analysis of surveys, this is assessed using Chronbac's alpha and is an evaluation on correlation of responses from similarly worded questions seeking information on a common criterion (Dillman et al., 2009). For this questionnaire, there was no duplication of questions needed since facts were sought rather than attitudes and opinions, which eliminated the need for redundancy.

A subsequent concern regarding surveys, and even questionnaires intent only on gathering factual information, is that various forms of bias may be present in the returned data. The two primary sources of bias considered here include low response rate bias and persuasive effort bias.

Low response rate bias is "the effect of nonresponses on survey estimates" meaning that had a large sample group responded, the results would have been significantly different (Creswell, 2003) or "in a way important to the study" (Dillman et al., 2009). One way to validate survey results against a low response rate bias proposed by Duncan and Hill, 1989, was to compare characteristics achieved in a sample against a benchmark survey from a larger sample size (Olson, 2006). Although not a direct comparison, this survey data was compared against the benchmark survey in the WERC 2012 study of the wholesale distribution industry and warehouse practices discussed in the variable selection section (Manrodt et al., 2013). Considering that the WERC survey was for distribution centers that are suppliers to the branches, an underlying assumption was that the KPIs for the branches would be the same or less than reported by WERC for fill rate and on-time shipments. For fill rate, the typical DC demonstrated values of 97% – 99% (Manrodt et al., 2013) whereas the respondent branches 95% confidence range was 73% - 91%. For on-time shipments, the typical DC demonstrated values of 98% - 99% (Manrodt et al., 2013) whereas the respondent branches 95% confidence range was 86% - 94%. As the WERC benchmark data and the survey results appeared to be properly aligned, low response rate bias appeared to be a non-issue. Additional supporting research by Curtin, Presser, and Singer, 2000, Keeter et al., 2000, and Merkle and Edelman, 2002, showed no strong relationship between nonresponse rates and nonresponse bias (Olson, 2006).

Also considered was bias error based on the theory that persuasive efforts may provide data filled with measurement error (Olson, 2006). Conflicting theories exist on the benefits of persuasive efforts, with the goal of high response rate being offset by measurement error due to pressure to provide answers without factual data (Olson, 2006). First, Dillman supports obtaining sponsorship of a legitimate authority to increase response rate (Dillman et al., 2009). This method was employed by requesting the recruiter to provide potential participant email addresses and contact information. Since all questionnaire emails provided a referral, all returned data was considered uniform, leaving only measurement error bias as a concern. However, referencing back to the WERC 2012 survey analysis, and a subsequent preliminary review of outliers in the data analysis, the results of the data analysis were considered valid.

Once questions were properly structured, the next goal was efficiency and time minimization for potential respondents. A target response time of not more than ten minutes was arbitrarily established in an effort to boost completion rate. To enhance efficiency and time, the instrument was structured into question groups: demographics, information and communication technology, automatic identification and data capture, best practices, and metrics. The goal of the survey design was to start with easy to answer questions and draw in potential respondents. Next questions regarding technology and best practices were asked, again seeking facts that were most likely common knowledge within the branch manager's purview. The final group of questions was "performance metrics," which considered that branch managers may need time to look up data for responses.

Within each group, questions were clustered where possible to pose a common question that had many sub-texts for responses, along with easy to respond to “point and click” fields. Grouping questions by common response type allowed for simpler participant interaction and reduced time. For further reference, please review the questionnaire found in the Appendix D, questionnaire pages three, four, and five.

Once the survey questions were properly vetted, and before contact with any participants, the research protocol and instrument design was submitted to the Indiana State University’s IRB to insure the protection of human subjects that would eventually be part of the research. The IRB review of the protocol resulted in an exempt status, as shown in Appendix A. Documentation of the communications to the company representatives and the participants are found in Appendicles B and C. A copy of the actual questionnaire is attached in Appendix D. Regardless of the exempt status, the instrument and communication design maintained the requirements as if the instrument had non-exempt status.

Analysis Procedure

0. The preliminary analysis step was an import of the raw data from the Qualtrics software downloaded in order to prepare inputs to facilitate proper analysis utilizing the SAS software JMP 10pro.
1. Questionnaire Response Summary: The first step was to summarize the demographic data and review the inputs from the survey. The goal was to eliminate any duplicate survey responses or delete any cases that were obviously flawed. Statistics were generated for number of responses and valid cases.
2. Data Preparation: A second preliminary review step was undertaken to prepare, or “clean” the data to convert text responses to numeric data where required and to interpret

input errors if possible. Raw data columns were coded to the requisite type (numeric, ordinal, nominal) for interpretation by the SAS JMP 10pro software, and multiple new variables created and re-coded to facilitate investigation of the research question's null hypotheses.

3. Descriptive statistics: These were developed for the questionnaire responses and computed using cross tabulation tables, histograms, scatterplots, and normality plots. Box and whisker plots, along with scatterplot graphs with best fit regression lines and 95% confidence intervals, were generated for visual review. Cases demonstrating outliers were evaluated for possible exclusion from the data set. This step allowed for the proper application of statistical techniques and selection of the predictor variables for analysis.
4. Outcome (Dependent) Variable Analysis: A correlation analysis was conducted on all of the outcome variables with the goal of determining if there was strong correlation between any variable pairs. If a strong correlation existed, then the statistical techniques performed on one variable would produce results that could be applied to the other variable with a degree of confidence (Hayden, 2008; Norusis, 2012a).
5. Research Q1 and Q2, Analysis for Technology Predictor Variable Groups: The analytical techniques used to evaluate the first two research questions were identical expect that Q1 investigated ICT and Q2 investigated AIDC. Q1 was defined with three null hypotheses, $H_{O1\text{-}1}$, $H_{O1\text{-}2}$, $H_{O1\text{-}3}$, to represent a null hypothesis that there is no difference for individual KPI between branch operations that utilize particular ICTs and those that do not. The second research question, Q2, was evaluated similarly to Q1, with

null hypotheses being defined as $H_{O2\text{-}1}$, $H_{O2\text{-}2}$, $H_{O2\text{-}3}$, to independently assess the outcome variables against AIDC predictor variables.

Mutli-collinearity, or the high correlation of independent variables, is an undesirable outcome of too many predictor variables. This concern can be mitigated by removing "redundant or unnecessary independent variables," as only one of a redundant set of variables is required for dependent variable prediction (Hayden, 2008). Thus the first step was a review of all predictor variables that were part of the question to determine if any could be excluded from the data based on descriptive statistics.

An iterative application of multiple linear regression analysis was undertaken to determine the contribution of predictor variables and ultimately decide which predictors may have an impact on the outcome variables. After the review eliminated a subset of predictors from consideration, multiple linear regression was run iteratively until the null hypothesis could be addressed. Procedurally, the multiple linear regression methodology used the following steps in SAS JMP 10pro software:

1. Analyze > Fit Model.
2. Establish predictors and outcome variables; select emphasis: effect screening.
3. Run model.
4. Interpret Full Model ANOVA for Prob > F statistic.
    a. If not significant, reduce over fitting of predictors using standard beta and restart at Step 2.
5. Interpret Parameter Estimates for Prob>|t| statistic.
    a. If none significant, restart at Step 4a.
6. Test assumptions for Model Validity: Normality of Residuals; Collinearity.

Each iteration required an evaluation of the standardized beta statistic, Step 4a, of the parameter estimate in order to establish relative importance of the individual independent variables. The larger the absolute value, the more important the variable (Klimberg & McCullough, 2013; Norusis, 2012a). Note that when utilizing dichotomous variables with a level of zero (0) and one (1), the parameter estimates may be utilized as they are all based on the same sample scale.

Ultimately, the statistical technique would either reject or fail to reject a null hypothesis that a distribution branch utilizing a subset of technologies had the same performance for an individual outcome variable. This procedure was repeated for ICT and AIDC, separately, and three times within each, once for each predictor variable.

6. The third research question, Q3, was to investigate if technology or business practices play a larger role in the outcome (dependent) variables. This methodology included a two-step approach: 1) an analysis similar to the first two research questions in order to identify statistically significant best practices, 2) an ANOVA evaluation of the significant technology predictors compared to the statistically significant best practices. This testing would be conducted for each outcome variable individually and independently. The procedure outlined in Step 5 was utilized for the first part of the approach, i.e. the determination of statistically significant predictor variables.
7. The fourth research question, Q4, was a summary question to create a prediction model for the research, i.e. potential development of three multiple linear regression models for each of the outcome (dependent) variables based on the analysis of Q1, Q2, and Q3. The procedure would be to take all of the relevant predictor variables and analyze them with multiple linear regression utilizing a stepwise analysis. This analysis would be conducted for each outcome

variable individually and independently. The stepwise process is the "automatic" execution by the algorithm outlined in Step 5, and the parameter estimates would be inserted into the regression formula based on a suitable *t* statistic at $\alpha = 0.05$.

Test of Assumptions: Multiple Regression Analysis Utilization

The underlying assumptions of multiple linear regression are restated below and discussed in detail (Hayden, 2008; Minium et al., 1999; Norusis, 2012a). The assumptions fall into two distinct groups, assumptions that required utilizing the multiple linear regression technique and a second set of assumptions required for linear regression model validity. The former assumptions are discussed next, the latter in the following subsection.

1. All of the observations must be independent, i.e. inclusion of observations may not influence each other. The sample was not random given that questionnaires were distributed to self-selected distribution branch operations. However, given that the facilities are separate entities, the data is considered independent and satisfied the assumption.
2. For each value of the predictor variable, the distribution of the values of the outcome variables must be normal. This was evaluated using histograms for each value of the predictor, i.e. the two dichotomous levels selected during the analysis. Homogeneity of variance of the dependent variables is an underlying concept of ANOVA, and therefore must be tested using the *F* statistic during regression analysis (Hayden, 2008). Additionally, if the number of cases for each (predictor) group is similar, the equality of variance assumption is "not too important" (Norusis, 2012a).
3. The variance of the distribution of the dependent variable must be the same for all values of the predictor. As this analysis is using nominal dichotomous variables, the regression mean square and the residual mean square (the variance of the residuals) are considered estimates

of the variance of the dependent variable for each combination of values of the independent variable, and will be evaluated during the regression analysis (Norusis, 2012a).

4. The relationship between the predictor (independent) and the outcome (dependent) variable must be linear in the population. This is measured with the overall regression *F* test ANOVA, evaluating if the probability of *F* is significant which would reject the null hypothesis that the population slope equals zero.

Test of Assumptions: Multiple Regression Model Validity

Normality of Residuals

1. From the output for Analyze > Fit Model, select red inverted triangle.
2. Select Row Diagnostics > Plot Residual by Predicted.
    a. Visually review, looking for homoscedacity, i.e. a uniform scattering of the residuals about the predicted line, which if evident implies a random set of normal residuals.
3. Analyze residuals by first saving the residual values, then utilize Analyze > Distributions.
    a. From the output for Analyze > Fit Model, select red inverted triangle, then save columns > residuals.
    b. Select Analyze > Distribution.
    c. Select the red inverted triangle, then Normal Quantile Plot (Q-Q Plot).
        i. OK if no significant departures between data points and fitted line.
        ii. Under fitted normal, select Goodness of Fit for Shapiro-Wilk W test for normality.

Collinearity

The objective of multiple linear regression is to have predictors that are correlated to outcome variables, but it is not desirable to have high correlation between the predictors as this will cause trouble when drawing inferences about the contribution of each (correlated) predictor. If any of the predictors are highly correlated with any or all of the other predictors, a condition of collinearity (sometimes referred to as multicollinearity) exists (Carver, 2010). Violation will lead to erroneous parameter estimates and potentially incorrect interpretation of the data.

A collinearity assumption test is done to confirm that the predictor variables vary independently with each other and do not have excessive correlation (Carver, 2010). If data is continuous, which is not the case with this research, scatter plot matrix and correlation analysis is useful. If there are no strong correlation coefficient r values, then there is no collinearity, which is required.

However, given the use of dichotomous data, if the overall regression ANOVA *F* statistic and the parameter estimate *t* statistic are both small, i.e. significant at a select α value, then no collinearity exists (Carver, 2010). When there is a small *F* statistic with a large *t* statistic, the collinearity assumption is violated.

CHAPTER 4

DATA ANALYSIS AND FINDINGS

Research Questions and Hypotheses

The research questions are restated below and include their associated null hypotheses.

Q1: Do branch operations that invest in information and communication technology (ICT) have better performance than those that do not?

H_{O1-1}: Branch operations that invest in ICT have the same performance with respect to fill rate as those that do not invest in ICT.

H_{O1-2}: Branch operations that invest in ICT have the same performance with respect to inventory accuracy as those that do not invest in ICT.

H_{O1-3}: Branch operations that invest in ICT have the same performance with respect to on-time shipping performance as those that do not invest in ICT.

Q2: Do branch operations that invest in automatic identification and data capture (AIDC) have better performance than those that do not?

H_{O2-1}: Branch operations that invest in AIDC have the same performance with respect to fill rate as those that do not invest in AIDC.

H_{O2-2}: Branch operations that invest in AIDC have the same performance with respect to inventory accuracy as those that do not invest in AIDC.

H_{O2-3}: Branch operations that invest in AIDC have the same performance with respect to on-time shipping performance as those that do not invest in AIDC.

Q3: Do branch operations that utilize “best (warehousing) practices” have better performance than those that invest only in technology?

$H_{O3\text{-}1}$: Branch operations that employ “best practices” have the same fill rate performance as those that rely solely on technology.

$H_{O3\text{-}2}$: Branch operations that employ “best practices” have the same inventory accuracy as those that rely solely on technology.

$H_{O3\text{-}3}$: Branch operations that employ “best practices” have the same on-time shipping performance as those that rely solely on technology.

Q4: What are the contributions of different technologies and best practices to inventory and customer service metrics in a distribution branch operation?

A model is built for each outcome variable based upon the contributing predictor (independent) variables from each of the three groups: ICT, AIDC, and best practices.

Questionnaire Response Summary

The questionnaire collected data through Qualtrics, packaged the data into the Statistical Package for the Social Sciences (SPSS) format, and downloaded into a SPSS.sav file; the SPSS.sav file was then imported into SAS Jump 10pro software for analysis.

A total of one hundred and eighty surveys were distributed and ninety-seven, or 54%, were opened by the recipients. Of the ninety-seven opened surveys, thirty-nine were eliminated due to lack of responses to any questions, which was interpreted as an opened survey that was immediately closed and never answered, or possibly a survey open in a cell phone environment that could not be executed by the user.

Of the fifty-eight remaining responses with data, a second review of respondent IP address was conducted to validate that duplicate surveys were not submitted. Since surveys were sent to both individual branch operations as well as district offices, it was plausible that some respondents may have had responsibility for a facility other than where they were located and thus duplicate IP addresses were possible. The data showed two instances where surveys came from a common IP address, which necessitated a further review of the raw data to determine if information was entered for different facilities or duplicate surveys taken. The result was that one survey was opened but only demographic information entered, and a second response with complete information, thus one of the duplicates was deleted from the response pool. The second instance was reviewed, and it was determined that data definitely represented two separate facilities entered using a common IP address. Therefore, the net yield was fifty-seven valid survey responses of the one hundred and eighty distributed, approximately a 32% response rate.

A review of the responses determined that 64% of the survey data is based on the general industrial product wholesale distribution sector, but all industries surveyed had some level of representation in the data.

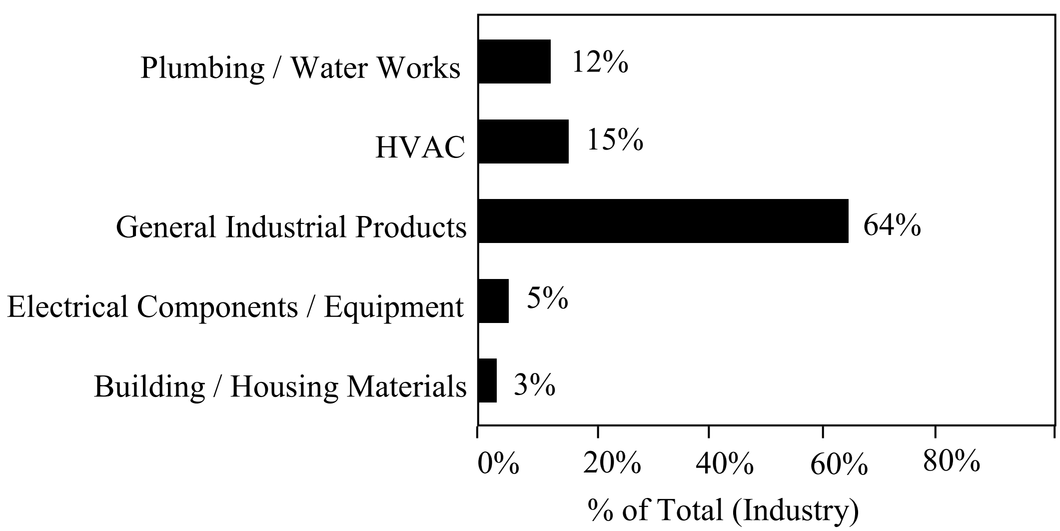


Figure 9. Responses by Industry (% of total cases before analysis)

A Pareto analysis of the survey response duration monitored by Qualtrics determined that 82% of survey responses were complete at a weighted average of 8.2 minutes, which fairly represented the estimated ten minute time commitment in the survey introduction sent to the participants and supported one of the design validity parameters.

Data Preparation

Data was initially reviewed to clean up responses where text was entered for numerical values, e.g. data entry fields for number of SKUs, number of stock locations, and responses included entries with ranges, such as 300-500, 1k, or 7,000. These were changed to insert proper data format: where ranges were entered, data entries were modified to the midpoint, where abbreviations were used, the numerical value as substituted, and where text data, i.e. commas used, the numbers were re-entered without the modifier.

The predictor variables were recoded to ordinal from text to show a progression from "not utilized" to "more than two years" of use. This allowed further creation of recoded variables to represent multiple interpretations of the results. The primary interpretation of the survey data was a dichotomous variable to show if the technology and/or best practice was either "utilized" or "not utilized", which aligned it closely with the research questions. These recoded column variables were renamed with an "YN" suffix to denote "Y" for utilized for any time period, or "N" for not utilized. Two other groupings of the raw data were established to pool the responses looking for learning curve and/or maturity of utilization effects. These groups were named with "Grouped" and "2yr" suffixes as discussed in the Methodology section of this paper. Additionally, the warehouse square footage column was recoded from nominal to ordinal data accounting for the input options within the survey allowed for estimates of warehouse size in 5,000 foot increments of increasing size.

Descriptive Statistics

Descriptive statistics were generated on the demographic data and response variables (outcomes) for all fifty seven data points. An initial review of the data using the Shapiro-Wilk W test rejected the null hypothesis that the distributions were from normal populations, and log and square root transformation did not provide any success. However, the intended multiple regression and/or ANOVA analysis is generally robust to the normality assumption with the caveat that data and interpretations may be significantly impacted by non-normal points, so additional review of the data was warranted (Norusis, 2012a).

The review of the raw data started with cases exhibiting non-normal data and showed several outliers for possible exclusion from the analysis data set. The first consideration was the size of the facility in the questionnaire response. As the target population of the research was the distribution branch operations (Figure 1) within the wholesale distribution channel, it was important to insure that questionnaires were not completed for facilities that would be considered as "regional" or "central" distribution centers. In particular, facilities that were 30,000 ft^2 or greater and showing outliers for demographics including SKUs stocked, inventory locations, inbound trucks, and labor were key considerations of data that truly described central distribution rather than distribution branch operations. In all, four cases with square footage over the 30,000 ft^2 threshold were considered; resulting in two cases being excluded from the data consideration as shown in Table 6.

Additionally, key performance indicators were examined for outliers to determine if potential data entry or other similar problems may be evident. Of particular note were cases involving data for excessively low on-time shipments with outliers in the other Key Performance Indicators (KPI) or instances with other missing data. Table 6 shows three cases that were excluded based on the evaluation that the reported on-time shipment entries invalidated the case since operations that truly had zero on-time shipments combined with other outliers considered would not be a viable business.

In all, this analysis resulted in five data points being excluded from the analysis data set. The net result of the preliminary data review and analysis was that fifty-two total cases would be used for evaluating the research questions. Descriptive statistics were rerun to reconsider population distributions.

Table 6. Raw Data Outlier Consideration Results

		SKU					Fill Rate		Inventory Accuracy		
Case	Ft^2 (000)	Stocked	Daily Ship	Location	Labor	Daily Trucks	Lines	Qty	Dollars	Units	OTS
53	25 – 30										
54*	> 30	Outlier				Outlier					
55	> 30		Outlier								
56*	> 30		Outlier	Outlier	Outlier						
57	> 30				Outlier						
4*	< 5						No data	No data	No data	Outlier	Outlier
25*	5 – 10						No data	No data	No data	No data	Outlier
43*	10 – 15						Outlier	No data	Outlier	Outlier	Outlier

* excluded from data table for analysis purposes

Outcome (Dependent) Variable Analysis

A preliminary correlation analysis of the outcome variables was completed using a scatterplot as shown in Figure 10. The objective of the analysis was to assess the measurement methods for the KPI of "fill rate" and "inventory accuracy." Since different companies and distribution branches may utilize different methods to monitor performance, the questionnaire provided two alternatives to each KPI: 1) fill rate had two treatments, either by “lines” or by “quantity,” and 2) inventory accuracy had two treatments, either by “dollars” or by “units.” The scatter plot matrix showed that fill rate by lines had a 0.87 correlation (*r* value) with fill rate by quantity, and inventory accuracy by dollars had a 0.94 correlation with inventory accuracy by units. These correlation coefficients were deemed strong enough to continue with a selection process for final analysis to include only fill rate by lines or fill rate by quantity, and either inventory accuracy by dollars or inventory accuracy by units. The strength of the correlation meant that a conclusion on one member of the pair would be suitable for both. It should be noted that on-time shipments had a maximum correlation with fill rate of 0.53 and a maximum correlation with inventory accuracy of 0.51. These low correlations meant the on-time shipment metric was required to be included as an outcome variable.

A second correlation analysis determined which fill rate KPI would be included. This required a comparison of correlation coefficients (*r* values) with the inventory accuracy pairs to select the one with the lower correlation since less correlation with other outcomes was desirable to reduce collinearity effects. The solid doubled headed arrow positioned inside Figure 10 shows that inventory accuracy by units had lower correlation coefficients to either fill rate, thus promoting it for inclusion in the modeling analysis. As a secondary comparison descriptive statistics were analyzed for both fill rate variables, neither population was normal but both had approximately the same sample size. Supporting the selection for fill rate by quantity was a median value closer to the population mean and less of an appearance of a bi-modal distribution. This selection came with some trepidation in that, by definition, fill rate should be based upon the number of lines shipped compared to the number of lines ordered. However, the misunderstanding of technical definitions in the supply chain industry was the original reason this questionnaire option was offered, and the response rate indicated it is extensively used and correlates to fill rate by lines.

A third correlation analysis determined which inventory accuracy, either by dollars or units, to include. The dotted double headed arrow in Figure 10 shows the evaluation for inventory accuracy. Accuracy by units had approximately equal correlation coefficients for fill rate by lines and fill rate by quantity. However, the dashed double headed arrow in Figure 10 pointed to fill rate by quantity having a much lower correlation coefficient with on-time shipments. Therefore, inventory accuracy by units was selected for inclusion in the model. As a secondary comparison, descriptive statistics were analyzed for both inventory accuracy variables; neither population was normal, both had approximately the same sample size. Supporting the selection for inventory accuracy by units was a median value closer to the population mean, fewer outliers, and less of an appearance of a bi-modal distribution. Another supporting factor for selecting inventory accuracy by units was that dollar impacts distort the true purpose of monitoring inventory, in that the units are shipped to support both fill rate and on-time shipments, whereas inventory accuracy by dollars is more of a financial concern rather than operational.

The net result was selection of three outcome (dependent) variables to be evaluated for the research questions: 1) fill rate by quantity, 2) inventory accuracy by units, and 3) on-time shipments. The correlation matrix in Table 7 summarizes the scatterplot matrix in Figure 11, and only considered the cases that included data points for the three included outcome variables, i.e. fill rate by lines and inventory accuracy by dollars were removed from the data.

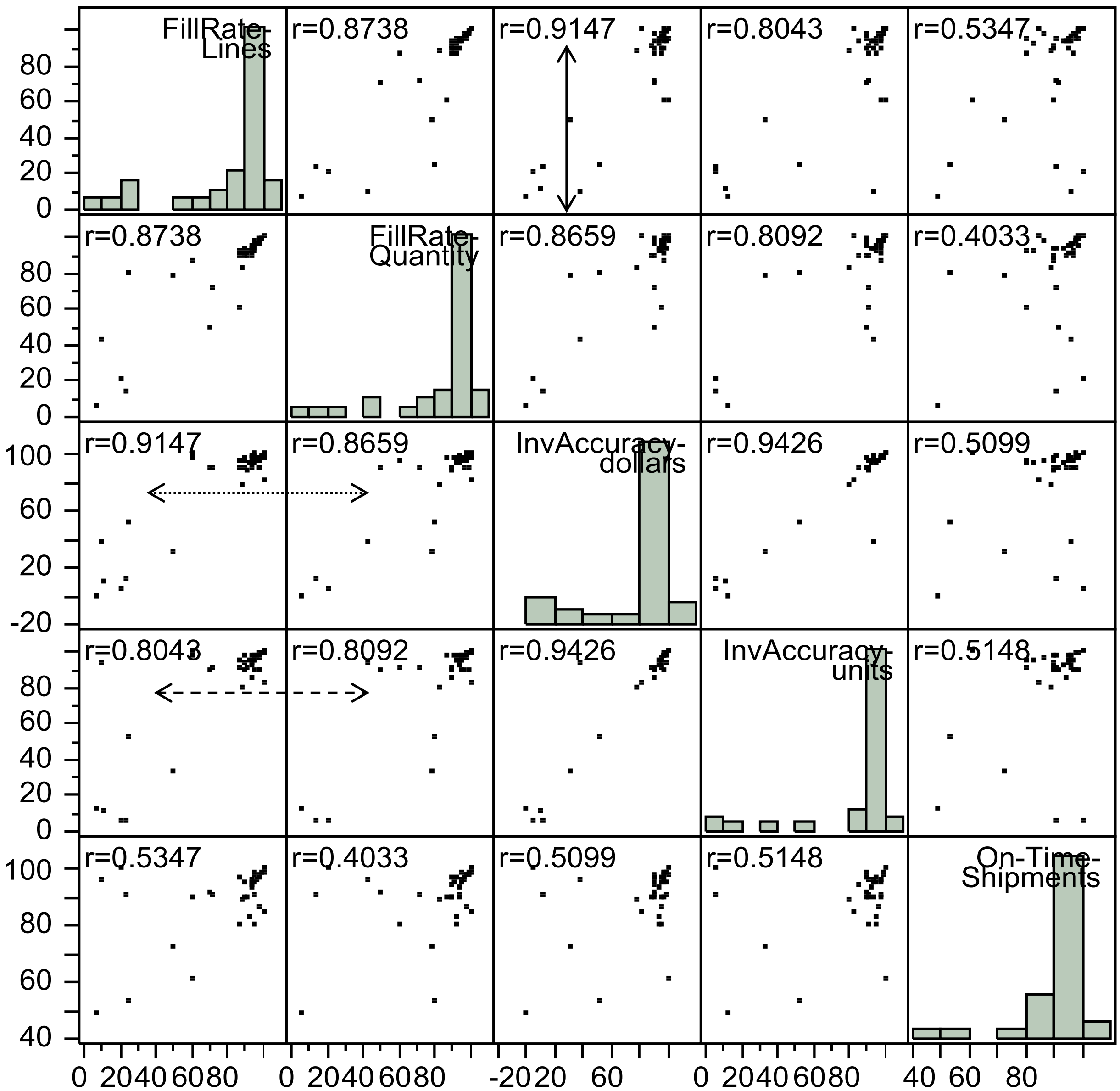


Figure 10. Outcome Variable Correlation

A review of Table 7 shows an acceptable degree of separation for the correlation coefficients, i.e. lack of correlation, between the outcome variables. This indicated that they were proper selections for analysis as they are relatively independent of each other and satisfy one of the assumptions for using multiple linear regression. Of note is that the scatter plot matrix and histograms in Figure 11 show possible bi-modal distribution and do not meet the Shapiro-

Wilk W test for a normal distribution. However, to restate from the review of literature, ANOVA and multiple regression are relatively robust to the assumption of a normal distribution as long as the researcher qualifies or limits generalization of the conclusions. (Hayden, 2008; Norusis, 2012a)

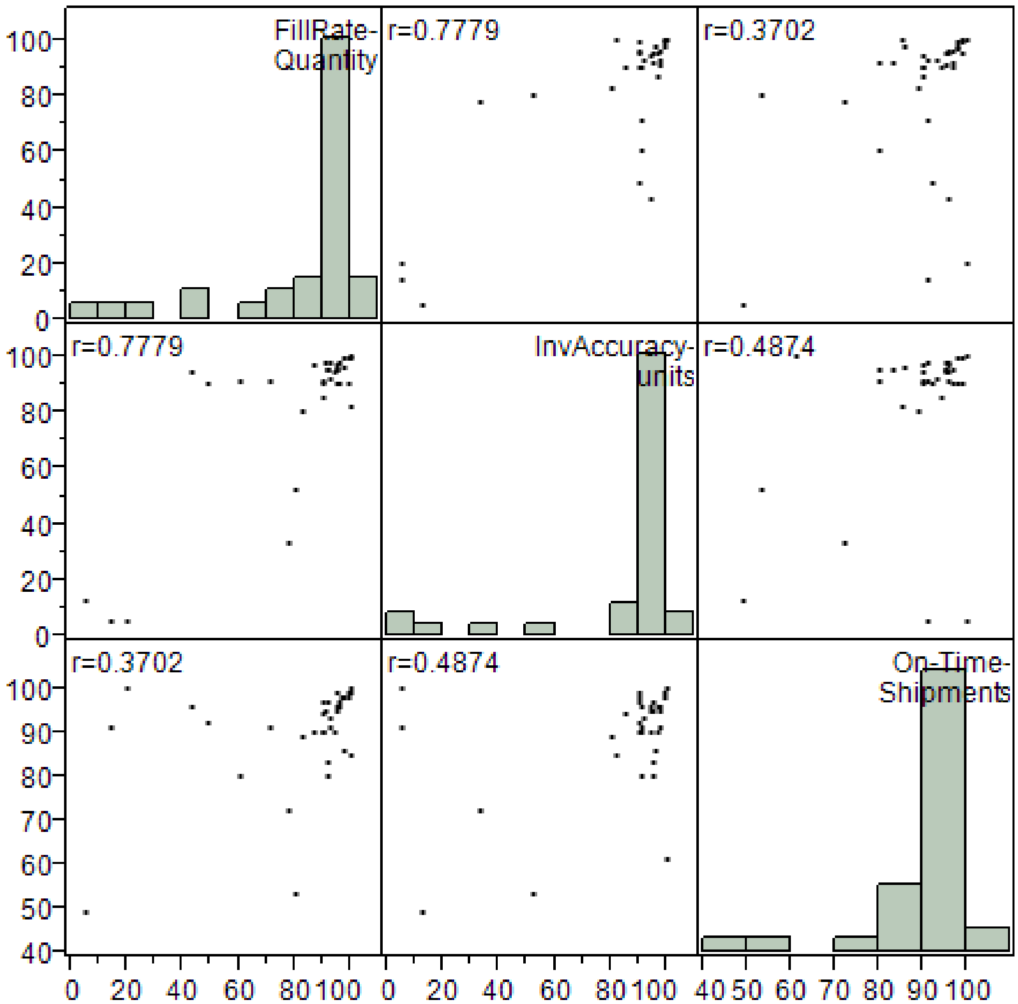


Figure 11. Selected Outcome (Dependent) Variables

Table 7. Correlation Coefficients for Outcome Variables

	Fill Rate-Quantity	Inv Accuracy-Units	On-Time-Shipments
Fill Rate – Quantity	1.000		
Inv Accuracy – Units	0.778	1.000	
On – Time – Shipments	0.370	0.487	1.000

Research Q1: Analysis for ICT Predictor Variables

The objective of the first research question was to determine if branch operations that invest in information and communication technology have better performance than those that do not. To research this, the three outcome variables were considered independently and individually against the full set of predictor variables.

An initial review of the data for the predictor variables included in the ICT group is shown graphically in Figure 12 with a share chart, and in Table 8 with a cross tabulation. The share chart represents the predictor's utilization in a horizontal bar chart stacked for each time period from the ordinal raw data. This chart is followed by a cross tabulation showing the actual percentages for each treatment. The data showed that tablet computer technology and hands free order picking technology were not utilized in over 95% of the wholesale distribution branches in the population. Therefore, it was decided to exclude these two technologies from the list of predictor variables prior to conducting statistical analysis.

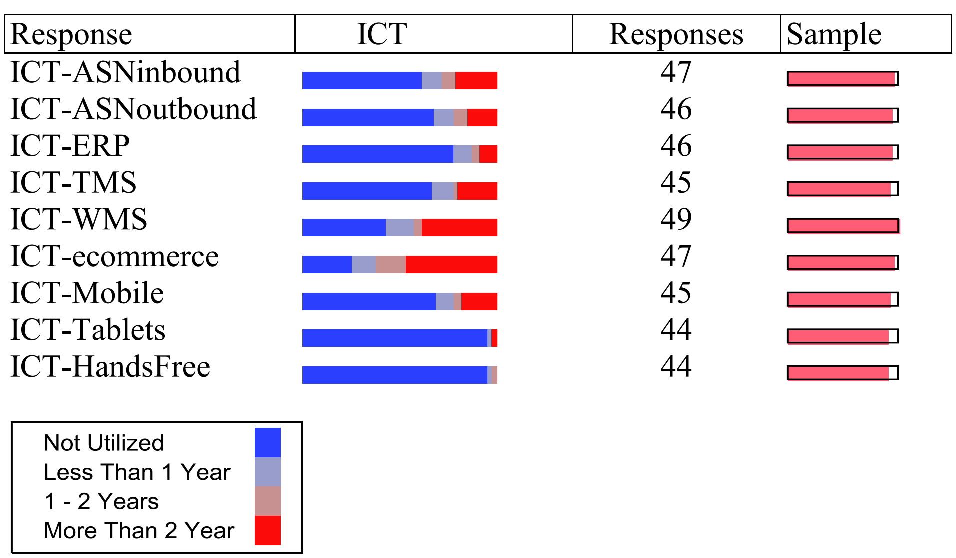


Figure 12. ICT Share Chart - All Predictor Variables

Table 8. ICT Response Frequency Chart – All Predictor Variables

Freq Share	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years	N
ICT-ASNinbound	29 0.617	5 0.106	3 0.064	10 0.213	47
ICT-ASNoutbound	31 0.674	5 0.109	3 0.065	7 0.152	46
ICT-ERP	36 0.783	4 0.087	2 0.043	4 0.087	46
ICT-TMS	30 0.667	5 0.111	1 0.022	9 0.200	45
ICT-WMS	21 0.429	7 0.143	2 0.041	19 0.388	49
ICT-ecommerce	12 0.255	6 0.128	7 0.149	22 0.468	47
ICT-Mobile	31 0.689	4 0.089	2 0.044	8 0.178	45
ICT-Tablets*	42 0.955	1 0.023	0 0.000	1 0.023	44
ICT-HandsFree*	42 0.955	1 0.023	1 0.023	0 0.000	44

* excluded based on high percent non-utilized

Additional consolidation of the raw data was required to address the research question looking for differences between "invest" and "not invest" in the individual technologies. Since the predictor variable raw data was obtained in one of four categories: "not utilized", "utilized less than 1 year", "utilized between 1 – 2 years", and "utilized more than 2 years", two approaches were undertaken to create the required dichotomous variables needed.

First, to address the literal interpretation of the research question for "invest" versus "not invest", a dichotomous variable was created to separate the cases as either "not utilized" or "utilized", regardless of the time period offered in the questionnaire. "Utilized" included any case that responded other than "not utilized", i.e. if a case had a response with technology utilized for less than one year, one to two years, or more than two years, it would be considered for the "invest" in technology treatment. The predictor variables were re-coded as a new column in the data table with an "YN" suffix for this purpose. Cases with a response of "not utilized" were coded as zero (0) and any case with a "utilized" response were coded as one (1).

Second, the raw data was reviewed to determine if there was an apparent learning curve or technology adoption maturity impact on each of the outcome variables. A cross tabulation comparing the raw data response categories for each time period against the outcome variables independently of each other is shown in Table 9. The goal of this analysis was to determine if blocking (grouping) data for subsets of the time frames of technology utilization were feasible in order to create dichotomous variables representing utilization time frames.

The first inference drawn from the Table 9 was that a break point of means was evident for all predictor variables in the column for fill rate at "more than one year". This is supported by a comparison of means between the "utilized less than 1 year" cells and the group of cells for both "one to two years" and "more than two year". Inventory accuracy demonstrated the same time separation point for all seven predictors, and on-time shipment for six of the seven predictors. However, for completeness of analysis and given that there were only two possible time utilization considerations, a third subset of predictors were established using the two year implementation points as a break point.

The result was two additional subsets of predictor variables that underwent an initial comparison to determine which would be used for investigating the research question. The first new subset of variables were created and re-coded as zero (0) for cases indicating "not utilized" and "utilized less than 1 year," cases indicating "utilized 1 – 2 years," and "utilized more than 2 years" were re-coded as one (1). The new recoded variables were renamed with a suffix "Grouped" to distinguish them. The second new subset of variables were created and re-coded as zero (0) for cases indicating "not utilized," "utilized less than 1 year," and "utilized 1 – 2 years," cases scored as "utilized more than 2 years" were re-coded as one (1). The new recoded variables were renamed with a suffix "2yr" to distinguish them.

To summarize, the data table in JMP 10pro had been restructured to show multiple recoded ICT predicator variables including: 1) seven new predictors with an "YN" variable suffix name, each having two levels (not utilized versus utilized, regardless of time period), and 2) seven new predictors with a "Grouped" variable suffix name with two levels (utilized greater than one year or utilized one year or not utilized at all), and 3) seven new predictors with a "2yr" variable suffix name with two levels (utilized greater than two years or not utilized and utilized less than 2 years.)

Due to the number of potential predictor variables, the selected analysis technique was multiple linear regression. ANOVA was considered, but there would be twenty one interactions along with the seven predictors which would over fit the model. Therefore, multiple regression analysis techniques were used to assess the predictor variable contributions and their interactions.

Multiple regression analyses were run in JMP 10pro using standard least square regression. An initial evaluation of the "YN", "Grouped", and "2yr" suffix variables is shown in Table 10 and established that the "Grouped" data set would be utilized for analysis based on the largest adjusted R^2.

In Table 10, R^2 is the correlation coefficient representing the amount of variance of fill rate explained by the combination of all the predictor variables used. In this preliminary analysis, only 31.3% of the predictors explain the variance in fill rate, but it had the largest value of the three test groups. The adjusted R^2 represents how well the model will fit another group of sample data and provides a measure of the generalization of the results. The Grouped data set showed the only positive value, while the negative value of the YN group indicates it is not useful for further consideration. Thus the "grouped" data set was selected for analysis.

Table 9. ICT Cross Tabulation of Predictor to Outcome Variables

	FillRate-Quantity		InvAccuracy-units		On-Time-Shipments		
ICT-ERP	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	N
Not Utilized	83.3	24.9	85.7	23.7	90.2	12.5	36
Less Than 1 Year	53.0	55.2	50.0	63.6	85.5	7.8	4
1 - 2 Years	87.0	12.7	65.5	46.0	84.0	17.0	2
More Than 2 Years	90.5	0.7	98.0	.	96.0	1.4	4
ICT-TMS							
Not Utilized	79.7	27.5	84.0	27.8	89.0	14.2	30
Less Than 1 Year	70.8	38.8	58.0	46.5	85.5	11.9	5
1 - 2 Years	.	.	.	.	.	.	1
More Than 2 Years	93.9	5.3	91.4	6.8	93.8	4.4	9
ICT-WMS							
Not Utilized	70.9	33.6	79.3	33.3	89.2	14.1	21
Less Than 1 Year	71.3	39.0	62.8	44.0	80.8	20.1	7
1 - 2 Years	87.0	.	97.0	.	90.0	.	2
More Than 2 Years	92.9	5.8	89.6	15.7	92.8	6.7	19
ICT-ecommerce							
Not Utilized	69.7	39.5	74.9	41.1	89.1	18.1	12
Less Than 1 Year	62.0	42.0	50.7	45.0	74.7	19.6	6
1 - 2 Years	90.7	11.2	77.8	30.0	90.5	12.4	7
More Than 2 Years	88.5	14.7	92.5	5.9	92.6	5.9	22
ICT-Mobile							
Not Utilized	80.6	26.9	81.2	27.8	88.6	14.2	31
Less Than 1 Year	66.7	46.0	67.0	53.7	93.3	4.9	4
1 - 2 Years	.	.	.	.	.	.	2
More Than 2 Years	90.7	10.1	94.2	3.7	92.0	6.4	8
ICT-ASNinbound							
Not Utilized	78.3	27.0	81.0	29.1	88.2	14.0	29
Less Than 1 Year	53.0	55.2	50.0	63.6	85.5	7.8	5
1 - 2 Years	91.0	1.4	90.0	7.1	95.5	2.1	3
More Than 2 Years	96.0	3.5	93.5	5.9	94.0	6.4	10
ICT-ASNoutbound							
Not Utilized	78.7	26.3	82.2	28.1	88.0	13.8	31
Less Than 1 Year	68.3	47.2	63.3	50.6	89.7	9.1	5
1 - 2 Years	93.0	4.2	91.5	9.2	95.0	1.4	3
More Than 2 Years	96.7	3.9	93.0	7.2	95.3	5.3	7

A first consideration for variable screening (selection) using all seven of the grouped predictor variables noted that the overall regression model *F* test did not show statistical significance, per Table 10. Therefore, the individual predictors were subjected to a screening and evaluation process to ascertain which would be removed from the predictor pool in order to find a set of statistically significant variables. This was accomplished by a review of the standardized beta values shown in Table 11.

Table 10. ICT Predictor Variable Utilization Time Impact

Predictors	R^2	Adjusted R^2	ANOVA: *F* ratio	Significance: Prob > *F*
Grouped	0.313	0.073	1.302	0.299
2 year	0.257	-0.002	0.991	0.465
YN	0.221	-0.051	0.643	0.764

* significant at $\alpha = 0.05$

In Table 11, the “estimate” column represents the partial regression coefficient determined by the least squares method; the intercept is represented by the constant and the predictor estimates are the β values in the regression equation. The standard error is the standard deviation of the residuals, i.e. the distance from the regression line to the actual data points. The t-ratio is the estimate divided by the standard error, representing the number of standard deviations of separation for the residual. The probability column, Prob>|t|, represents the null hypothesis that the sample and population means are the same. Given that Prob>|t| are all greater than an alpha (α) level of 0.05, none of the results were significant enough to include in a model if the ANOVA *F* statistic were significant.

A review of the parameter estimates showed that the model was, by definition, “over fitted” in that too many predictors were contributing influence and thereby not allowing any to become significant. Therefore, the standardized beta column was evaluated to proceed with a reduction in predictor variables.

The standardized beta represents the mean value of the partial regression coefficient adjusted to a standard mean of zero with a standard deviation of one, i.e. an approximation of the standard normal distribution. Variables with the largest absolute standard beta values represent those with the largest variation, and thus the most influence on rejecting the null hypothesis that there is no difference in utilizing or not utilizing the technology. Variable screening with standard beta is required with continuous variables of non-uniform scale, the variables are often not equal and thus a comparison of the parameter estimates would not be valid (Carver, 2010). With dichotomous variables, all the magnitudes are the same, which would allow a comparison of the parameter estimates without consideration of the standard beta. However, for discussion purposes and general utilization of the regression technique, the standard beta values are used within this dissertation.

As shown by the asterisk in the "Std Beta" column in Table 11, the predictor variables ASNoutbound, ERP, TMS and mobile technology had the lowest absolute values, i.e. the weakest estimates. These predictors were eliminated from the predictor pool and a second regression analysis was conducted on the grouped variable set. The results are shown in Table 12.

Table 11. ICT Fill Rate: Whole Model Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	82.969	10.804	7.68	*<.0001	0
ICT-ASNinbound Grouped[0]	-6.013	6.446	-0.93	0.3620	-0.205
ICT-ASNoutbound Grouped[0]	-0.976	7.855	-0.12	0.9024	** -0.030
ICT-ERP Grouped[0]	1.225	8.490	0.14	0.8867	** 0.032
ICT-TMS Grouped[0]	0.406	7.540	0.05	0.9575	** 0.012
ICT-WMS Grouped[0]	-8.376	6.916	-1.21	0.2400	-0.316
ICT-e-Commerce Grouped[0]	-5.903	6.185	-0.95	0.3513	-0.214
ICT-Mobile Grouped[0]	-3.036	6.592	-0.46	0.6500	** -0.094

* significant at $\alpha = 0.05$

** lowest absolute value std beta, first predictors to be removed

Table 12. ICT Fill Rate Second Iteration of Predictors - ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	6035.023	2011.67	3.7957
Error	26	13779.644	529.99	Prob > F
C. Total	29	19814.667		*0.0221

* significant at $\alpha = 0.05$

After removing these variables, a review of the overall regression model ANOVA *F* statistic showed a Prob > F value of 0.022, indicating that the predictor elimination had produced statistically significant results. In multiple linear regression, the null hypothesis is that there is no association between the outcome (dependent) variable and any of the predictor (independent) variables (Carver, 2010). Therefore, a preliminary conclusion was the rejection of the null hypothesis that there is no difference in the fill rate for branch operations that use the specific ICT technologies of ASNs for inbound shipments (ASNinbound), warehouse management systems (WMS), and e-Commerce than those that don't. Now that a significant subset of factors was established, a preliminary interpretation of the factors within the model was undertaken to assess the significance of the individual predictors.

A review of the variable name means that the absence of the technology predictor is indicated by the coded [0] variable, which was created for a technology that was utilized for less than one year or not utilized at all. With multiple regression and dichotomous variables, the interpretation is that fill rate would increase by the absolute value of the parameter estimate if a technology were present and nothing changed, i.e. the other two predictors were not utilized. A key to the interpretation is that the predictor variables are defined as [0], indicating the absence of the technology. Thus, if the technology was present, the impact would be the opposite and show an increase of fill rate performance, which is the desired impact for adding a technology.

However, even though the model shows statistical significance in Table 12, the three predictors, ASNinbound, WMS, and e-Commerce do not show as significant when combined in the model, as shown by the Prob>|t| statistic column in Table 13. In addition, when evaluating the model validity assumptions for normal residuals, in the absence of collinearity, the data showed normal residuals but collinear results. Therefore, more analysis is required as the model assumptions failed. The conclusion drawn here was that two of the effects were too “intertwined” in the overall model and at least one needed to be screened out.

Table 13. ICT Fill Rate Second Regression Results for Predictors

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	80.733	4.833	16.70	*<.0001	0
ICT-ASNinbound Grouped[0]	-5.668	4.833	-1.17	0.2515	-0.207
ICT-WMS Grouped[0]	-7.327	4.741	-1.55	0.1343	-0.284
ICT-e-Commerce Grouped[0]	-7.001	4.741	-1.48	0.1518	-0.256

* significant at $\alpha = 0.05$

Given that only three predictors remained, the use of standard beta value was ignored in favor of testing each combination of two variables. This was accomplished by running the regression analysis with ASNinbound separately with WMS and e-commerce, and testing, WMS and e-commerce together. These subsequent regression runs produced the results shown in Table 14 from the overall regression ANOVA *F* test. The only pairing of predictor variables to produce a significant model, as shown in Table 14, was the e-commerce and WMS pair. The conclusion drawn was that ASNinbound was eliminated as a contributing predictor variable.

Based on overall regression ANOVA in Table 14, another regression analysis was run using e-commerce and WMS. The ANOVA results are found in Table 15. Given the variables produced a model with $\alpha = 0.0149$, the parameter estimates were acceptable to be evaluated and are shown in Table 16. The WMS grouped [0] variable was considered close enough to 0.05 significance level to establish it as the primary contributing factor.

Table 14. ICT Fill Rate Predictor ANOVA Analysis

Predictor Pair	Prob > F
ASNinbound and e-commerce	0.2615
ASNinbound and WMS	0.0562
e-commerce and WMS	*0.0149

* significant at $\alpha = 0.05$

Table 15. ICT Fill Rate ANOVA with Final Predictors

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	5305.963	2652.98	4.9371
Error	27	14508.704	537.36	Prob > F
C. Total	29	19814.667		*0.0149

* significant at $\alpha = 0.05$

Table 16. ICT Fill Rate - Parameter Estimates with Final Predictors

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	78.560	4.494	17.48	*<.0001
ICT-WMS Grouped[0]	-9.203	4.494	-2.05	*0.0504
ICT-e-Commerce Grouped[0]	-7.478	4.756	-1.57	0.1275

* significant at $\alpha = 0.05$

The next step required was a test of the assumptions to see if the developed linear regression model could be considered valid. Assumptions were checked using the residual values as shown in the scatter plot depicted in Figure 13, which was evaluated by considering the distribution of points within each group, i.e. vertical column of points (Carver, 2010). In this case, the spread of points of the predicted value within each group were relatively equal about the dotted line representing the zero value for the residuals, allowing an assumption of normality. Additionally, the Q-Q plot in Figure 14 showed the residuals plotted fairly equally to the prediction line, given that the three outliers were still within the confidence bands of the normal distribution histogram. To confirm the inference that the data could be considered normal, a

Shapiro-Wilk test was run, which yielded a Prob<W = 0.108 statistic, failing to reject the null hypothesis that the residuals were from a normal distribution.

Given that only a single variable was selected, the collinearity assumption is not required. However, a one way ANOVA was conducted using WMS to validate the results that WMS had a statistically significant impact on fill rate. Per the ANOVA in Table 17, WMS is significant based on the Prob > F value of 0.014 and the depiction of the 95% confidence intervals shown in Figure 14 where zero (0) is WMS not utilized or utilized less than one year, and one (1) is WMS utilized for at least one year.

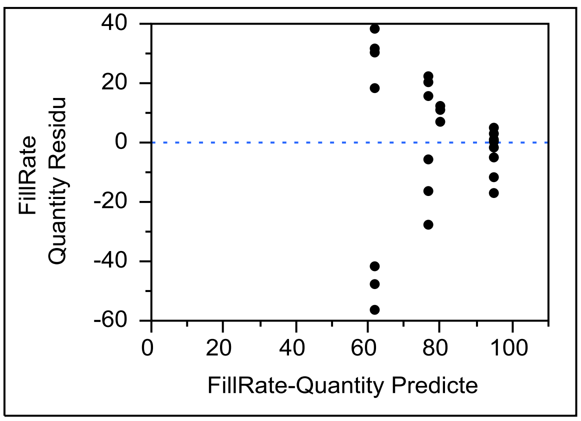


Figure 13. ICT Fill Rate Residuals – Variance Assumption Check

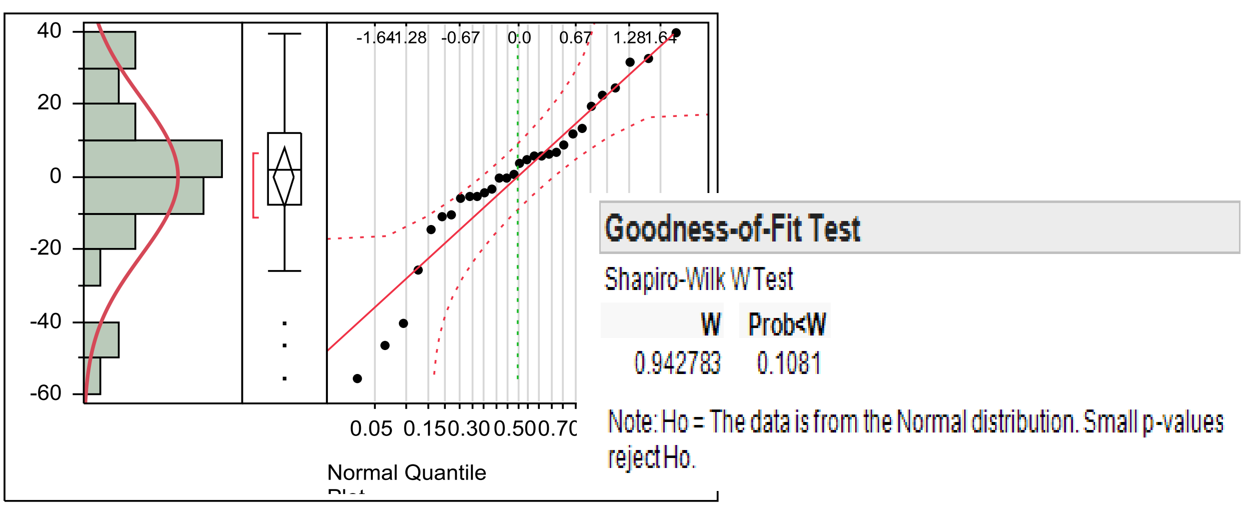


Figure 14. ICT Fill Rate Residuals – Normality Assumption Check

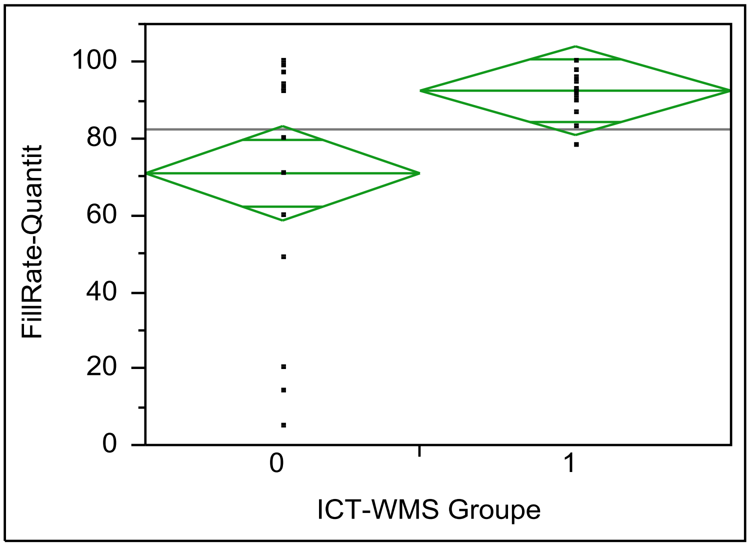


Figure 15. ICT One Way ANOVA: WMS v. Fill Rate

Table 17. ICT One Way ANOVA: WMS v. Fill Rate

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
ICT-WMS Grouped	1	3713.851	3713.85	6.7894	*0.0141
Error	30	16410.118	547.00		
C. Total	31	20123.969			

* significant at $\alpha = 0.05$

Thus, the conclusion drawn is that the null hypothesis, $H_{O1\text{-}1}$, branch operations that invest in ICT have the same performance with respect to fill rate as those that do not invest in ICT, may be rejected when WMS is present as an ICT. Of note are the results shown in Table 18 that show a low value of $R^2 = 0.267$, which demonstrates a relatively poor fit of the data to the model. Along with the adjusted $R^2 = 0.213$, the results do not lend themselves to generalization purposes.

Table 18. ICT Fill Rate WMS Statistics

RSquare	0.267
RSquare Adj	0.213
Root Mean Square Error	23.181
Mean of Response	81.666
Observations (or Sum Wgts)	30

The procedural analysis was repeated for outcome variables InvAccuracy – Units and on-time shipments. The two predictor variables previously excluded per Table 8, tablet computers and hands free technology, were not considered as they were eliminated from the entire technology group. The "Grouped" variable suffix was again used as per the earlier conclusion regarding the validity of the mean separation at the one year of implementation point.

The first iteration for the regression analysis for Inventory accuracy did not yield a satisfactory overall regression ANOVA *F* statistic. The parameter estimates were evaluated to screen out the predictors with low contribution to the model, as shown in Table 19.

Table 19. ICT Inventory Accuracy: Whole Model Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	77.604	13.927	5.57	*<.0001	0
ICT-ASNinbound Grouped[0]	-5.460	7.654	-0.71	0.4831	-0.169
ICT-ASNoutbound Grouped[0]	1.064	9.776	0.11	0.9143	** 0.027
ICT-ERP Grouped[0]	6.107	10.029	0.61	0.5488	0.128
ICT-TMS Grouped[0]	0.250	8.304	0.03	0.9762	** 0.007
ICT-WMS Grouped[0]	-5.232	7.516	-0.70	0.4936	-0.184
ICT-e-Commerce Grouped[0]	-8.047	6.723	-1.20	0.2440	-0.272
ICT-Mobile Grouped[0]	-1.697	8.012	-0.21	0.8342	** -0.044

* significant at $\alpha = 0.05$
** removed for subsequent regression analysis

Consequently, TMS, Mobile, and ASNoutbound predictor variables were selected for exclusion. The resultant linear regression analysis did not establish a significant overall regression ANOVA. The parameter estimates in Table 20 summarized the results and the next set of predictors selected for exclusion.

The standard beta was extremely similar for ASNinbound and ERP, thus both were removed and the regression re-run. Of note is that the removal of these mirrored the results of the fill rate analysis in that WMS and e-commerce would be the two remaining predictor variables.

Table 20. ICT Inventory Accuracy Second Iteration of Predictors - Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	76.243	9.078	8.40	*<.0001	0
ICT-ASNinbound Grouped[0]	-4.153	5.566	-0.75	0.4620	** -0.139
ICT-ERP Grouped[0]	5.932	8.687	0.68	0.5005	** 0.125
ICT-WMS Grouped[0]	-4.728	5.768	-0.82	0.4195	-0.170
ICT-e-Commerce Grouped[0]	-8.032	5.467	-1.47	0.1533	-0.276

* significant at α = 0.05
** removed for subsequent regression analysis

With only two predictor variables remaining, WMS and e-commerce, the overall regression ANOVA did not yield a significant model. At this point, an interaction variable was inserted into the analysis, with the results shown in Table 21 and Table 22. Table 21 shows the overall regression ANOVA with a level of Prob > *F* = 0.027, allowing for statistical significance.

When evaluating the factors individually, only the interaction between WMS and e-commerce showed a statistical significance at Prob>|t| = 0.045. When considered independently, neither WMS nor e-commerce was significant, as shown in Table 22. Thus, the preliminary conclusion drawn is that the null hypothesis may be rejected and that WMS and e-commerce have a significant effect upon inventory accuracy if both are utilized together within a facility, but not if used exclusive of each other.

Table 21. ICT Inventory Accuracy Third Iteration of Predictors - ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	6709.762	2236.59	3.5367
Error	28	17707.113	632.40	Prob > F
C. Total	31	24416.875		*0.0274

* significant at α = 0.05

Table 22. ICT Inventory Accuracy Third Iteration of Predictors - Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	83.751	5.156	16.24	*<.0001
ICT-WMS Grouped[0]	-8.724	5.156	-1.69	0.1017
ICT-e-Commerce Grouped[0]	-6.605	5.156	-1.28	0.2107
ICT-WMS Grouped[0]*ICT-e-Commerce Grouped[0]	-10.796	5.156	-2.09	*0.0454

* significant at α = 0.05

To validate the conclusion, a test of assumptions was required to look for constant variance for the residuals. This was done by plotting the residuals on a Q-Q chart and analyzing the histogram, both depicted in Figure 16. The residuals were not as positive as the fill rate residuals, and therefore the results cannot be considered valid. This led to the conclusion that we cannot reject $H_{O1\text{-}2}$ that branch operations that invest in ICT have the same performance with respect to inventory accuracy as those that do not invest in ICT.

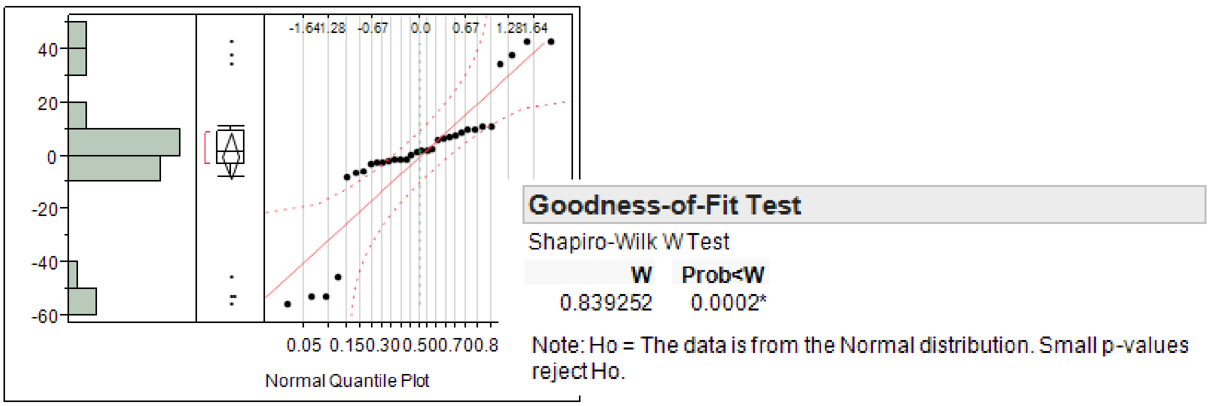


Figure 16. ICT Fill Rate Inventory Accuracy Residuals

The final outcome variable analyzed for the ICT predictors was on-time shipments. The initial regression analysis is Table 23, and as with prior analysis, showed an over fit model. The variables considered for exclusion were established by the smallest absolute value of the standard beta from Table 23. Given that the standard beta was relatively lower for ASNoutbound, ERP, TMS, and Mobile technology, all were removed and the regression re-run. The results failed to develop a significant model as shown in Table 24 resulting in the removal of WMS as a predictor.

A third regression analysis was performed with the results shown in Table 25, which failed to demonstrate a significant regression model with the two remaining predictor variables, as established by the Prob > *F* value of 0.1479 in the overall model ANOVA table.

Table 23. ICT On-Time Shipments: Whole Model Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	89.772	5.579	16.09	*<.0001	0
ICT-ASNinbound Grouped[0]	-1.798	3.307	-0.54	0.5921	-0.129
ICT-ASNoutbound Grouped[0]	-1.355	3.999	-0.34	0.7378	** 0.088
ICT-ERP Grouped[0]	1.222	4.380	0.28	0.7828	** 0.067
ICT-TMS Grouped[0]	-0.349	3.744	-0.09	0.9265	** 0.023
ICT-WMS Grouped[0]	-1.348	3.516	-0.38	0.7050	-0.109
ICT-e-Commerce Grouped[0]	-2.522	3.057	-0.83	0.4181	-0.193
ICT-Mobile Grouped[0]	-0.173	3.342	-0.05	0.9590	** -0.011

* significant at α = 0.05
** removed for subsequent regression analysis

Table 24. ICT On-Time Shipments Second Iteration of Predictors - Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	89.556	2.498	35.85	*<.0001	0
ICT-ASNinbound Grouped[0]	-2.263	2.447	-0.92	0.3629	-0.175
ICT-WMS Grouped[0]	-1.223	2.360	-0.52	0.6083	** -0.101
ICT-e-Commerce Grouped[0]	-2.908	2.400	-1.21	0.2358	-0.224

* significant at α = 0.05
** removed for subsequent regression analysis

Table 26 confirmed the conclusion from Table 25, as no predictor could achieve a threshold value at α = 0.05. The conclusion drawn was that none of the variables selected were predictors of On-Time Shipping performance.

To validate this result, a 3x2 ANOVA was run on the three predictor variables from Table 24. The results are shown below in Table 27 and Table 28, which confirmed the regression analysis given the Prob > *F* value of 0.4927 demonstrated a lack of statistical significance.

Table 25. ICT On-Time Shipments Third Iteration of Predictors - ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	567.736	283.868	2.0428
Error	29	4029.763	138.957	Prob > F
C. Total	31	4597.500		0.1479

* significant at α = 0.05

Thus, the final conclusion was confirmed that the null hypothesis, $H_{O1\text{-}3}$, branch operations that invest in ICT have the same performance with respect to on-time shipping performance as those that do not invest in ICT, may not be rejected. Hence, none of the predictor variables present can be construed to produce a significant difference upon on-time shipments as a performance metric.

Table 26. ICT On-Time Shipments Third Iteration of Predictors - Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	89.663	2.457	36.48	*<.0001
ICT-ASNinbound Grouped[0]	-2.686	2.278	-1.18	0.2480
ICT-e-Commerce Grouped[0]	-3.251	2.278	-1.43	0.1643

* significant at α = 0.05

Table 27. ICT On –Time Shipments 3 x 2 ANOVA Factor Results

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	836.809	139.468	0.9271
Error	25	3760.690	150.428	Prob > F
C. Total	31	4597.500		0.4927

* significant at α = 0.05

Table 28. ICT On –Time Shipments 3 x 2 ANOVA Factor Results

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	89.526	3.452	25.93	*<.0001
ICT-ASNinbound Grouped[0]	-1.125	4.513	-0.25	0.8052
ICT-WMS Grouped[0]	-3.244	4.124	-0.79	0.4390
ICT-e-Commerce Grouped[0]	-2.619	3.029	-0.86	0.3955
ICT-ASNinbound Grouped[0]*ICT-WMS Grouped[0]	1.520	3.001	0.51	0.6168
ICT-ASNinbound Grouped[0]*ICT-e-Commerce Grouped[0]	-0.354	4.104	-0.09	0.9319
ICT-WMS Grouped[0]*ICT-e-Commerce Grouped[0]	-2.848	3.672	-0.78	0.4453

* significant at α = 0.05

Research Q2: Analysis for AIDC Predictor Variables

Research question 2 investigated if branch operations that invest in automatic identification and data capture (AIDC) have better performance than those that do not. To research this, the three outcome variables were considered independently and individually against the full set of predictor variables.

An initial review of the data for the predictor variables included in the AIDC group is shown graphically in Figure 17 with a share chart and in Table 29 with a cross tabulation. The share chart represents the predictor's utilization in a horizontal bar chart stacked for each time period from the ordinal raw data. This chart is followed by a cross tabulation showing the actual percentages for each treatment. The data showed that RFID technology was not reported by any of the questionnaire respondents and therefore was excluded from the analysis.

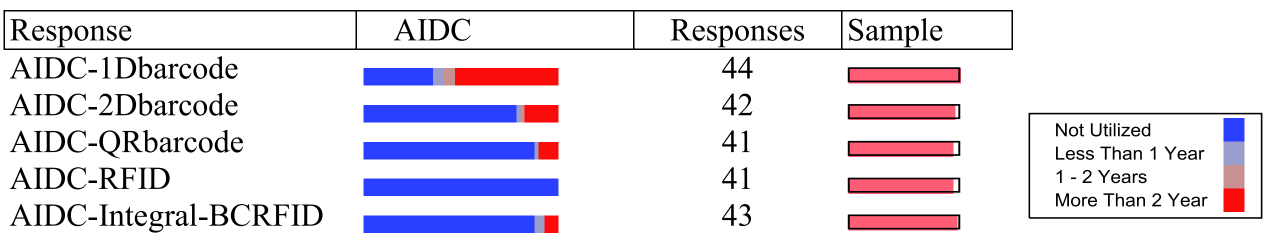


Figure 17. AIDC Inventory Accuracy Share Chart - All Predictor Variables

Table 29. AIDC Response Frequency Chart

Freq Share	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years	N
AIDC-1Dbarcode	16 0.364	2 0.045	3 0.068	23 0.523	44
AIDC-2Dbarcode	33 0.786	1 0.024	1 0.024	7 0.167	42
AIDC-QRbarcode	36 0.878	1 0.024	0 0.000	4 0.098	41
AIDC-RFID	41 1.000	0 0.000	0 0.000	0 0.000	41
AIDC-Integral-BCRFID	38 0.884	2 0.047	0 0.000	3 0.070	43

The remaining predictors, one dimensional (1D), two dimensional (2D), QR, and integral RFID bar codes were re-coded in a similar fashion as the ICT variables in order to evaluate implementation time effects. Thus, an "YN" variable was established representing any case with a response of "not utilized", and consequently recoded as zero (0). A "Grouped" variable was established for "not utilized" and "utilized less than 1 year," recoded as (0), and a "2yr" variable established to include only cases that had employed the technology for at least two years, recoded as (1). To complete the data table, all remaining cases were coded as one (1) or zero (0), opposite to the prior assigned code.

Once all the new variables were created, each was tested using multiple linear regression analysis to determine if a model could be determined for a given set of predictor variables. The results are shown in Table 30. None of the predictor variables could combine to produce a statistically significant overall regression ANOVA *F* test, and in general, showed poor correlation and fit to the model as indicated by R^2.

A preliminary conclusion is that all of the null hypotheses regarding AIDC would fail to be rejected, and that we could not conclude that branch operations that invested in AIDC had different means for fill rate, inventory accuracy, and on-time shipments compared to branches that did not use AIDC.

Table 30. AIDC Outcome Variable Adoption Time Review

Outcome Variable	Predictors	R^2	Adjusted R^2	Significance: Prob > *F*
Fill Rate (Quantity)	YN	0.103	-0.076	0.683
	Grouped	0.123	-0.052	0.600
	2 year	0.126	-0.049	0.590
Inventory Accuracy (Units)	YN	0.119	-0.041	0.573
	Grouped	0.024	-0.153	0.966
	2 year	0.040	-0.134	0.918
On-Time Shipments	YN	0.047	-0.126	0.891
	Grouped	0.055	-0.116	0.858
	2 year	0.094	-0.070	0.685

To confirm this conclusion, a 4x2 ANOVA using predictor variables of 1D, 2D, QR bar codes and integral RFID bar code labels was used rather than linear regression modeling. The limited number of predictors and treatments made this a viable possibility. The two treatments considered were that the technologies were "utilized" or "not utilized," i.e. the "YN" suffix variable. This approach was based upon a lack of clear direction provided from Table 30 and the literal interpretation of the research question.

Results for the first outcome variable, fill rate, are shown in Table 31 which indicated no significant value, per the Prob > $F = 0.2253$. From this, the conclusion was a failure to reject null hypothesis $H_{O2\text{-}1}$ that branch operations that invest in AIDC have the same performance with respect to fill rate as those that do not invest in AIDC.

Table 31. AIDC Fill Rate 4x2 ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	7361.943	1051.71	1.5233
Error	17	11737.097	690.42	Prob > F
C. Total	24	19099.040		0.2253

* significant at $\alpha = 0.05$

The next predictor variable tested was the inventory accuracy. Again, a 4x2 ANOVA was utilized, and the ANOVA results are shown in Table 32. Based on the Prob > $F = 0.3$ value, the result of this ANOVA was a failure to reject null hypothesis $H_{O2\text{-}2}$ that branch operations that invest in AIDC have the same performance with respect to inventory accuracy as those that do not invest in AIDC.

Table 32. AIDC Inventory Accuracy 2x2 ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	6676.176	1112.70	1.3044
Error	20	17061.009	853.05	Prob > F
C. Total	26	23737.185		0.3003

* significant at $\alpha = 0.05$

The final predictor variable tested was on-time shipments. Again, a 4x2 ANOVA was utilized and the results shown in Table 33. Based on the Prob > F = 0.9831 value, the result of this ANOVA was failure to reject null hypothesis $H_{O2\text{-}3}$, branch operations that invest in AIDC have the same performance with respect to on-time shipping performance as those that do not.

Table 33. AIDC On-Time Shipments Accuracy 2x2 ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	290.174	41.453	0.1940
Error	19	4060.788	213.726	Prob > F
C. Total	26	4350.963		0.9831

* significant at $\alpha = 0.05$

Figure 18 graphically validated these conclusions. A review of the box plots shows relatively equal medians and an overlap of the middle 50% quartile box. Each of the three outcome variables was plotted with responses of zero (0) representing “not utilized” and one (1) representing any time period of utilization. The outcome KPIs are, in order from left to right: on-time shipments, inventory accuracy, and fill rate.

The 1D bar code box plots shown in the upper left chart showed an increase in variation without any relative change in the mean. The increase of variance and presence of outliers for all plots added support to the inference that use or non-use of 1D barcodes will not change the performance outcomes measured. Of note was that variance increased for all KPIs, but the largest increase was in fill rate.

The 2D bar code box plots shown in the upper right chart demonstrated a non-significant difference in means for all three KPIs, but each showed a reduction in variation, evidenced by the lack of outliers in the utilized group, and the tighter plot for fill rate.

The QR bar code box plots shown in the lower left chart demonstrated non-significant difference in means, but significant increase in variance for inventory accuracy and fill rate.

Seemingly the most significant observation came from the integral RFID bar code plots shown in the lower right chart, showing a significant reduction of variance in all three performance metrics, although non-significant difference in means. The value of this chart is diminished by the small sample size, but provides an avenue for future study into the impact of the combined technologies making a greater contribution than the 1D bar code.

In summary, considering the most prevalent AIDC, the 1D bar code may be construed to add a reliance on technology leading to a lapse in performance. An interesting observation that may provide an avenue of future research is that bar codes that provide more information than the common 1D format, i.e. the 2D and integral RFID bar code, add value to an operation.

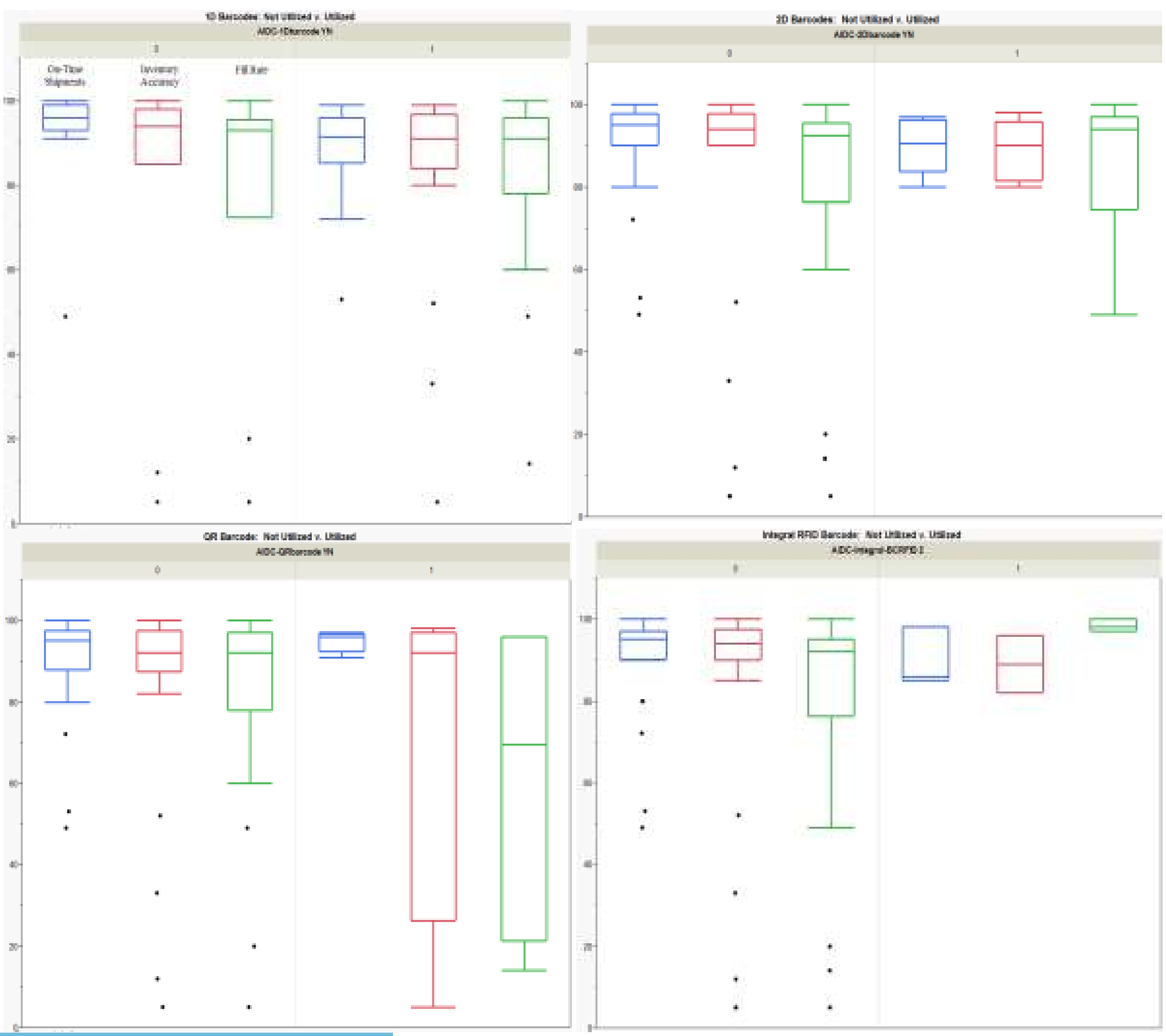


Figure 18. AIDC Box Plots for Predictors

Research Q3: Technology and Best (Business) Practice Effects

Research question 3 investigated if branch operations that utilize "best warehousing practices" have better performance than those that invest only in technology. To research this, the three outcome variables were once more considered independently and individually.

The questionnaire collected business practice data utilizing seven variables, with four possible responses to consider utilization maturity. An initial review of the data for the predictor variables included in the Best Practices group is shown graphically in Figure 19 with a share chart, and in Table 34 with a cross tabulation. The share chart represents the predictor's utilization in a horizontal bar chart stacked for each time period from the ordinal raw data. This chart is followed by a cross tabulation showing the actual percentages for each treatment.

A review of time utilization showed a bias toward the "more than 2 years" of utilization response, but to retain continuity of data analysis, a preliminary review of data utilized the same time cut off points for learning curve and maturity. Thus, an "YN" variable was established representing any case with a response of "not utilized," coded as zero (0). A "Grouped" variable was established for "not utilized" and "utilized less than 1 year" coded as (0), and a "2yr" variable established to include only cases that had employed the technology for at least two years coded as (1).

To complete the data table, all remaining cases were coded as one (1) or zero (0), opposite to the prior assigned code. Additionally, the practice of "GoldenZone" was not utilized in approximately 93% of the branch operation responses and was therefore excluded from consideration for the comparison analysis.

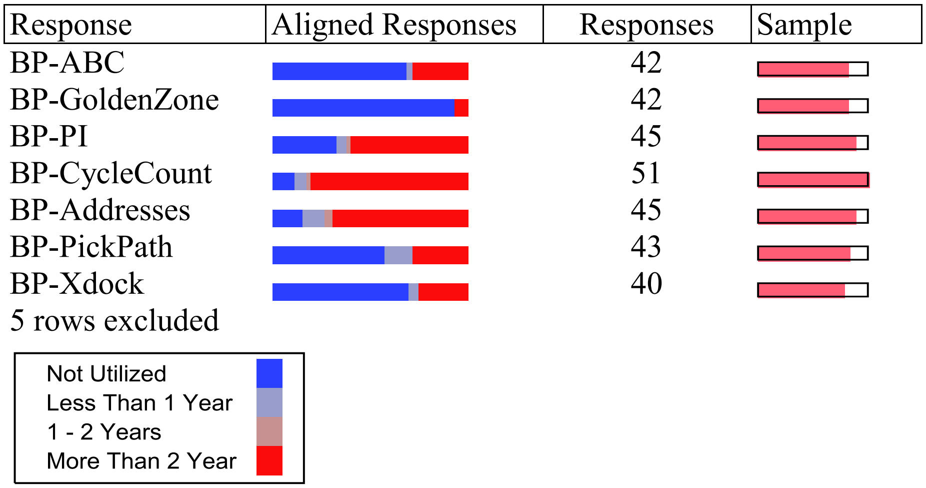


Figure 19. Best Practices Aligned Responses

Table 34. Best Practices Utilization Crosstab

Freq Share	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years	
BP-ABC	29 0.690	1 0.024	0 0.000	12 0.286	42
BP-GoldenZone *	39 0.929	0 0.000	0 0.000	3 0.071	42
BP-PI	15 0.333	2 0.044	1 0.022	27 0.600	45
BP-CycleCount	6 0.118	3 0.059	1 0.020	41 0.804	51
BP-Addresses	7 0.156	5 0.111	2 0.044	31 0.689	45
BP-PickPath	25 0.581	6 0.140	0 0.000	12 0.279	43
BP-Xdock	28 0.700	2 0.050	0 0.000	10 0.250	40

* excluded from further analysis due to lack of utilization

Once all the new variables were created, each was tested using multiple linear regression analysis to determine if a model could be determined for a given set of predictor variables, and the results are shown in Table 35.

Table 35. Best Practices Outcome Variable Adoption Time Review

Outcome Variable	Predictors	R^2	Adjusted R^2	Significance: Prob > F
Fill Rate (Quantity)	YN	0.208	-0.041	0.557
	Grouped	0.200	-0.052	0.585
	2 year	0.162	-0.102	0.716
Inventory Accuracy (Units)	YN	0.194	-0.036	0.550
	Grouped	*0.234	*0.016	*0.410
	2 year	0.217	-0.007	0.469
On-Time Shipments	YN	0.150	-0.093	0.962
	Grouped	0.128	-0.128	0.808
	2 year	0.176	-0.059	0.619

* largest R^2 and time adoption point with positive effect

The Grouped data set for inventory accuracy demonstrated the highest R^2 value, indicating it had the best representation of the predictors analyzed. In addition, the review of the adjusted R^2 value indicated that the "grouped" suffix predictors would have the best possibility of producing generalizable results since it was the only time utilization break point to demonstrate a positive adjusted R^2. Therefore, similar to Q1, the "grouped" predictor variables were used for analysis purposes.

An initial multiple linear regression analysis was run investigating which predictors impacted the fill rate performance measurement. The overall regression ANOVA, Table 36, showed a 0.5855 value for the Prob > F, indicating the model did not show significance, prompting a review of the parameter estimates for screening utilizing the standard beta values found in Table 37.

Table 36. BP Fill Rate Overall Regression ANOVA - All Predictors

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	3167.995	527.999	0.7948
Error	19	12622.505	664.342	Prob > F
C. Total	25	15790.500		0.5855

* significant at $\alpha = 0.05$

Table 37 shows the parameter estimates and the standard beta values which determined that warehouse addressing systems (Addresses) and cross docking (Xdock) predictors would be removed; the analysis was rerun with the four remaining predictors. The results did not yield a significant overall regression ANOVA *F* statistic, and the parameter estimates, Table 38, showed that PickPath and PI were the next variables to be removed from the analysis.

A final regression analysis using only ABC and Cycle Counting produced statistically significant results for fill rate, by approximating the Prob > *F* statistic to be equivalent at the $\alpha = 0.05$ level, as per Table 39. Although not below a threshold of $\alpha = 0.05$, the result was satisfactory enough to evaluate the partial regression coefficients shown in Table 40. Given the ABC variable is significant at $\alpha = 0.05$, the results from Table 40 allow us to reject the null hypothesis that branch operations that employ "best practices" have the same fill rate as those that do not.

A test of assumptions for the model validity was then undertaken, evaluating the residuals using a scatter plot for constant variance and a histogram and Q-Q plot for normality.

Table 37. BP Fill Rate Parameter Estimates - All Predictors

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	85.213	9.995	8.52	*<.0001	0
BP-ABC Grouped[0]	-10.036	7.830	-1.28	0.2154	-0.387
BP-PI Grouped[0]	-3.900	6.829	-0.57	0.5746	-0.150
BP-CycleCount Grouped[0]	8.518	7.750	1.10	0.2855	0.249
BP-Addresses Grouped[0] **	0.821	6.477	0.13	0.9004	0.029
BP-PickPath Grouped[0]	3.353	7.506	0.45	0.6601	0.114
BP-Xdock Grouped[0] **	2.672	8.069	0.33	0.7441	0.085

* significant at $\alpha = 0.05$
** removed for subsequent regression analysis

Table 38. BP Fill Rate Predictor Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	86.308	7.898	10.93	*<.0001	0
BP-ABC Grouped[0]	-8.673	5.923	-1.46	0.1573	-0.344
BP-PI Grouped[0] **	-3.655	6.050	-0.60	0.5519	-0.141
BP-CycleCount Grouped[0]	8.200	6.959	1.18	0.2513	0.239
BP-PickPath Grouped[0] **	2.620	6.391	0.41	0.6857	0.089

* significant at $\alpha = 0.05$

** removed for subsequent regression analysis

Table 39. BP Final Predictor Overall Regression ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	4231.171	2115.59	3.2987
Error	25	16033.686	641.35	Prob > F
C. Total	27	20264.857		0.0535

* significant at $\alpha = 0.05$

Table 40. BP Fill Rate Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	88.490	7.092	12.48	*<.0001
BP-ABC Grouped[0]	-11.529	5.015	-2.30	*0.0301
BP-CycleCount Grouped[0]	9.274	6.867	1.35	0.1889

* Statistically significant at $\alpha < 0.05$

The scatter plot in Figure 20 was evaluated by considering the distribution of points within each group, i.e. vertical column of points (Carver, 2010). The review showed a "fanned" appearance of the residuals, considering the vertical point plots about the dotted line representing the zero value for the residuals. At approximately 70% in the predicted fill rate, the residuals show heteroscedacity, but relative homoscedacity for higher fill rate above 70%, as evidenced by the point plot at around the 90% mark. This infers that the predictive value of the model is much better for branches that have high fill rate performance, but there are other factors impacting fill rate not associated with the study for branches with lower fill rate.

Figure 21 showed a fairly stable Q-Q plot of the residuals. Although not a perfect approximation of the straight line, all points were within the 95% confidence interval and considered sufficient enough to consider that the data is relatively normally distributed.

Given the results of Figures 20 and 21, and that multiple linear regression can be considered generally robust to the assumptions as long as the conclusions are properly interpreted for generalization (Hayden, 2008; Norusis, 2012a), the predictor variable was considered useable to test the research question null hypothesis. However, the R^2 value of the model was 0.209 and the adjusted R^2 was 0.145, neither of which showed a great deal of confidence for generalization of the results.

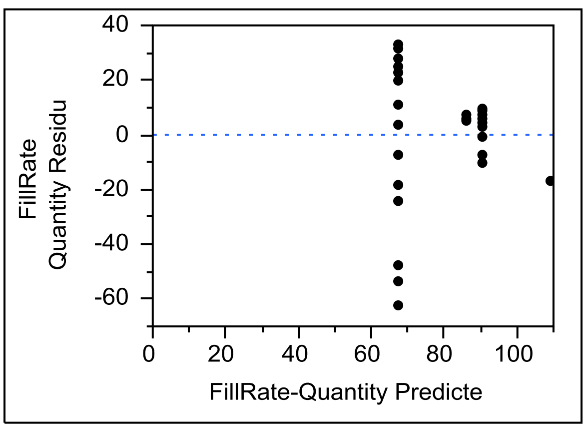


Figure 20. BP Fill Rate Residuals Scatter Plot

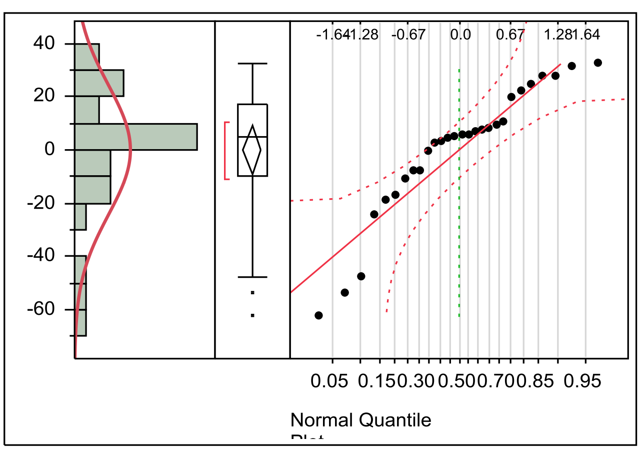


Figure 21. BP Fill Rate Residuals Q-Q Plot

With a best practice predictor established, i.e. the use of ABC analysis, a comparison to the technology predictor of warehouse management systems was undertaken in order to address the null hypothesis $H_{O3\text{-}1}$ that branch operations that employ "best practices" have the same fill rate as those that rely solely on technology. To test the hypothesis, a 2x2 ANOVA using fill rate as the outcome (dependent) variable and ABC and WMS as predictor (independent) variables, along with interaction between the two was done.

The ANOVA *F* statistic in Table 41 checked for equality of group means for the two predictors and the interaction between them. Given the Prob > *F* value of both factors and their interactions are less than $\alpha = 0.05$, the null hypothesis that branch operations that use technology have the same fill rate than those that only use best practices was rejected. However, the use of either of the predictors alone or using both in combination would not be sufficient to explain the difference. Whatever difference is created by ABC analysis and WMS may be evident, but there are more factors that are involved that were outside the scope of this research. In summary, $H_{O3\text{-}1}$ branch operations that employ "best practices" have the same fill rate as those that rely solely on technology was rejected.

Table 41. Fill Rate: BP v. Technology ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	5245.322	1748.44	2.9338
Error	23	13707.345	595.97	Prob > F
C. Total	26	18952.667		0.0549

* significant at $\alpha = 0.05$

Table 42. Fill Rate: BP v. Technology ANOVA Effects

Source	DF	Sum of Squares	F Ratio	Prob > F
BP-ABC Grouped	1	1044.352	1.7524	0.1986
ICT-WMS Grouped	1	1021.545	1.7141	0.2034
ICT-WMS Grouped*BP-ABC Grouped	1	562.266	0.9434	0.3415

* significant at $\alpha = 0.05$

Next to be evaluated was inventory accuracy and the procedural analysis was repeated for the outcome variable representing inventory accuracy by units. The predictor variable "GoldenZone" that was previously excluded per Table 34 was again excluded for this analysis. The "Grouped" variable suffix was also used again as per the earlier conclusion regarding the contribution of the predictor variables to the model.

The initial run of all the remaining best practice predictors failed to produce a significant overall regression ANOVA *F* statistic, as shown in Table 43.

Table 43. BP Inventory Accuracy Overall Regression ANOVA - All Predictors

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	4145.958	690.993	1.0724
Error	21	13531.006	644.334	Prob > F
C. Total	27	17676.964		0.4099

* significant at α = 0.05

Table 44. BP Inventory Accuracy Parameter Estimates - All Predictors

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	87.948	9.009	9.76	*<.0001	0
BP-ABC Grouped[0]**	-3.753	6.267	-0.60	0.5557	-0.143
BP-PI Grouped[0]	-7.657	6.334	-1.21	0.2402	-0.292
BP-CycleCount Grouped[0]**	5.830	7.463	0.78	0.4434	0.177
BP-Addresses Grouped[0]	7.467	6.073	1.23	0.2324	0.257
BP-PickPath Grouped[0]**	-1.900	6.997	-0.27	0.7886	-0.065
BP-Xdock Grouped[0]**	4.957	6.868	0.72	0.4784	0.161

* significant at α = 0.05
** removed for subsequent regression analysis

The associated parameter estimates shown in Table 44 indicated that PickPath, ABC, Xdock, and CycleCount were all eliminated in the initial predictor screening. The subsequent multiple linear regression analysis, shown in Table 45, failed to produce statistically significant results.

Table 45. BP Inventory Accuracy Final Predictor ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	2746.041	1373.02	2.4711
Error	28	15557.830	555.64	Prob > F
C. Total	30	18303.871		0.1027

* significant at $\alpha = 0.05$

Given the absence of statistical significance, no individual best practice predictor variables were identified that could be utilized for an evaluation of the null hypothesis of $H_{O3\text{-}2}$ that branch operations that employ "best practices" have the same inventory accuracy as those that rely solely on technology.

The analysis was repeated a third time for on-time shipments, again using the "Grouped" suffix variables and excluding the GoldenZone predictor variable. The initial run of all the remaining best practice predictors failed to produce a significant overall regression ANOVA *F* statistic, as shown in Table 46.

The review of Table 47 for the parameter estimates indicated that PickPath, CycleCount, ABC, Addresses were all eliminated in the initial predictor screening. The regression model did not produce statistical significance, and the Addresses variable was removed from consideration.

The final regression model, utilizing PI and Xdock, yielded a lack of statistical significance in the overall regression ANOVA shown in Table 48. Based on the results in Table 48, we could not evaluate the null hypothesis, $H_{O3\text{-}3}$ that branch operations that employ "best practices" have the same on-time shipping performance as those that rely solely on technology.

Table 46. BP On-Time Shipments Overall Regression ANOVA - All Predictors

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	542.109	90.352	0.4896
Error	21	3875.319	184.539	Prob > F
C. Total	27	4417.428		0.8087

* significant at $\alpha = 0.05$

Table 47. BP Inventory Accuracy Parameter Estimates - All Predictors

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta
Intercept	86.302	5.125	16.84	*<.0001	0
BP-ABC Grouped[0]**	-0.978	3.581	-0.27	0.7875	-0.074
BP-PI Grouped[0]	-3.490	3.232	-1.08	0.2925	-0.266
BP-CycleCount Grouped[0]**	0.959	4.074	0.24	0.8161	0.053
BP-Addresses Grouped[0]	1.841	3.334	0.55	0.5865	0.126
BP-PickPath Grouped[0]**	0.379	3.874	0.10	0.9229	0.024
BP-Xdock Grouped[0]	5.463	4.145	1.32	0.2017	0.333

* significant at α = 0.05

** removed for subsequent regression analysis

Table 48. BP On-Time Shipments Final Predictor ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	380.441	190.221	1.2025
Error	26	4112.730	158.182	Prob > F
C. Total	28	4493.172		0.3166
Parameter Estimates				
Term		Estimate	Std Error	t Ratio
Intercept		86.250	3.247	26.56
BP-PI Grouped[0]		-3.730	2.645	-1.41
BP-Xdock Grouped[0]		3.480	3.103	1.12

* significant at α = 0.05

Research Q4: Technology and Best Practice Contributions to KPI

Q4: What are the contributions of different technologies and best practices to inventory and customer service metrics in a distribution branch operation?

The analysis of Q4 was conducted by inputting all the predictor variables into a multiple linear regression stepwise reduction procedure. This entailed using the variables selected in the analysis of Q1, Q2, and Q3, i.e. the “Grouped” variable sets from AIDC and best practices, and the “YN” variables from the AIDC predictors. All variables were entered into the regression and the JMP 10pro stepwise algorithm configured to admit variables into the model at α = 0.25

threshold, but be eliminated if they could not hold significance at $\alpha = 0.05$. For stepwise regression analysis, each variable is entered sequentially and each variable's contribution assessed (Brace et al., 2012). As variables are entered, the already included variables are re-assessed for contribution and are removed from consideration if they fall below $\alpha = 0.05$.

Each of the outcome variables was tested independently and separately. Each outcome variable was analyzed using a stepwise regression using the seventeen predictors (seven ICT, four AIDC, and six best practices) that resulted from the share chart and cross tabulation analysis conducted for Q1, Q2, and Q3. Using stepwise regression, the output table generates in one pass through the predictor variables to assess significance.

Fill rate was evaluated first with the result shown in Table 49. Note that no ANOVA tables are generated with stepwise regression since the exit level accomplishes the same evaluation as checking an overall regression ANOVA F statistic against $\alpha = 0.05$.

Additionally, Table 49 showed that WMS and PI were significant contributors to a regression model defining fill rate. The output regression formula is

$$\text{Fill Rate} = 76.5 + 11.2(\text{WMS}) + 11.3(\text{PI})$$

Note that the minus sign is reversed since the variable is for a "lack of" the predictor based on the 0-1 orientation of the variable in the software, as shown in Table 49. This resultant indicated that branches employing a warehouse management system (WMS) and utilizing physical inventory (PI) as a best practice could achieve a fill rate of 99.0%.

The summary statistics for this model are shown in Table 50. The R^2 value, the proportion of the variance in the outcome variable accounted for by the model and a measure of "how good" the prediction is, is weak at 0.3866, but better than the results generated in Q1 and Q3. The adjusted R^2 value showed this model can account for 31.4% of the variance in the fill rate; not a superlative number but a place to continue future research.

As a validity check of the stepwise regression analysis, the residuals were evaluated for normality as shown in Figure 22 and Figure 23. The Q-Q plot and Shapiro-Wilk W test in Figure 23 provided evidence of normality, although the scatterplot in Figure 22 narrowed the assumptions a bit, limiting the conclusion to address a small subset of the data. Based on the fanning effect and the uneven variance of the residuals, the predictive value of the formula is more applicable for branch operations with fill rate in excess of about 85%, which coincidentally is the mean value shown in Table 50.

Table 49. Fill Rate Stepwise Regression

Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
Intercept	76.500	1	0	0.000	1
ICT-ASNinbound Grouped[0-1]	0	1	226.397	0.440	0.5167
ICT-ASNoutbound Grouped[0-1]	0	1	48.941	0.093	0.7643
ICT-ERP Grouped[0-1]	0	1	140.566	0.270	0.6103
ICT-TMS Grouped[0-1]	0	1	81.250	0.155	0.6989
ICT-WMS Grouped[0-1]	-11.166	1	2466.484	4.952	0.0398
ICT-e-Commerce Grouped[0-1]	0	1	108.388	0.207	0.6548
ICT-Mobile Grouped[0-1]	0	1	107.756	0.206	0.6558
AIDC-1Dbarcode YN[0-1]	0	1	42.250	0.080	0.7806
AIDC-2Dbarcode YN[0-1]	0	1	386.390	0.765	0.3947
AIDC-QRbarcode YN[0-1]	0	1	10.227	0.019	0.8911
AIDC-Integral-BCRFID YN[0-1]	0	1	42.187	0.080	0.7807
BP-ABC Grouped[0-1]	0	1	46.542	0.088	0.7700
BP-PI Grouped[0-1]	-11.333	1	2312.000	4.641	0.0458
BP-CycleCount Grouped[1-0]	0	1	0.780	0.001	0.9698
BP-Addresses Grouped[1-0]	0	1	67.977	0.129	0.7236
BP-PickPath Grouped[0-1]	0	1	838.323	1.758	0.2034
BP-Xdock Grouped[0-1]	0	1	156.175	0.301	0.5910

Table 50. Fill Rate Stepwise Summary Stats

SSE	DFE	Root Mean Square Error	RSquare	RSquare Adj
8468	17	22.318	0.3866	0.3145

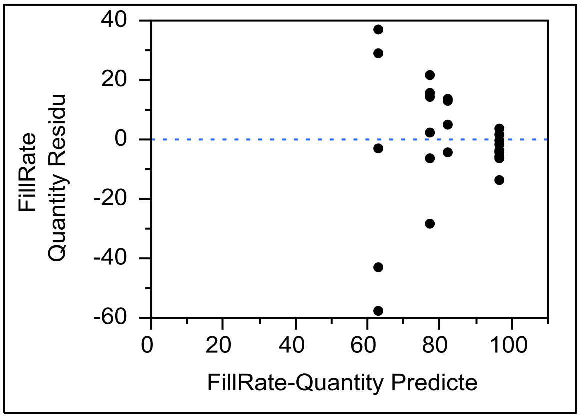
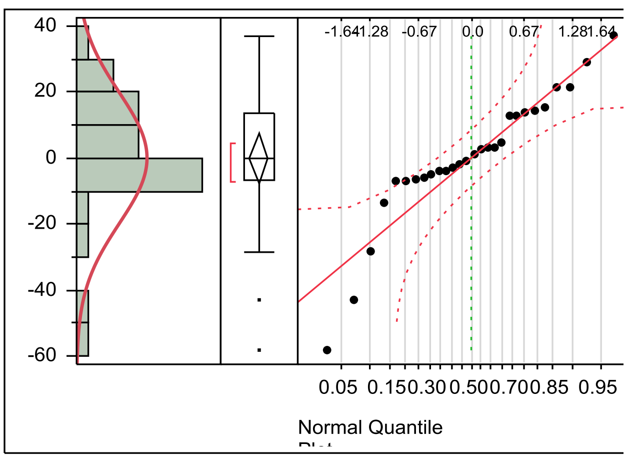


Figure 22. Fill Rate Stepwise Residuals Scatterplot



Shapiro-Wilk W Test

W	Prob<W
0.913961	0.0247*

Note: Ho = The data is from the Normal distribution.
Small p-values reject Ho.

Figure 23. Fill Rate Residuals Histogram, Q-Q Plot, and Normality Test

Inventory accuracy was evaluated next with the results shown in Table 51, demonstrating that PI was the only significant contributor to a regression model defining inventory accuracy. The output regression formula is

$$\text{Inventory Accuracy} = 78.0 + 12.8(\text{PI})$$

Note that the minus sign is reversed as the variable is for a “lack of” the predictor based on the 0-1 orientation of the variable. This result indicated that branches utilizing physical inventory (PI) as a best practice could achieve an inventory accuracy of 90.8%.

The summary statistics for this model are shown in Table 52. The R^2 value is relatively poor at 0.194 inferring that the model does not predict well. The adjusted R^2 value shows that this model can account for only 15.4% of the variance in the inventory accuracy, which is also a poor confidence level for a prediction model.

Table 51. Inventory Accuracy Stepwise Regression

Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
Intercept	78.017	1	0	0.000	1
BP-ABC Grouped[0-1]	0	1	34.300	0.048	0.8297
BP-PI Grouped[0-1]	-12.767	1	3319.643	4.829	0.0399
BP-CycleCount Grouped[0-1]	0	1	167.207	0.234	0.6341
BP-Addresses Grouped[Not Utilized-0]	0	1	31.690	0.044	0.8362
BP-PickPath Grouped[0-1]	0	1	144.642	0.202	0.6581
BP-Xdock Grouped[0-1]	0	1	102.857	0.143	0.7092
ICT-ASNinbound Grouped[0-1]	0	1	339.716	0.481	0.4961
ICT-ASNoutbound Grouped[0-1]	0	1	18.720	0.026	0.8738
ICT-ERP Grouped[1-0]	0	1	122.660	0.171	0.6838
ICT-TMS Grouped[0-1]	0	1	378.950	0.539	0.4719
ICT-WMS Grouped[0-1]	0	1	1016.541	1.517	0.2330
ICT-e-Commerce Grouped[0-1]	0	1	783.781	1.149	0.2972
ICT-Mobile Grouped[0-1]	0	1	17.190	0.024	0.8790
AIDC-1Dbarcode YN[0-1]	0	1	4.077	0.006	0.9409
AIDC-2Dbarcode YN[0-1]	0	1	2.357	0.003	0.9550
AIDC-QRbarcode YN[0-1]	0	1	56.049	0.078	0.7833
AIDC-Integral-BCRFID YN[0-1]	0	1	7.440	0.010	0.9202

Table 52. Inventory Accuracy Stepwise Summary Stats

SSE	DFE	RMSE	RSquare	RSquare Adj
13747.857	20	26.218	0.194	0.154

The final outcome variable, On-Time Shipping performance, was evaluated last with the result shown in Table 53. The zero entries in the “estimate” column indicate that the stepwise regression could not determine that any of the predictor variables were suitable for a model. In addition, the JMP 10pro output showed a R2 and adjusted R2 value of zero (0) as well. These results infer that there are other factors not present in predicting On-Time Shipping performance.

Table 53. On-Time Shipments Stepwise Regression

Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
Intercept	89.045	1	0	0.000	1
ICT-ASNinbound Grouped[0-1]	0	1	229.425	1.158	0.2946
ICT-ASNoutbound Grouped[0-1]	0	1	132.426	0.653	0.4286
ICT-ERP Grouped[0-1]	0	1	4.454	0.021	0.8854
ICT-TMS Grouped[0-1]	0	1	146.272	0.723	0.4051
ICT-WMS Grouped[0-1]	0	1	147.681	0.731	0.4028
ICT-e-Commerce Grouped[0-1]	0	1	245.651	1.245	0.2776
ICT-Mobile Grouped[0-1]	0	1	18.182	0.087	0.7708
AIDC-1Dbarcode YN[1-0]	0	1	54.365	0.263	0.6137
AIDC-2Dbarcode YN[0-1]	0	1	13.270	0.064	0.8035
AIDC-QRbarcode YN[0-1]	0	1	50.668	0.245	0.6261
AIDC-Integral-BCRFID YN[0-1]	0	1	0.287	0.001	0.9708
BP-ABC Grouped[1-0]	0	1	5.650	0.027	0.8711
BP-PI Grouped[0-1]	0	1	147.079	0.727	0.4038
BP-CycleCount Grouped[1-0]	0	1	123.165	0.606	0.4455
BP-Addresses Grouped[1-0]	0	1	109.761	0.538	0.4718
BP-PickPath Grouped[0-1]	0	1	64.121	0.311	0.5834
BP-Xdock Grouped[1-0]	0	1	126.954	0.625	0.4385

CHAPTER 5

CONCLUSIONS AND DISCUSSION

Introduction

Research points to a need for focusing on “the operational management of warehousing systems where the different processes in a warehouse are considered jointly” and “multiple objectives are considered simultaneously” (J. Gu et al., 2007). The purpose of this study is to determine the extent to which technology and best practices impact key performance indicators (KPIs) for wholesale distribution branch warehouse operations. Specifically, this research measured the impact of information and communication technology (ICT) and automatic identification and data capture (AIDC) on the fundamental priorities of inventory accuracy and customer service for branch operations in the wholesale distribution channel.

The research was designed around four questions. The first two questions investigated ICT and AIDC separately, using three independent null hypotheses for each technology group in order to understand the impact for the performance metrics of order fill rate, inventory accuracy, and on-time shipments. The third research question was in two parts. The first part determined the significant best practices. The second part used the results as comparison predictor variables to answer three independent null hypotheses for each outcome (dependent) variable. The fourth research question developed predictive models, where possible, for each outcome variable based on the predictor variable grouping per the analysis for Questions 1, 2, and 3.

Table 54 summarizes the results for the individual null hypotheses from Research Questions 1, 2, and 3, as well as the results from Research Question 4 with regard to predictive formulas. Each research question is subsequently discussed in detail, followed by a discussion of the overall findings, contributions of the research, limitations, and future research direction.

Table 54. Summary of Research Question Results

Research Question	Topic	Fill Rate	Inventory Accuracy	On-Time Shipments
1	ICT	Reject H_O: WMS	Cannot Reject H_O (validity)	Cannot Reject H_O
2	AIDC	Cannot Reject H_O	Cannot Reject H_O	Cannot Reject H_O
3	Comparison	Reject H_O: ABC & WMS	Cannot Reject H_O	Cannot Reject H_O
4	Predictive Formula	WMS & PI	PI	Not Possible

Prior to addressing the research questions, a correlation analysis was performed on the outcome (dependent) variables from the questionnaire. This analysis determined a sufficient correlation existed between two different types of fill rate measurements and two different types of inventory accuracy measurements. In turn, the analysis was then able to continue with the three outcome variables: Fill rate by quantity shipped within an order, inventory accuracy by units, and On-Time Shipping performance.

Using these three specific outcome variables, the research questions then analyzed the predictor (independent) variables from the questionnaire to evaluate blocking techniques for time related performance effects. Research shows that there is a "productivity impact" and "performance dip" across a range of new technologies for new introductions (McAfee, 2002). Therefore, the original questionnaire included "utilization time" components for time effects.

The ICT predictors showed marked differences after one year of utilization and were thus analyzed using branches with at least one year of utilization. AIDC did not show time effects, and was analyzed with a "utilized" or "not utilized" blocking. Additionally, best practices were analyzed for time effects and demonstrated the same one year transition as ICT resulting in an analysis using branches with at least one year of utilization as a differentiation point.

Once outcome variables were selected and time effects analyzed, individual null hypotheses were established for Research Questions 1, 2, and 3 to be evaluated using a combination of multiple linear regression and analysis of variance (ANOVA) to determine the impact of the predictor variables. Inherent in the analysis was a screening and reduction process of the predictors based on the principle of parsimony, i.e. "the smaller number of variables the better" (Klimberg & McCullough, 2013). Research Question 4 was evaluated using stepwise regression to develop predictive formulae for each outcome variable. Detailed discussion on the research questions follow.

Research Question 1: ICT v. Performance Measurements

The first research question asked if branch operations that invest in ICT have better performance than branch operations that do not. The question was subsequently broken down into three separate null hypotheses to evaluate against KPIs of fill rate, inventory accuracy, and on-time shipments.

Q1: Do branch operations that invest in ICT have better performance than those that do not?

$H_{O1\text{-}1}$: Branch operations that invest in ICT have the same performance with respect to fill rate as those that do not invest in ICT.

Conclusion: We reject the null hypothesis that branch operations that do not invest in ICT have the same fill rate performance as those that do not. The adoption of warehouse management system (WMS) information technology demonstrated a positive impact on improving performance metrics for fill rate, and possibly for inventory accuracy.

A review of the data determined that WMS will have a positive effect on fill rate if utilized for at least one year. However, a low R^2 value of 0.27 demonstrated a relatively poor fit of the data to the model, and an adjusted R^2 of 0.21 limited the result for generalization purposes in that it may not replicate with different samples. Additionally, the results of the analysis were marginal with regard to the assumptions needed for validity. The summary conclusion was that while warehouse management systems will have a positive effect, there are more factors that need to be present, and that warehouse management systems alone will not be sufficient to change fill rate.

$H_{O1\text{-}2}$: Branch operations that invest in ICT have the same performance with respect to inventory accuracy as those that do not invest in ICT.

Conclusion: We cannot reject the null hypothesis. This means that there was no difference in inventory accuracy for branch operations that invested in ICT as those that did not.

A preliminary conclusion, supported by data in Table 22, established that the null hypothesis may be rejected if both WMS and e-commerce are utilized together within a facility, but not if used exclusive of each other. However, the conclusion was ultimately rejected based on the lack of model validity when the normality and collinearity assumptions were tested. Therefore, no predictors were found to have a significant impact on inventory accuracy for this study, but the results are intriguing enough to consider a point for future research.

$H_{O1\text{-}3}$: Branch operations that invest in ICT have the same performance with respect to on-time shipping performance as those that do not invest in ICT.

Conclusion: We cannot reject the null hypothesis. This means that there was no difference in on-time shipments for branch operations that invested in ICT as those that did not.

None of the predictor variables analyzed could be determined to present a significant effect upon the on-time shipments metric, either when considered individually or taken in consideration with other predictors, as supported by Table 27 and Table 28.

Research Question 2: AIDC v. Performance Measurements

The second research question asked if branch operations that invest in AIDC have better performance than branch operations that do not. The question was subsequently broken down into three separate null hypotheses to evaluate against KPIs of fill rate, inventory accuracy, and on-time shipments. As discussed below, the data showed that none of the AIDC predictor variables had a significant impact on any of the three outcome variables.

Q2: Do branch operations that invest in automatic identification and data capture (AIDC) have better performance than those that do not?

$H_{O2\text{-}1}$: Branch operations that invest in AIDC have the same performance with respect to fill rate as those that do not invest in AIDC.

Conclusion: We cannot reject the null hypothesis. This means that there was no difference in fill rate for branch operations that used ADIC and those that did not.

$H_{O2\text{-}2}$: Branch operations that invest in AIDC have the same performance with respect to inventory accuracy as those that do not invest in AIDC.

Conclusion: We cannot reject the null hypothesis. This means that there was no difference in inventory accuracy for branch operations that used ADIC and those that did not.

$H_{O2\text{-}3}$: Branch operations that invest in AIDC have the same performance with respect to on-time shipping performance as those that do not invest in AIDC.

Conclusion: We cannot reject the null hypothesis. This means that there was no difference in on-time shipments for branch operations that used ADIC and those that did not.

Research Question 3: Best Practices v. Technology

This question was investigated in two parts. First, an analysis similar to the first two research questions was conducted in order to identify statistically significant best practices. Once established, these were then compared to the statistically significant technology predictors using analysis of variance (ANOVA). This analysis was conducted for each outcome variable individually and independently, using the three null hypotheses below.

Q3: Do branch operations that utilize “best warehousing practices” have better performance than those that invest only in technology?

$H_{O3\text{-}1}$: Branch operations that employ “best practices” have the same fill rate performance as those that rely solely on technology.

Conclusion: The null hypothesis that branch operations that employ “best practices” have the same fill rate as those that rely solely on technology was rejected. This means that there was no difference in fill rate for branch operations that used best practices and those that did not.

To arrive at this conclusion, it was first determined that a best practice of using ABC stock analysis had a significant effect on fill rate performance. Once this predictor was determined, a subsequent ANOVA compared the technology predictor for fill rate, WMS, against the best practice predictor ABC. Table 41 and Table 42 provide support that the use of either of the predictors alone, or using both in combination, would not be sufficient to explain the difference in fill rates. The analysis of the residuals shown in Figure 20 determined that the finding had more predictive value for branch operations that have a "high" fill rate, i.e. above 70%.

Whatever difference in fill rate that was created by ABC analysis and WMS may be evident, but there are more factors that are involved that were outside the scope of this research to draw a definitive conclusion. However, this opens the door for future research building on these two predictors to test best practices against technology.

$H_{O3\text{-}2}$: Branch operations that employ "best practices" have the same inventory accuracy as those that rely solely on technology.

$H_{O3\text{-}3}$: Branch operations that employ "best practices" have the same on-time shipping performance as those that rely solely on technology.

Hypotheses $H_{O3\text{-}2}$ and $H_{O3\text{-}3}$ drew the same result, which was a failure to produce any statistically significant predictor variables that showed an effect on either of their respective outcome variables. Therefore, without either a technology or a best practice predictor to compare, the null hypotheses could not be rejected.

Research Question 4: Predictive Models

Research Question 4 investigated the contributions of different technologies and best practices upon inventory and customer service metrics. Stepwise regression was utilized to analyze all predictor variable blocks against the three outcome KPIs. The net result was that predictive formulas were developed for fill rate and inventory accuracy as shown below. The stepwise regression could not resolve, i.e. develop significant predictors, for on-time shipping performance.

Fill Rate = 76.5 + 11.2(WMS) + 11.3(PI)

Inventory Accuracy = 78.0 + 12.8(PI)

Where:

WMS = use of a warehouse management system for at least 1 year

PI = a practice of conducting a physical inventory, implemented for at least 1 year

The caveat behind both prediction formulae was that a relatively low R^2 value for both, 0.39 and 0.19, respectively, inferred that the models do not predict well. Additionally, low adjusted R^2 values, 0.35 and 0.15, respectively, are interpreted to infer that the results are relatively poor predictors for other data sets, i.e. other branch operations. Additionally, the predictive value of the fill rate model was limited to branch operations demonstrating fill rate performance greater than approximately 85%.

Discussion

The ICT technologies investigated by Research Question 1 appear to show a positive impact on distribution branch inventory and customer service KPIs. The most significant result from the study of ICT utilization was with order fill rate, and to a lesser extent with inventory accuracy. The primary technology influencing the metrics was a WMS, which is a positive result for the technology as it appears to be serving its primary purpose of inventory control. Inventory accuracy is by definition an inventory control function and the premise is that customer service is impacted by order fill rate, which needs high levels of inventory accuracy, inventory control, and effective order picking.

The finding is intuitive to a degree, in that fill rate is a function of the WMS application for control of material stored, for both quantity and location, thus lending itself to positive outcomes for material availability to fill customer orders. On the other hand, inventory accuracy had somewhat less rigorous results, indicating it is impacted by more than the information technology and WMS controlling ordering, receiving, and storage of goods. Also the research served to confirm implementation related performance dips relative to the introduction of ICT (McAfee, 2002). This research concluded that a positive impact by technology did not materialize until at least one year into implementation. In some cases, performance actually declined in the first year of utilization before recovering to add value to the organization.

AIDC did not show any effect on fill rate, inventory accuracy or on-time shipments. This was somewhat disappointing but not completely unexpected. At its core, AIDC's primary benefits are labor efficiencies, both in time and data input accuracy. In that respect, AIDC really is a productivity tool with the added benefits of supporting other technologies such as ICT, and best business practices, but in and of itself, is not a performance improvement technology with respect to inventory control and/or customer service.

The raw data provided some interesting observations on AIDC in general. For example, only about two thirds of distribution branches utilized bar codes for inventory control purposes, which was surprising given the maturity of this technology. On the other hand, the lack of use was supported by the study in that there were no significant effects on the KPIs studied.

Another interesting observation was that while there were no reported cases of stand-alone RFID applications, 12% of the responses used integral RFID bar codes, with 40% of those introduced within the past year. This revealed an emerging enhancement to bar code applications, as the emerging use of integral RFID bar code labels was primarily by organizations with mature 1D bar code utilization, although there were branches utilizing the integral RFID bar code label as a start-up technology. RFID has struggled to find cost effectiveness at the item level when competing against bar codes, as the 1 dimensional bar code was clearly the dominant technology in this study, but the integral RFID bar code label may provide the additional benefits to make RFID more cost effective.

Comparing the utilization of ICT against AIDC, there appears to be a larger influence upon KIPs by the information and communication technologies than the automatic identification and data capture. This is supported by failing to reject all null hypotheses for AIDC, which did not find any difference on the three KPIs studied, whereas ICT showed an impact against fill rate and inventory accuracy.

The research was for the most part inconclusive on comparing best practices to technology, given that KPIs of inventory accuracy and on-time shipments appeared to be influenced by either too many variables to model, or there are more significant predictors than studied. The data was not able to show any conclusive comparison between the two approaches, technology or best practices, on inventory accuracy and outbound on-time shipping performance.

Research Contributions

The objective of the research was to contribute to the field by exploring the relationships between types of technologies available to the distribution industry and how technology interacts with business practices to impact inventory control and customer service performance metrics.

The first contribution of the research was to confirm that the impact of information and communication technology and business practices did not fully materialize until at least one year after adoption. The time of utilization, evaluated by blocking techniques, indicated there is a learning curve impact present. Management should take this conclusion into consideration to calibrate their goals and expectations for performance when adopting new ICT and/or best practices, making necessary adjustments to safety stock and/or developing contingency plans in anticipation of start-up effects.

A second contribution was on the efficacy of warehouse management systems at the distribution branch level. There were two useful observations involving interactions with WMS, one with ABC analysis and the other with e-commerce systems. First, ABC is inventory control slang for application of the Pareto Principle within inventory management, and therefore has a direct effect on inventory control. ABC analysis is used to develop inventory control and storage policies, replenishment policies and safety stock levels. This research supported that branches utilizing a WMS are more effective, realized through utilization for at least one year, if they employ ABC stock analysis to provide data inputs for this particular type of ICT. The second complementary ICT, e-commerce, appeared to be another complementary technology, but the research was inconclusive in this regard. However, there are intuitive benefits of tying the ordering capability of e-commerce to the inventory control technology provided through a WMS. Operations that have a WMS in place should investigate the adoption of e-commerce to improve overall inventory performance.

A third benefit of the research was to establish the efficacy of the best practice of physical inventory at the distribution branch level. Long considered a non-value added process required only for financial accounting purposes, the physical inventory predictor appeared to have a tenuous predictive value for customer order fill rate and inventory accuracy. For fill rate, physical inventory found significance when used in conjunction with WMS. As with the finding on WMS and e-commerce for inventory control, branches that use PI and WMS together may be able to establish a 99% minimum fill rate expectation. With respect to inventory accuracy, the best practice of physical inventory may establish a threshold value at 91%. The fill rate and inventory accuracy numbers establish "tentative" benchmarks as the data in this research did not meet suitable standards for R^2 and adjusted R^2. However, the research is sufficiently suitable to establish an external benchmark to measure performance and challenge operations similar to the ones in this study. The use of the results as a benchmark must be separate from using these values for investment or personnel decisions. As benchmarks, these values provide corrective action thresholds for employment of the technology or practices modeled.

Limitations

The research was limited by the number of branch operations that returned data for the questionnaire, which manifested itself in several ways.

First, extreme data points may have biased the multiple linear regression analysis, ANOVA comparisons, and stepwise regression modeling. With a larger sample size, the outlier effects would have been minimized or eliminated.

Second, the ICT result for the inventory accuracy was deemed inconclusive since the residuals did not show a normal distribution with constant variance. Larger sample sizes would have improved the variance, and in most cases, larger sample sizes will outweigh a test of normality (Brace et al., 2012; Norusis, 2012b).

Third, multiple linear regression analysis requires a large number of cases to be effective. Five to ten cases per independent variable are considered an acceptable minimum, but responses of twenty or more are considered best to prevent Type II errors, i.e. not reject the null hypothesis when we should reject it (Brace et al., 2012; Hayden, 2008; Norusis, 2012a, 2012b). The goal of ten observations per independent variable was established at the onset to allow for analysis validity, but low response rate contributed to poor normality assumptions.

From a data collection standpoint, many consider survey and questionnaire instruments a dubious methodology due to potential for low response rate bias, poor question formulation, and other sampling errors. The main concern for this study was the potential for low response rate to cause validity issues, with a 40% minimum established to preclude concerns (Best & Kahn, 2006). The closed form questionnaire instrument used had a net response rate of 32% which contributed to the low R^2 values and multiple regression analysis validity assumption concerns. This was despite using recommended techniques by involving administrative supervisors and referrals to gain increased returns (Best & Kahn, 2006; Dillman et al., 2009).

Recommendations for Future Research

The data and findings present a wide range of possible future research initiatives. One of the surprising results of the investigation was a lack of correlation between on-time shipment performance and inventory metrics. It seemed intuitive that a distribution branch cannot have a high on-time shipping performance without a high level of inventory control. However, the variables studied did not produce any such correlation, suggesting that there may be other KPIs that affect this relationship that need to be uncovered in order to provide managerial direction.

The data suggested that when considered independently, neither WMS nor e-commerce was significant, as shown in Table 22, but that when used concurrently, they may have a significant effect upon inventory accuracy. However, since the modeling validity assumptions were violated, the conclusion could not be confirmed. The analysis was limited due to a relatively small number of cases being considered. With a larger sample, the model assumptions may be realized and statistically valid conclusions drawn.

When evaluated in Research Question 1, warehouse management systems and e-commerce utilized together within a facility appeared to have an impact on inventory accuracy, but not if used exclusive of each other. However, the conclusion was ultimately rejected based on the lack of model validity when the normality and collinearity assumptions were tested.

Interestingly, as evidenced by the scatter plots of two predictor variables shown in Figure 24, warehouse management systems and e-commerce showed a potential for effecting on-time shipping performance with respect to a reduction in variation rather than a change in mean values. When this observation is combined with the Research Question 1 analysis, there exist possibilities of future research into the efficacy of the two technologies as a problem prevention predictor, rather than as a provider of incremental performance improvement.

Additionally, future research providing a larger sample size would serve to validate any performance (mean) changes and potentially allow establishment of a useful set of predictor variables.

In investigating Research Question 3, whatever difference in fill rate that was created by ABC analysis and WMS may be evident, but there are more factors that are involved that were outside the scope of this research to draw a definitive conclusion. This observation opens the door for future research building on these two predictors to test best practices against technology.

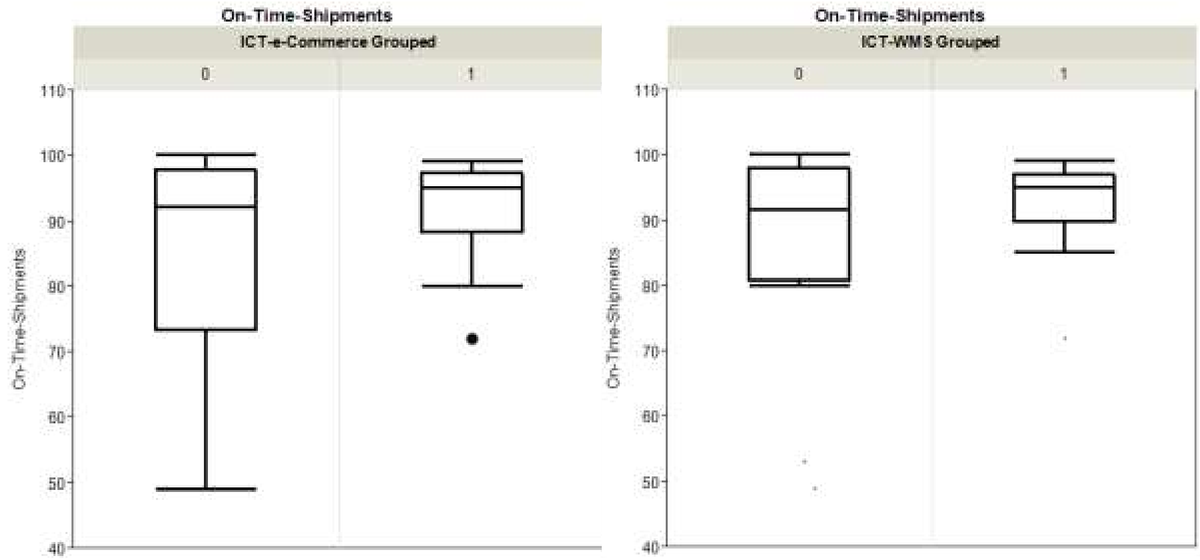


Figure 24. WMS and e-commerce Impact on On-Time Shipments

An interesting observation from Research Question 4 was the potential predictive value versus the association of physical inventories as a best practice rather than cycle counting. In the review of literature, cycle counting is by far the preferred technique for inventory control and was the dominant tool as far as frequency in the study population. However, as evidenced by Table 56 in Appendix E, physical inventory showed better performance than cycle counting in the outcome variables. This seeming disconnect provides a research possibility for a direct comparison of competing inventory control warehousing practices.

Finally, the research questions and data analysis considered the outcome variables independently since there is not a common set of KPIs for the distribution industry. A further analysis of the data may be able to produce observations regarding interactions of KPIs, i.e. is performance different for branch operations that track one, two, or all three KPIs?

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APPENDIX

APPENDIX A: IRB APPROVAL LETTER

Indiana State University
More. From day one.

Institutional Review Board

Terre Haute, Indiana 47809
812-237-3092
Fax 812-237-3092

DATE:	July 8, 2013
TO:	Mark Angolia, MS
FROM:	Indiana State University Institutional Review Board
STUDY TITLE:	[476524-3] A STUDY ON TECHNOLOGY IMPACT ON WHOLESALE DISTRIBUTION BRANCH OPERATIONS
IRB REFERENCE #:	
SUBMISSION TYPE:	Revision
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	July 8, 2013
REVIEW CATEGORY:	

Thank you for your submission of Revision materials for this research study. The Indiana State University Institutional Review Board has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations (45 CFR 46). You do not need to submit continuation requests or a completion report. Should you need to make modifications to your protocol or informed consent forms that do not fall within the exempt categories, you will have to reapply to the IRB for review of your modified study.

Internet Research: You are using an internet platform to collect data on human subjects. Although your study is exempt from IRB review, ISU has specific policies about internet research that you should follow to the best of your ability and capability. Please review Section L. on Internet Research in the IRB Policy Manual.

Informed Consent: All ISU faculty, staff, and students conducting human subjects research within the "exempt" category are still ethically bound to follow the basic ethical principles of the Belmont Report: a) respect for persons; 2) beneficence; and 3) justice. These three principles are best reflected in the practice of obtaining informed consent.

If you have any questions, please contact Dr. Kim Bodey within IRBNet by clicking on the study title on the "My Projects" screen and the "Send Project Mail" button on the left side of the "New Project Message" screen. I wish you well in completing your study.

APPENDIX B: QUESTIONNAIRE PARTICIPANT REQUEST

As a follow up to my voice mail from today, this is a request for help in gathering information on technology applications and warehousing practices of wholesale distribution companies that recruit students from East Carolina University's (ECU) Industrial Distribution and Logistics program.

My request is for you to supply me with branch manager names and emails for all of your distribution branches/stores (not central distribution centers). I will then send them a link to an on-line survey that will take about 5 – 10 minutes to complete. I also ask your permission to use your name as a reference within the introductory email containing the survey link. Please note that the survey will only collect data on non-commercial / non-proprietary aspects of your company's distribution operations to research the utilization and impact of technology on our industry.

I am conducting this research as a PhD candidate to complete my dissertation, and will also use the information to help improve the quality of education delivered to our students at ECU. Your participation is voluntary and responses will not be identified with you or your company. If you have any questions or concerns about providing names or participating, please contact me at (252) 737-1036 or at angoliam@ecu.edu.

Thanks for your consideration,

Mark Angolia, Instructor
Department of Technology Systems
East Carolina University

Please note that this study, (IRB # 476524-3), was reviewed by the Institutional Review Board (IRB) from Indiana State University (ISU) on 07/08/2013 to insure it is conducted in an ethical and legal manner. You may contact the IRB by mail at Indiana State University, Office of Sponsored Programs, Terre Haute, IN 47809, by phone at (812) 237-8217, or by email at irb@indstate.edu.

APPENDIX C: QUESTOINNAIRE INTRODUCTION

(Name redacted) provided me your contact information and sent an email notice separately to provide a heads up that participating in this survey was approved through your corporate management.

You are receiving this email as a request for help in gathering information on technology applications and warehousing practices of wholesale distribution companies that recruit students from East Carolina University's (ECU) Industrial Distribution and Logistics program. I am reaching out to all companies that have a relationship with ECU in order to conduct research as a PhD candidate to complete my dissertation and also develop information to help improve the quality of education delivered to our students.

The link below will take you to an on-line survey that will take about 10 minutes to complete. It will ask for non-commercial / non-proprietary data for your branch operation regarding the utilization and impact of technology within our industry.

Even though your management team has approved the survey, your participation is voluntary and nobody will know if you do not complete this. In addition, responses will not be identified with you or your company; only the Institutional Review Board (IRB) at Indiana State University (ISU) may inspect the individual data records. Note that the IRB's role is to insure surveys are conducted in an ethical and legal manner. If you have any questions or concerns about participating in this study, please contact me at (252) 737-1036 or at angoliam@ecu.edu

Sincerely,

Mark Angolia, Instructor (and PhD student)
East Carolina University, Department of Technology Systems

If you have any questions about your rights as a participant, you may contact the ISU IRB by mail at Indiana State University, Office of Sponsored Programs, Terre Haute, IN 47809, by phone at (812) 237-8217, or by email at irb@instate.edu. This study (IRB # 476524-3) was reviewed by the ISU IRB on 07-08-213.

Follow this link to the Survey:
(links expired / deleted)

Or copy and paste the URL below into your internet browser:
(links expired / deleted)

Follow the link to opt out of future emails:
(links expired / deleted)

APPENDIX D: QUESTIONNAIRE

Introduction Page

The following 14 question / 5 - 10 minute questionnaire asks about technology applications and wareh practices of wholesale distribution companies that recruit students from East Carolina University's (EC Distribution and Logistics program. I am asking for your help to collect data on non-commercial / non- aspects of your operation to research the utilization and impact of technology on our industry.

There are no known risks to you, and no cost. The results/summary information will not be traceable t individual person or company. Please note that you may answer or skip questions at your discretion.

I am conducting this research as a PhD doctoral candidate at Indiana State University (ISU), but many me as an ECU faculty member. Your participation in this study will also help improve the quality of education delivered to our students.

Your participation is voluntary and responses will not be identified with you or your company; only the Review Board (IRB) at ISU may inspect the individual data records. To proceed/consent, simply click button at the bottom of the page. If you do not wish to participate, simply click the "x" in your browser window and use the delete function on your e-mail account to remove the link to the survey. You will r any follow up e-mail contacts with regard to this questionnaire.

If you have any questions or concerns about completing the questionnaire or participating, you may co (252) 737-1036 or at angoliam@ecu.edu. If you have any questions about your rights as a participant contact the Indiana State University IRB by mail at Indiana State University, Office of Sponsored Progr Haute, IN 47809, by phone at (812) 237-8217, or by e-mail at irb@indstate.edu. This study (IRB # 47 reviewed by the ISU IRB on 07-08-2013.

All Questions

Which industry is most closely associated with your wholesale distribution branch?

- Building / Construction / Housing Materials
- Electrical Components / Equipment
- Food / Beverage
- General Industrial Products
- HVAC
- Plumbing / Water Works
- Retail / Consumer Products
- Other

Approximately how many square feet of warehousing space is in your facility?

- Less than 5,000
- 5,001 - 10,000
- 10,001 - 15,000
- 15,001 - 20,000
- 20,001 - 25,000
- 25,001 - 30,000
- Greater than 30,000

On a shipping volume basis, how would you describe your main customer base?

- Private Individuals
- Contractors
- Manufacturing Operations
- Retail Outlets
- Big Box Stores
- Other

Approximately how many different SKUs do stock within your wholesale distribution branch?

Approximately how many different SKUs do you ship daily?

Approximately how many addressable stock locations (slots) are in your warehouse?

On average, how many total employees are primarily engaged in warehouse operations of receiving, s
put-away, order picking, and shipping?

Slide the bar to show the estimated number of trucks serviced by your warehouse staff on a daily basi

	0	2	4	6	8	10	12	14	16	18	20	22	24	26	28	3
Inbound Receipts																
Outbound Shipments																

Which of the following Information and Communication Technologies (ICT) are used in your wholesale branch operation?

	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years	If applicable, please list the software and/or hardware vendor
Advance Shipping Notices (ASN) for inbound material					
Advance Shipping Notices (ASN) for outbound shipments					
Enterprise Resource Planning (ERP) System					
Transportation / Logistics Management Software (TMS)					
Warehouse Management System (WMS)					
Internet / E-Commerce Portal for Customer Order Entry					
Mobile Computers for Warehouse Employees					
Computer Tablets for Warehouse Employees					
Hands Free Communication Technology for Warehouse Employees - Describe					
Other, please describe					

Which of the following Automatic Identification and Data Capture (AIDC) technologies are used in you

	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years	If applicable, how does the technology interact with the inventory control software? Real Time / Instantaneous	Batch Update	If applicable, please list the software and/or hardware vendor
1 dimensional bar codes							
2 dimensional bar codes							
Other types of bar codes, e.g. QR							
Radio Frequency Identification (RFID) tags / labels							
Integral Bar Code and RFID label							
Other, please describe							

Which of the following Warehouse Practices are used in your operation?

	Not Utilized	Less Than 1 Year	1 - 2 Years	More Than 2 Years
ABC Stock Analysis				
Annual Physical Inventory				
Cross Docking				
Cycle Counting				
Golden Zone Stock Locations				
Pick Path Routing / Sequencing				
Stock Location / Warehouse Addresses				
Other, please describe				

What type of storage policy is used for SKUs in your warehouse?

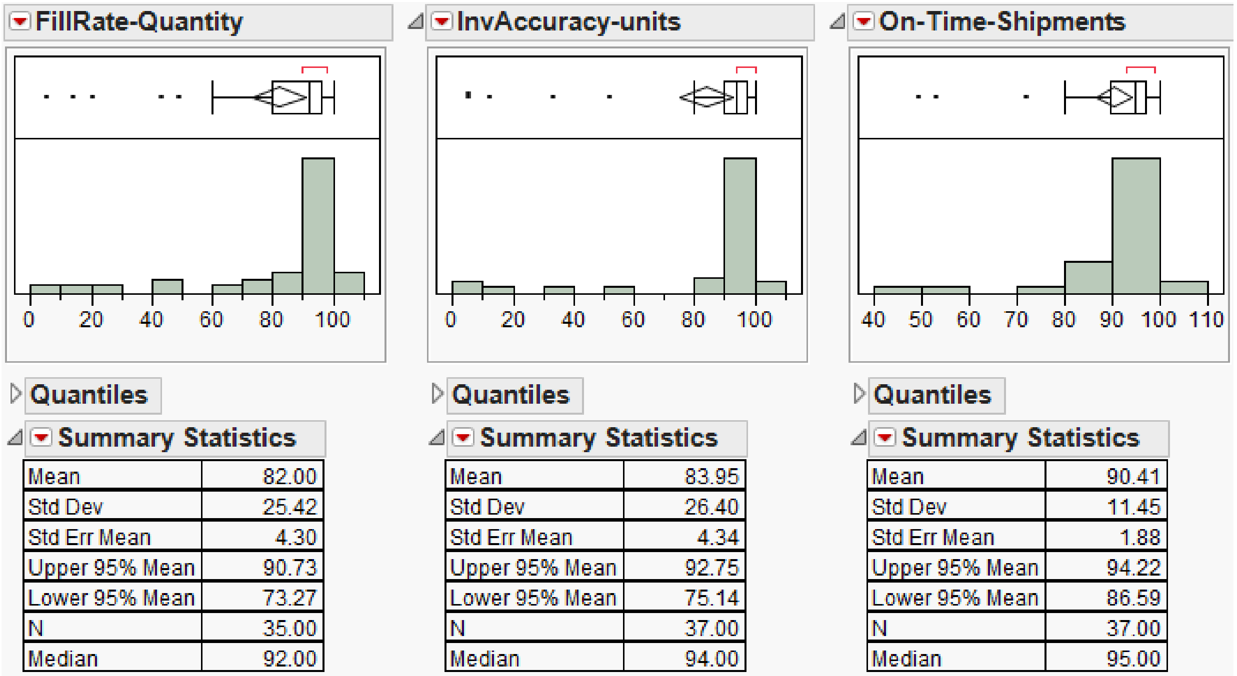
- Stock is always placed in the same location, i.e. dedicated storage
- Stock is placed in different locations based on order frequency and space availability, i.e. random storage
- Both methods are utilized

This second to last question is intended to determine which performance metrics are used in your brai operation. If applicable, please move the slider bar to approximate your average value. Please add a customer service or inventory accuracy metrics utilized.

	0	10	20	30	40	50	60	70	80	90	100	Not Applicable
Fill Rate - by number of total lines												☐
Fill Rate - by order volume / quantity												☐
Inventory accuracy - by inventory / sales dollars												☐
Inventory accuracy - by number of units												☐
On-Time Shipments												☐
Other Customer Service Metric, please describe												☐
Other Inventory Accuracy Metric, please describe												☐

What did I miss? This final question / space is to describe any warehouse technology and/or "best pra
you feel is beneficial to your operation. Thank you for completing this survey.

APPENDIX E: MISCELLANEOUS STATISTICS



Note: histogram blocks between 100-109 represents raw data values of 100%

Figure 25. Outcome Variable Descriptive Statistics

Table 55. AIDC Cross Tabulation of Predictor to Outcome Variables

	FillRate-Quantity		InvAccuracy-units		On-Time-Shipments		
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	N
	82.0	25.4	83.9	26.4	90.4	11.4	52
AIDC-1Dbarcode YN							
Not Utilized	78.0	34.8	78.9	35.1	92.0	14.6	16
Utilized	82.8	21.7	83.4	24.8	88.9	11.0	28
AIDC-2Dbarcode YN							
Not Utilized	79.4	28.8	79.8	31.9	89.6	13.6	33
Utilized	86.0	19.0	89.2	7.1	89.8	6.6	9
AIDC-QRbarcode YN							
Not Utilized	81.6	25.5	82.9	27.0	89.6	13.4	36
Utilized	62.3	40.7	71.8	44.6	95.0	2.7	5
AIDC-Integral-BCRFID YN							
Not Utilized	78.6	28.3	81.3	29.7	90.2	13.0	38
Utilized	95.4	4.2	91.0	7.8	89.2	7.9	5

5 rows have been excluded.

Table 56. Best Practices Cross Tab of Predictor to Outcome Variables

	FillRate-Quantity		InvAccuracy-units		On-Time-Shipments		
BP-ABC	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	N
Not Utilized	69.5	31.9	77.3	34.3	89.8	12.6	29
Less Than 1 Year	*92.0	.	*95.0	.	*80.0	.	1
More Than 2 Years	92.6	6.7	88.7	14.0	89.2	12.8	12
BP-PI							
Not Utilized	69.8	37.7	77.3	36.5	89.4	16.4	15
Less Than 1 Year	*85.0	*9.9	*64.0	43.8	*76.0	5.7	2
1 - 2 Years	*93.0	.	*92.0	.	*93.0	.	1
More Than 2 Years	87.3	16.4	91.5	11.0	91.6	10.2	27
BP-CycleCount							
Not Utilized	*92.3	1.5	*96.8	2.8	*94.0	3.6	6
Less Than 1 Year	*92.5	0.7	*93.5	2.1	*86.5	9.2	3
1 - 2 Years	*20.0	.	*5.0	.	*100.0	.	1
More Than 2 Years	82.3	25.1	84.2	24.9	90.0	12.2	41
BP-Addresses							
Not Utilized	*74.6	26.2	*93.6	2.1	*91.2	5.2	7
Less Than 1 Year	74.5	40.5	*72.8	45.3	*90.8	7.9	5
1 - 2 Years	*99.0	.	*90.0	.	*98.0	.	2
More Than 2 Years	81.1	25.7	81.9	28.1	88.6	14.0	31
BP-PickPath							
Not Utilized	71.2	31.6	73.2	34.8	87.2	15.1	25
Less Than 1 Year	*92.8	3.7	*93.0	5.1	*93.0	6.7	6
More Than 2 Years	89.0	17.9	95.1	5.8	92.7	5.3	12
BP-Xdock							
Not Utilized	77.8	28.0	82.0	28.0	90.7	11.5	28
Less Than 1 Year	*53.0	55.2	*50.0	63.6	*85.5	7.8	2
More Than 2 Years	90.7	7.7	88.6	17.5	86.5	17.5	10

5 rows have been excluded.

* Data not considered due to sample size