UNIVERSITY OF NAIROBI

SCHOOL OF COMPUTING AND INFORMATICS

EVALUATING THE IMPACT OF BUSINESS INTELLIGENCE ON DECISION-MAKING: A SURVEY OF LOGISTICS COMPANIES IN KENYA

By

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Submitted in partial fulfillment of the requirements for the Degree of Masters of Science Information Technology Management of the University of Nairobi.

DECLARATION

Student Declaration

I Robin Chumari Wachaga, student registration number P54/85554/2016, hereby declare that this MSc. Project entitled "Evaluation of business Intelligence on decision-making: A survey of selected Logistics companies in Kenya" to the best of my knowledge and belief, is my original work and has not been submitted for examination in this university or other universities for an award of any other degree.

Signature ……………………………. Date……………………………...

CHUMARI WACHAGA

P54/85554/2016

Supervisor's declaration

This research has been submitted for review with my approval as a university supervisor.

Signature…………………………… Date ………..................................

Prof. Timothy M. Waema

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ABSTRACT

The cost of logistics in Kenya is very high accounting for as high as 25% of production costs in some sectors. Kenya Association of Manufacturers have listed “cost, time and complexity of transport and logistics system in the country” as one of the major challenges to the Manufacturing sector. This is despite the Kenyan logistics industry embracing and using technology by implementing particularly company-wide ERP frameworks as their most vital processing platforms. Further, a good number have now integrated BI capabilities to their ERP systems to pick up an upper hand. The motivation behind this research was to decipher the role of BI to Logistics companies in Kenya, investigate its impact to business decision making and propose a model for BI use in decision making. The study adopted a descriptive transverse research design. The response rate for the target population was 82.5% which is statistically significant to analyze the data. Information gathered was broken down utilizing both illustrative and inferential insights. The study established that Analytical and Intelligent Decision Support (AIDS), Experiment and Integration with Environmental Information (EIEI), Optimization and Recommended Model (ORM) and Reasoning were the main BI functions affecting business decision making. The study also brings out the various bottlenecks in existing BI systems used in the logistics industry in Kenya and offers suggestions on how to deal with various challenges in the BI environment.

Keywords: Business Intelligence (BI), business decision making, logistics, BI functions, BI benefits.

LIST OF ABBREVIATIONS

AIDS: Analytical and Intelligent Decision Support

BI: Business Intelligence

BPR: Business Process Reengineering

CAR: Computer Assisted reasoning

CRM: Customer Relationship Management

DSS: Decision Support System

DW: Data Warehouse

EIEI: Experiment and Integration with Environmental Information.

ERP: Enterprise Resource Planning

GIS: Geographic Information System

IC: Intellectual Capital

IPDSS: Intelligent Predictive Decision Support System

OLAP: Online Analytical Processing

OLC: Organizational Learning Capability

ORM: Optimization and Recommended Model

SCM: Supply Chain Management

SFAS: Statement of Financial Accounting Standards

SPSS: Statistical Package for Social Science

TAM: Technology Acceptance Model,

TOE: Technology-Organization-Environment framework

CHAPTER ONE

INTRODUCTION

1.1 Background

Kenya is ranked 68th globally in the 2018 World Bank's Logistics Performance Index (LPI) - a weighted normal of the nation scores on six key measurements; Efficiency of the clearance process, Nature of trade and transport-related establishment, Ease of masterminding aggressively priced shipments, Competence and nature of logistics, Ability to track and trace consignments and shipments arrival Timeliness. The report posits that nations described by low logistics execution face surprising expenses, not just on account of transportation costs but rather likewise in light of untrustworthy supply chains, a noteworthy debilitation in incorporating and competing in worldwide worth chains, citing '*Digital transformation of supply chains'* as one of the top emerging differentiators.

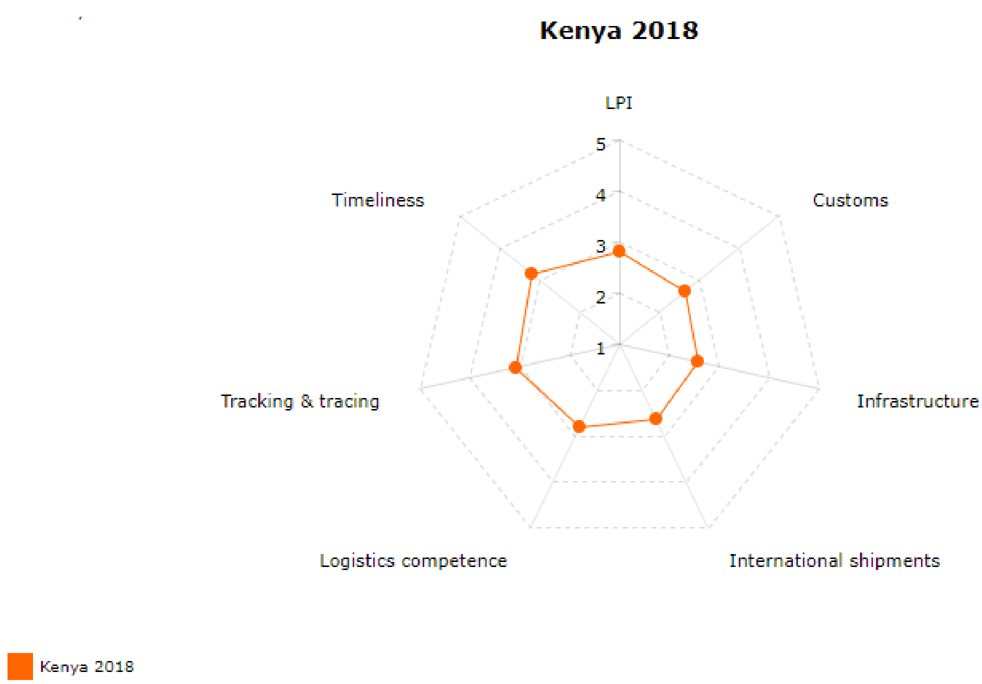

Figure 1.1: Kenya's LPI Score (2018) - The World Bank

Because of the expanding significance of data knowledge for managers and their business environment presently, companies have made momentous investments in business intelligence (BI) frameworks (Hou, 2012). Research has shown that technology use in Logistics in Kenya is in the rise as evidenced by Musyoki and Moturi (2016). Kopáčková and Škrobáčková, (2006) alluded that business intelligence (BI) is the "gathering, analyzing, managing and sharing of information to gain insights which can be used for better decision making". The basic role of BI is to help decision-making in organizations (Eckerson, 2003; Buchanan and O'Connell, 2006). A decision is programmed on the off chance that it is repetitive and scheduled, and it is nonprogrammed when there is no fixed technique of handling it and the decision is weighty (Simon, 1960). By and large, programmed and nonprogrammed choices are alluded to as "structured" and "unstructured" respectively. BI enables organizations to meet their data handling needs by joining; information gathering, information storage and knowledge management with diagnostic devices, so that, decision-makers can convert complex data into viable decisions (Negash, 2004). Branko et al. (2015), asserts that these days, business requests are demanding, and enterprises should constantly look for ways for business improvement. Improvement pointers vary from reducing operational expenses, giving palatable customer service, to limiting existing disruption dangers and Kenyan logistics firms are increasingly faced with the need to show this if the logistics industry is to be more competitive and a better facilitator to trade. It can only be achieved by more informed, better decision making achieved by utilization of BI tools to better forecast and predict demand and supply. This is underscored by Işık Ö. et al. (2010): First, BI underpins decision making for managerial exercises. Second, BI utilizes an information vault (as a rule a data warehouse) to store at various times information and to run data analyses. BI is likewise aimed at improving individual user performance through helping individuals manage gigantic measures of data while deciding

1.2 Problem Statement

In the recent few decades, numerous Kenyan Corporates' information technology strategy has pursued the methodology of implementing company-wide enterprise resource planning (ERP) frameworks as their most strategic computing platform. Most corporates now integrate BI capabilities to their ERP systems in order be competitive. While studies have been done on the challenges and success factors of BI implementations, very little focus has been put on the evaluation of BI solutions on business decision-making. There is a need to explore Business Intelligence solutions (business processes re-engineering, workflow automation, mobility, governance, risk and compliance, and business reporting) in order to leverage on systems' capabilities to deliver business value.

This study intends to investigate to what extent the Kenyan Corporates in the logistics sector are leveraging on their ERP business intelligence evaluation, highlighting the achievements as well as the challenges faced on business decision-making.

1.3 Objectives

The targets of the research will be:

1. To distinguish the role of BI to Logistics companies in Kenya.
2. To investigate the impact of Analytical and Intelligent decision support, Experiment and integration with environmental information, Reasoning and Optimization and recommended model on decision making in logistics companies in Kenya.
3. To propose a model for business decision-making in a BI environment in logistics companies in Kenya.

1.4 Significance

This study in achieving its objectives makes the following contributions; first it will add to the literature on leveraging business intelligence capabilities in achieving current and future organizational values.

Second, this research will serve to answer numerous calls to research on BI post implementation in Kenya (Nyaga, 2006; Nyandiere, 2002), and provide insights into leveraging and attaining long term benefits and competitive advantages from BI systems.

Through this research, managers in the Logistics sector in Kenya will gain insight on the necessary requirements of BI systems and the components that should be fully utilized to achieve business value and an upper hand.

Through this research system developers will be able to focus on the BI components increasing the business value in decision making.

1.5 Scope of the Study

The research covers only the logistics companies who have adopted BI solutions into their companies in Kenya.

1.6 Assumptions and Limitations

We assume that all respondents answered the questionnaires scrupulously to the best of their knowledge and that the study instrument provided attributes required for the research study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section surveys literature relating to leveraging enterprise resource planning (ERP) systems' implementations in Kenyan corporates.

2.2 BI Architecture

The figure below shows layers of business intelligence system

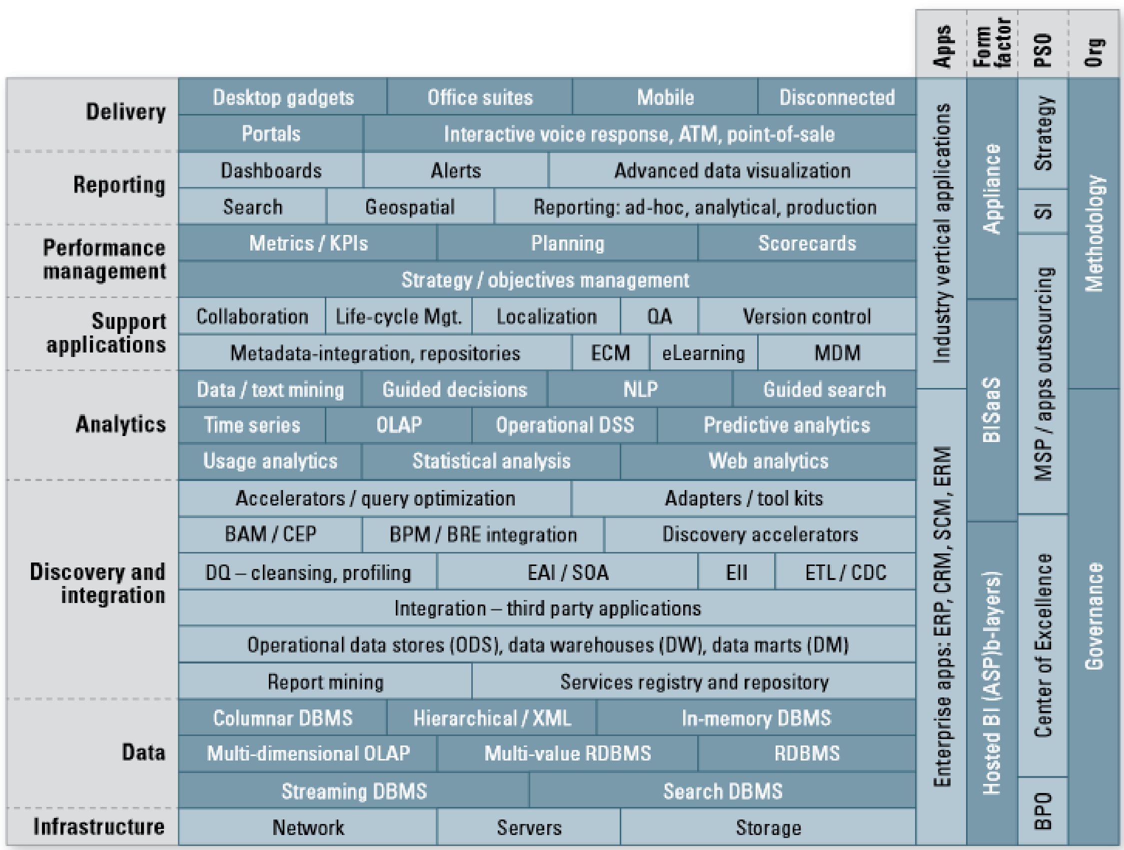

Figure 2.1: BI Architecture - Forrester, A.T. Kearney

2.3 Theoretical Literature

2.3.1 The theory of Effective use

Moving from use to compelling use requires comprehension of an information system's purpose and nature; this requires a theory of information systems. Information systems are comprised of a few structures that speak to some part of the world which a client and different partners must understand. Burton-Jones and Grange (2012), derived a sophisticated framework of evolution of effective use and its drivers. This framework assisted in explaining any IS use and insights.

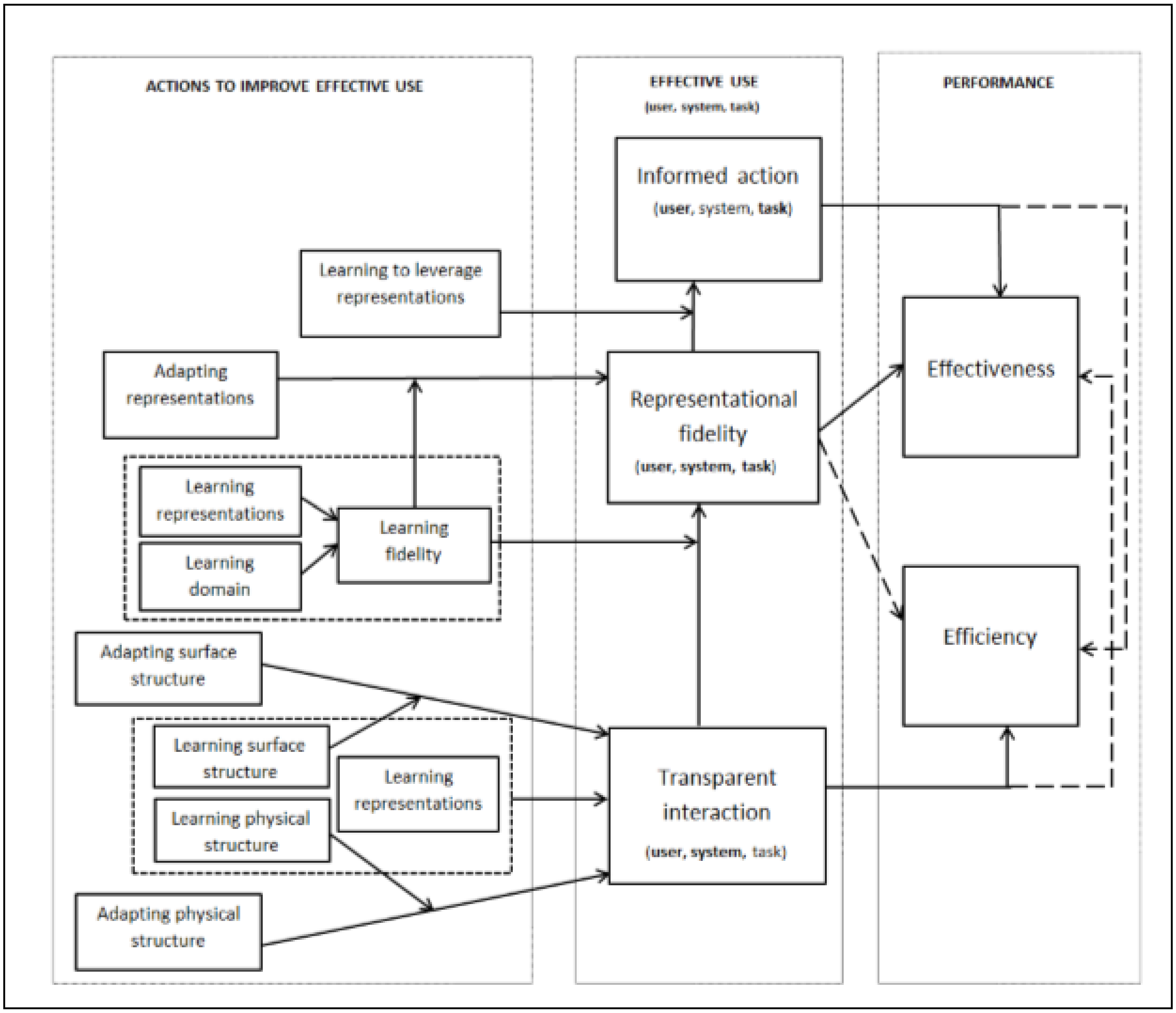

Figure 2.2: Simplified Theory of effective use (Burton-Jones and Grange, 2013)

Learning is referred to as any act a user takes to understand: a) the domain it represents; b) the system's surface, representation and structure; c) faithful representation of domain (fidelity); d) how to leverage the system in a more informed acts (Burton-Jones & Grange, 2013). Learning actions are important to system use as they moderate the link between variables of effective use and adaptation actions. Constructs of effective use were defined as follows: 1) representational fidelity, "the extent to which users obtain representations from the systems faithfully reflecting the domain being represented by the systems' surface and physical structures". 2) Transparent interaction; refers to how users access the system's representations unimpeded by the systems' physical structures and surface. Burton-Jones and Grange (2013), assert that effective BI users can retrieve content from the system that is clear, meaningful, and complete and correct since representation fidelity is measured based on consideration of users' needs.

2.3.2 Business Intelligence Evaluation Framework

The tool was developed by Ghazanfari, Jafari, & Rouhani (2011), to measure the capabilities of BI systems. The tool was recommended for business enterprises, and systems that could be used to facilitate companies in achieving competitive advantage by providing better decision support. The tool established six (6) factors to be considered for the evaluation: "Analytical and Intelligent Decision-support", "Optimization and Recommended Model", "Experimentation and Integration with Environmental Information", "Enhanced Decision-making Tools", "Reasoning", and lastly "Stakeholder Satisfaction", Ghazanfari, Jafari, & Rouhani (2011).

	Factor name	Criteria
F1	Analytical and Intelligent Decision-support	Visual graphs, Alarms and warnings, OLAP, Data mining techniques, Data warehouses, Web channel, Mobile channel, Intelligent agent, Multi agent, Summarization, E-mail channel
F2	Providing related experiment and integration with environmental information	Group sorting tools and methodology (Groupware), Flexible models, problem clustering, import data from other systems, Export reports to other systems, Combination of experiments, Situation awareness modelling, Group decision making, Environmental awareness,
F3	Reasoning	Financial analysis tools, Backward and forward reasoning, knowledge reasoning
F4	Enhanced Decision-making tools	Fuzzy decision-making, MCDM tools
F5	Stakeholders' satisfaction	Stakeholders' satisfaction, Reliability and accuracy of analysis
F6	Optimization and recommended model	Optimization techniques, learning technique, Simulation models, Risk simulation, Evolutionary prototyping model, Dynamic model prototyping, Dashboard/recommender

Table 2.1: Business Intelligence Evaluation Framework (Ghazanfari, Jafari, & Rouhani, 2011).

Ghazanfari, Jafari, & Rouhani, (2011) assessment of big business systems with BI is pivotal to the formation of decision-support networks in a business association, therefore, organizations need to assess those BI specifications of the system, which can enhance decision support systems. Their results deduced that organizations ought to assess their BI frameworks so as to improve decision-making and consequently improve the performance of the association.

2.3.3 ERP Benefits Framework by Shang and Seddon's (2000).

BENEFIT DIMENSION	BENEFIT CATEGORIES
1. OPERATIONAL	1.1 Cost reduction 1.2 Cycle time reduction 1.3 Productivity improvement 1.4 Data quality improvement 1.5 Customer services improvement
2. MANAGERIAL	2.1 Better resource management 2.2 Better decision making 2.3 Better performance control
3. STRATEGIC	3.1 Supports current and future business growth plan 3.2 Supports business alliances 3.3 Supports business innovation 3.4 Supports cost leadership 3.5 Supports product differentiation 3.6 Supports external linkages 3.7 Enables world wide expansion 3.8 Enables ebusiness
4. IT INFRASTRUCTURE	4.1 Increased business flexibility 4.2 IT cost reduction 4.3 Increased IT infrastructure capability
5. ORGANIZATIONAL	5.1 Supports business organizational changes 5.2 Facilitate business learning and broaden employee skills 5.3 Empowerment 5.4 Changed culture with a common vision 5.5 Changed employee behaviour with a shifted focus 5.6 Better employee morale and satisfaction

Figure 2.3: ERP Benefits Framework by Shang and Seddon's (2000)

The framework categorized different benefits organizations can benefit by leveraging on ERP system's capabilities, from a management viewpoint. Operation: ERP systems enable process changes and automation of business processes.

Managerial: ERP systems provide information to managers through their database and built-in capabilities of data analysis. Strategic: ERPs provide companies with an opportunity of achieving competitive advantage by customizing services and products for individual customers at a cheaper price. There are three conventional methodologies IT could be used to accomplish an upper hand: differentiation, cost leadership, and focus (porter & Miller, 1985). IT infrastructure: these presents the reusable and sharable ERP (IT) resources. Shang and Seddon considered ERP architecture and applications as a) business flexibility for future changes, b) economic implementer of new applications and c) reduced cost of business units. Organizational: ERP are seen as systems affecting the foundation of organizational capabilities.

2.3.4 Technology-Organization-Environment Framework

Specialists have realized the significant components, of IT project deployments, from non-deterministic hypotheses, which take a gander at the environment, technology and organization and how they impact its adoption, usage and organization ventures. Such hypotheses incorporate Porter Five Forces and Technology-Organization-Environment (TOE) framework as identified by Opoku et. al., (2016). DePietro, Wiarda, & Fleischer, (1990) Suggest that the procedure by which a firm embraces and actualizes technological innovations is impacted by the technological setting, the organizational setting, and the ecological setting.

Technological context/characteristics

Tornatzky and Fleizcher (1990), asserts that for an organization to embrace a creative innovation the setting of both the inner and outer technologies is critical. Baker (2012), in a comparable view clarified that these technologies are not just restricted to those that are currently utilized by the firm yet additionally those that are obtainable commercially even where the firm does not productively utilize them right now. Tornatzky and Fleizcher, (1990), emphasize that "Technology is *knowledge embedded tool* and *is a mixture of social/behavioral elements and physical elements."* It is significant, therefore, that human beings understand a particular technology before they start using it. Relative advantage is a significant determinant that can impact a firm or an organization decision to execute a given technology. Being alert and receptive to emerging technologies enables organizations to join technological headways and hence venture ahead of their rivals to gain an upper hand. At the point when a firm is portrayed as a higher level of technological advantage, it is proactive to improve itself consistently. Such a firm has the capacity, abilities and accumulated knowledge to gain information about technology chances and invest (Sabwa, 2013). Be that as it may, Chandy and Tellis (1998) contemplated that an organization with great innovation detecting capacities may not be willing to react to new technologies as they may tear apart existing products, markets, and organizational connections. Over the top intricacy of an innovation is likely to block its execution or deployment. The most prominent technology-related factor influencing IS adoption and post-adoption behavior is perceived usefulness. Complexity and relative advantage were considered in the study.

Organizational context

This delineates the size, degree, and regulatory structure of an association and its internal resources. Despite the depiction of the constituents of the hierarchical setting are furthermore the interfacing structures that exist between workers similarly as intra-organizational procedures, the level of centralization of the firm, formalization, and the nature of its human resource (Opoku et. al., 2016). Earlier research finds that bigger organizations are frequently progressively well-furnished with assets and foundation to encourage innovation adoption, while small firms may experience the ill effects of resource destitution (Sabwa, 2013). Organizational size comprises of the association's assets, transaction volumes or workforce size. Further, huge organizations frequently have more progressive and differentiated assets, which add to organizational creativity. Opoku et. al., (2016) posit that if political conditions within a firm have standards supporting a change then advancement and technology deployment would be more probable. Thus, espousing technologies that leverage on implemented ERPs e.g. Business Intelligence will rely upon whether backing from top administration is accessible. Given the constrained nature of organizational assets and the many contending ventures, top administration backing guarantees that an ERP project gets the vital assets and capacities to leverage on its adoption. In estimating the organizational setting, two elements were utilized: organizational size and top administration support.

Environmental context

Any firm's operating environment will be regulated by a government and may have several other competitors in a similar industry according to Opoku et. al., (2016). The environment likewise consolidates the market structure and its attributes. Ecological setting identifies with encouraging and repressing variables coming about because of outside conditions and huge components incorporate competitive pressure, trading partners' readiness, and government strategies. Rivalry improves the probability of innovation reception as ecological vulnerability brought about by rivalry helps increment both the need and pace of innovation appropriation (Sabwa, 2013). Competition may drive down an industry's profit potential depending on two factors; the force with which organizations compete and, the premise on which they compete. The force of contention is most prominent if contenders are many or have generally equal size and power. Opoku et. al., (2016) further suggests that an organization's performance is estimated or judged by a client's convictions about service delivery that fill in as principles or reference focuses. Further they reckon that the fear of losing clients rouses a firm to deploy certain innovative services to retain them. For instance, a firm may want to deploy a “bolt-on” like a CRM or mobility to enhance its customer’s experiences. As for environmental elements, the research considers competitive pressure and clients’ expectations

2.4 Empirical Review

Bingi et al. (1999), suggests that the process of introducing the ERP system is relatively complex and moderately unpredictable. Organizations should initially have an unmistakable prospect of accessible assets and future visions. They additionally should comprehend what impacts and qualities will rise once the ERP is introduced and consider if these yields will match their future visions and objectives. To achieve such benefits business process reengineering may be necessary. The productivity of an ERP may not be self-evident making its introduction in an organization relatively risky. Therefore, once introduced, how to manage it to fully accomplish its expected performance becomes critical.

There is a paucity of research on the topics of leveraging the benefits of an ERP implementation (Wanjohi, 2016; Fosser et al. 2008; Nguyen et al. 2015). The existing insufficiently treat the issue of leveraging on implemented ERP systems’ capabilities and extended capabilities in a relatively simplistic manner. Antoniadis et al. (2015) investigates the pivotal variables influencing the fruitful adoption and implementation of ERP systems, the advantages derived in utilizing them, and the significance of the Business Intelligence capacities that are typified in an ERP system. They further contend that despite the significance of these systems (ERPs), the implementation and leveraging of the advantages stemming from the use of these systems is still a struggle. Some argue that it is not the actual implementation of ERPs that drives a competitive edge and better performance, but the interaction of the ERP system with other organizational resources. Fosser et al. (2008) argues that the real value of an ERP system is in the way managers exploit it rather than the system itself. Nguyen et al. (2015) focus on the interaction of ERP implementation with other organizational resources (organizational learning capacity and intellectual capital) to create benefits. Whereas the implementation of the system would not be enough on its own the full leveraging of the implemented system is completely dependent on the environment in which the system operates. Akin to this is the position adopted by Fosser et al. (2008), in developing their hypotheses on competitive advantage where they argue that we utilize the asset-based view to characterize competitive advantage, expanding on two essential suppositions: the assets and the abilities controlled by competing firms may vary- "asset heterogeneity" - and these distinctions might be long-lasting - "resource immobility".

The ERP post implementation success was cited to be “a continuous improvement process” (Wanjohi, 2016). Nguyen et al., (2015), further contend that the there's requirement for nonstop “improvement of the organizational contextual environment” videlicet; Project Management, System Configuration, Leadership Involvement, Organization Fit, ERP Vendor support, ERP Consultants and Trading Partners. Key strategic assets have the attributes of “rareness, value, blemished imitability, and non-substitutability” that help firms to hold focused positions. As needs be, on the grounds that IT items are contended to be a commodity, for IT assets to wind up being valuable firm-explicit resources, they should be joined with other organizational assets as well as abilities to prompt positive effects and better organizational performance. Effectively to leverage the ERP systems, corporates must deliberately synergize their resources – and not only in the implementation stages - towards this.

Nguyen et al. (2015) further argues that the organizational effect of executing a solitary module is probably going to be lower than a progressively far reaching usage, paying little heed to how effectively the association completes its execution. Subsequently the extent of ERP usage mirrors the degree to which ERP frameworks are diffused inside an organization and its business forms and has three measurements: “breadth, depth, and magnitude”. The expansiveness of execution shows the degree to which the usage of the system and business process reengineering (BPR) is diffused on a level plane across the organization. The quantity of business units, the quantity of locales that are incorporated by the system and BPR exercises, among others, are instances of this measurement. The profundity of usage alludes to the degree to which the implementation of the system and BPR is diffused vertically in the association. This measurement can be estimated by surveying the quantity of clients of the system and the quantity of employees whose exercises are changed due to BPR. The extent of ERP usage speaks to how much the framework changes “employees’ work and business processes”. This can be surveyed by multiplying the percentage of exercises reengineered with the degree of alteration they were exposed to.

According to Nguyen et al. (2015), the capacity of an organization to use the capability of an ERP execution is dictated by encouraging elements. These encouraging elements are other resources necessary to enhance the intrinsic potential of an ERP. In their case they focus on two resources; the “organizational learning capability (OLC) and intellectual capital (IC)”. Fosser et al. (2008) broadly categorize the factors into four domains; “competitive advantage, organizational capabilities, system foundations and processes”. ***Competitive advantage*** incorporates discoveries concerning advantages and disadvantages of ERP systems, what has been named the " common system paradox " and discoveries concerning whether ERP systems have affected the advantage**.** ***Organizational capabilities*** are to be comprehended as facilities that research has demonstrated should be available to accomplish competitive advantage with an ERP usage. These incorporate managers' information of the organization and the ERP framework, top administration backing, open and adaptable culture, training, learning (bricolage) and correspondence just as a business equipped IT/IS division and organizational structures and procedures. A ***systems foundation*** incorporates the execution and utilization of the system and incorporates subjects, for example, innovative use, extraction of data and expansions or alleged " bolt-on " to the system***. Processes*** incorporate arrangements for accomplishing competitive advantage, managing obstacles experienced including acceleration of assets, concentrating on the future and the managers' process generally

From these theories, we construe that the following influences the appropriation of tools that leverage the ERP implementations; context (TOE), individual (TAM) and estimated against the advantages or potential challenges it will give. This mostly identifies with Diffusion of Innovations model (Rogers, 1995, 2003 and Sabwa, 2013).

2.5 Conceptual Framework

A conceptual framework includes shaping ideas regarding relations between factors in the research and demonstrating the relationships diagrammatically, according to Mugenda and Mugenda, (2003). The study adopted Business intelligence evaluation framework tool by (Ghazanfari, Jafari, & Rouhani, 2011) for the independent constructs and Simon (1977) classification of decision-making for the dependent variable.

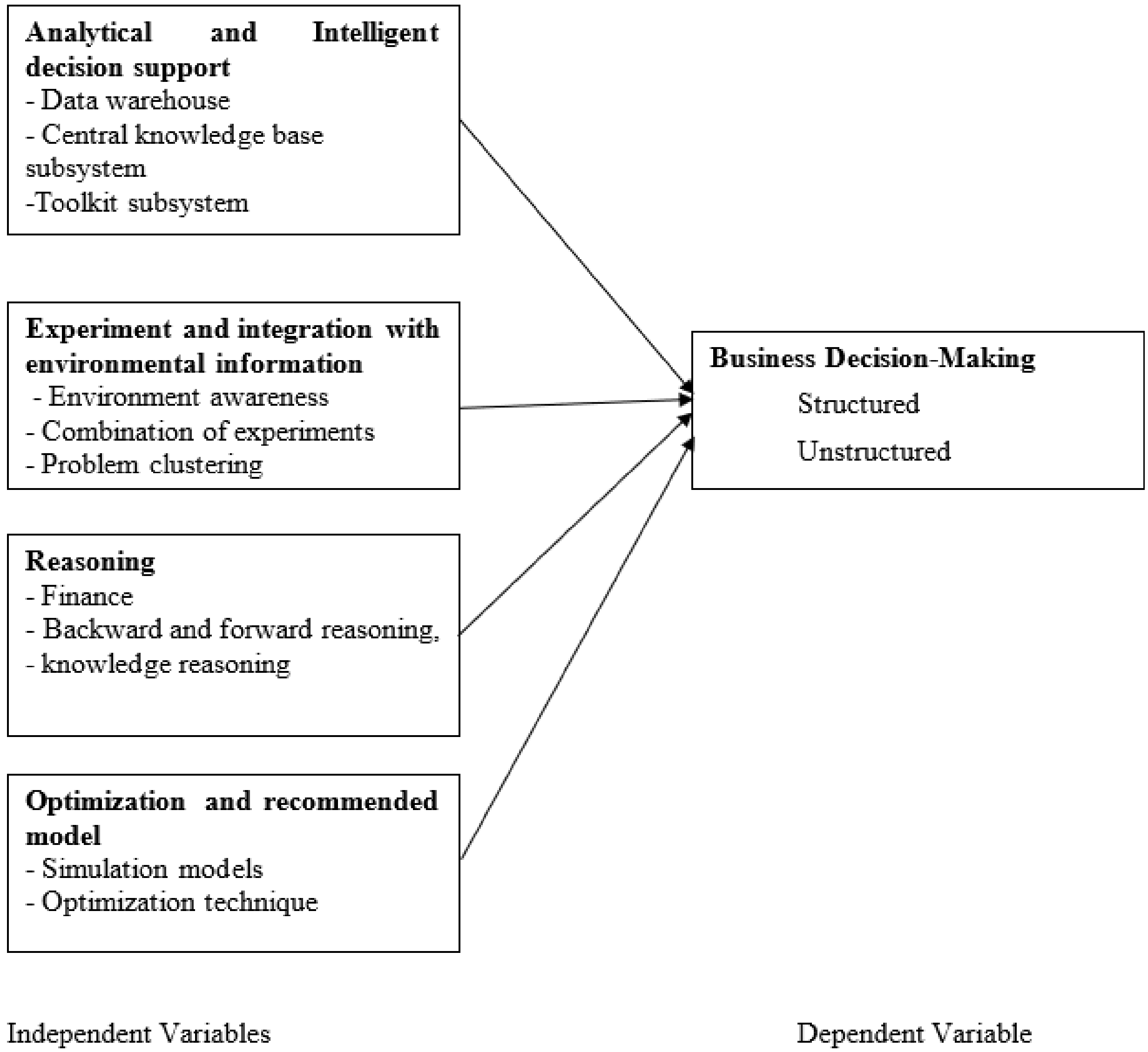

Figure 2.4: BI Evaluation Framework (Ghazanfari, Jafari, & Rouhani, 2011)

Analytical and Intelligent decision support

Ralph and Eric describe DSS as computer-based frameworks helping decision-makers resolve poorly organized issues through direct interaction with information and analysis tools. BI-DSS is composite group decision problem based. Wei, Xiaofei, Lei, Quanlong, & Hao, (2001), classified BI-DSS (Business Intelligence group Decision Support System) into three categories: toolkit, data warehouse, and Central knowledge subsystems.

Data warehouse: the major objective is to stock and sustain big amounts of data meant for all types of applications. Data warehouse: define physical storage pattern, define metadata including its semantic meaning, maintenance of data, integration and display data by visualization method. The information maintained in the DW must be accurate, timely and actionable, these must also be supported by how organizations make decisions, e.g. use facts and intuitions.

Central knowledge base: stores and maintains different knowledge that decision reasoning instruments need. Its main objectives are; define structure including logical structure and knowledge storage pattern, explain knowledge and reasoning results with visual data and discover hidden knowledge in data. Central knowledge base expands with time periodically.

Toolkit subsystem: Provide users with data analysis and decision support apparatus e.g. OLAP traditional reasoning tools and decision function objects. Decision function objects assist users make conclusions with the information and knowledge from knowledge base and data warehouse. Online analytical processing (OLAP) is defined as a software technology enabling executives, analysts and managers conduct multidimensional analysis of data in a consistent, fast, and interactive manner (Karacapilidis, 2006).

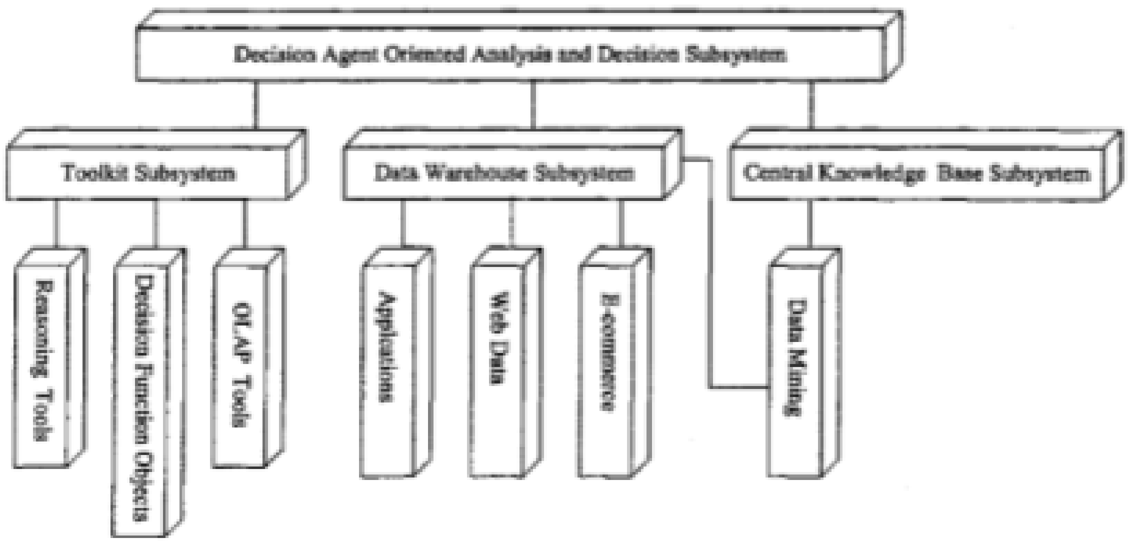

Figure 2.5: Architecture of BI - Group DSS (Wei, Xiaofei, Lei, Quanlong, & Hao, 2001)

Provide related experiment and integration with environmental information

Statement of Financial Accounting Standards (SFAS), environmental information is a comprehensive analysis of the information report related to policies, strategies, costs, pollution effects of regulation and future actions to respond to environmental issues given to firms for decision making purposes. For a system to be denoted as the environmental database, the database has to store the environment data and has to fulfill the following conditions: 1) the majority of data are environmental, 2) the database system is used for the storage of environmental data and 3) the database is established as the basis for environmental uses and inquiries (Voigt 1998).

Environmental awareness: Nadj, Morana, & Maedche, (2015), referred to environmental awareness as the situation awareness, which gives strong basis for comprehending the operations and decision-making of businesses in a dynamic and complex situation. Decision makers are able to make informed and time critical decisions thereby increase the business processes.

Combination of experiments: Combination of data, information, data sources and experiments can sometimes overwhelm the decision makers, and therefore a suite of systems are required for interpretation. This helps decision makers produce comprehensive decisions, which are more grounded than those retrieved from single sources.

Problem clustering: Gives the best possible alternatives and solutions that are suitable, feasible and flexible to a situation.

Reasoning

Krieger, Kiefer, and Declerck, (2008), define reasoning as the integration of semantic web and human etymological technologies, combining declarative rule-based methods and statistical approaches for knowledge acquisition. Time is a critical factor and the information is automatically extracted from unstructured and structured documents using information extraction system. Krieger et al., measured BI reasoning into three domains: Finance, Internationalization and operational risk management.

Finance: development and validation of next generation BI solutions, with a reference to credit risk management. *Internationalization*: development and validation of international platforms.

Operational risk management: development and validation of semantic-driven knowledge system for estimation and alleviation tools to operationalize risks faced by organizations.

Forward reasoning: the system uses the initial facts to exploit rules to make conclusions or take an action (data driven approach).

Backward reasoning: the system tries to ascertain the goals in the goal stack by finding rules concluding the information required and attempts to satisfy the “ifs” of those rules (goal-driven approach) (Karacapilidis, 2006).

Lang, and Toussaint, (2010), for intelligent agents to act autonomously, they need to learn how the environment works and secondly, they have to use the knowledge acquired efficiently to choose on which actions to take to attain the goals and fully utilize on the expected results. Their results showed that bidirectional probabilistic reasoning led to more efficient and accurate planning compared to pure forward reasoning.

Optimization and recommended model

Enhanced decision-making involves creating and applying both descriptive and optimization models. The integration of BI systems and models are motivated by the senior managerial needs to raise the KPIs set by the BI system in a decision-making environment.

Simulation models: decision-makers normally use simulation tools to accurately predict the performance, new policies, and practices before the implementation. The model transforms huge real data into timely and accurate information for decision making (Telhada, Sampaio, Pereira, & Carvalho, 2012).

Optimization techniques: BI technique for the dynamic and optimal decision making in todays' world (Prem, & Karnan, (2013).

Business Decision-making

Better decision making in the organizations can enhance the organization's revenue, reduce its unnecessary costs and improve its goals and objectives. Decision-making is the method of examining and progressing alternatives in order to derive a decision or solution to a problem (Kopáčková, & Škrobáčková, 2006). Managers are encouraged to use the following techniques and principles for better decision making: Increased knowledge, De-bias judgement, be creative, use intuition, don't overstress the finality of the decision and make sure the timing is right. The adoption of business intelligence technology is seen as an agent of influencing decision making in the study by (Khan, Amin & Lambrou, 2010). BI gives management executives with refined useful information for better decision making on management, planning and decision making of the company. For one to understand decision-making, one is required to understand the importance of information and the knowledge or insight processed according to the information given. Šuman, Gligora Marković, and Jadro, (2014) referred to knowledge management as the distribution and assembling of knowledge and acquiring new knowledge as methods of collecting and analyzing data and the information. Managers with the required knowledge can use the BI analytical tools and decision support software to adjust the business situation and strategic decisions. These help them acquire enough knowledge for the performance of business functions and objectives. Simon (1977) classified decision-making as programmed and non-programmed decisions. Programmed decisions are repetitive and routine and a routine procedure is worked out to handle the problems. Non-programmed decisions are unstructured and consequential, and deal with problem solving.

Structured / Operational decisions	**Unstructured / Strategic decisions**
How is BI used in structured / operational decision making?	How is BI used in unstructured / strategic decision making?
What kind of BI is used in structured / operational decision making?	What kind of BI is used in unstructured / strategic decision making?

Table 2.2: Decision Analytical framework (Shollo, (2011, September)

2.6 Operationalization of Variables

Variables	Indicators	Meaning	Authors
Analytical and Intelligent decision support **(Independent V.)**	Data warehouse	Maintain and store big data and display data by visual method	Wei, Xiaofei, Lei, Quanlong and Hao, (2001)
	Central knowledge base subsystem	Store and maintain different knowledge that decision reasoning tools need. It used to discover new knowledge hidden in data.	Wei, Xiaofei, Lei, Quanlong and Hao, (2001)
	Toolkit subsystem	Provide users with data analysis and decision support tools	Wei, Xiaofei, Lei, Quanlong and Hao, (2001)
Experiment and integration with environmental information. **(Independent V.)**	Environment awareness	Assist managers adopt decisions faster, thus reduce decision making time.	Voigt (1998). (Evers,2008; Phillips-Wren *et al.*, 2004)
	Combination of experiments	Patterns for solving operational decisions	Ghazanfari, Jafari, & Rouhani, (2011)
	Problem clustering	Help in obtaining non-dominated solutions instead of a single solution	Recio, G., & Deb, K. (2013)
Reasoning	Finance	BI solutions providing accounting analytics with a reference to credit risk management.	Krieger, Kiefer, and Declerck, (2008)

	Back and forward reasoning	Also referred to as bidirectional reasoning. Learning the environment and using the knowledge acquired to achieve its goals	Lang, and Toussaint, (2010)
	Knowledge reasoning	Managing knowledge for the organizations for the purpose of better decision-making	Krieger, Kiefer, and Declerck, (2008)
Optimization and recommended model (Independent V.)	Simulation models	Tool used by decision-makers to accurately predict the performance new policies and practices before the implementation	Telhada, Sampaio, Pereira, and Carvalho, (2012).
	Optimization technique	BI technique for the dynamic and optimal decision making in todays' world.	Prem, and Karnan, (2013)
Decision making (Dependent Variable)	Unstructured	Also referred to strategic decision making and deal with problem solving.	Shollo, (2011); Simon (1977)
	Structured	Are repetitive and routine, also known as operational	Shollo, (2011); Simon (1977)

Table 2.3: Operationalization of variables

CHAPTER THREE

RESEARCH METHODOLOGY

This section displays the methodology that was taken to realize the study. The chapter traces the: research design, study's populace, test and examining methods, information gathering methodology, and information analysis.

3.1 Research Design

The study will utilize a clear cross-sectional review research structure. Kothari (2012) states that "descriptive research incorporates reviews and fact-finding enquiries of various types". These may include questionnaires and interviews. The research design is appropriate in depicting the attributes of an individual, or a group of individuals, for a situation where the researcher does not have authority over the variables (Kothari, 2006). The cross-sectional design enables specialists to make measurable inferences to more extensive populaces and permits the generalizations of the discoveries to genuine circumstances, thus expanding the outside legitimacy of the study (Chava and Nachmias, 2004). As per Mugenda (2008), descriptive study is utilized to recognize incongruities inside a community and the kind of mediations that a researcher could structure and execute to lessen such inconsistencies.

3.2 Target Population

This study targets all staff in the local logistics corporates – that have implemented a BI system - who directly interact with the BI systems. These employees include Senior Managers, Managers and Supervisory staff in the various departments in the organizations.

3.3 Sampling

The study will employ stratified convenience sampling technique to ensure that all types of logistics players are incorporated into the sample. Stratification will accomplish this by gathering the heterogeneous populace into homogenous subsets (per logistics type) to guarantee representativeness. Convenience sampling technique will be utilized to test individual corporates inside the stratum.

3.3.1 Sampling Frame

This is the "source material" or "gadget" from which a sample is drawn, it is a summary of all of those inside a populace who can be examined (Mugenda & Mugenda, 2003). This study adopted a survey method of collecting data.

Section	Target Population	Percentage
Managing Directors	18	8.7
Directors	18	8.7
Managers	50	24
Supervisors	100	49
Other management team	20	9.7
Total	**206**	**100**

Table 3.1: Sampling Frame

3.3.2 Sample Design

The following formulae as developed by Yamane (1967) and cited by Harper and Glenn (2013) in Determining sample size will be used.

$$n = \frac{N}{1 + N(e)^2}$$

Where n= sample size

N = Population size

e = level of precision

3.3.2 Sample Size

Section	Target Population	Sample Size
Managing Directors	18	17
Directors	18	17
Managers	50	44
Supervisors	100	80
Other management team	20	19
Total	**206**	**177**

Table 3.2: Sample size

3.4 Data Collection

Essential information will be gathered through organized surveys. The surveys will consolidate both unrestricted and restricted inquiries to assemble the research data. The survey will first be pre-tested on appropriateness, structure and relevance to the study. As indicated by Cooper and Schindler (2008), the questionnaire is advantageously utilized in light of the fact that it is less expensive and faster to administer, it is “over researcher’s effect and changeability”, and is exceedingly apposite for the respondents as they fill them during free times or when remaining tasks at hand are reasonable. The questionnaires will be self-administered lessening the measurement errors.

3.5 Data Analysis and Presentation

Deficiently filled surveys will be omitted from the record. Data collected will be both qualitative and quantitative. Hence, elucidating examination methods will be utilized; consistent with the research design. Quantitative data will be inspected to dispense with tremendous irregularities, abridged and coded for basic grouping so as to facilitate classification, tabulation, and elucidation. Enlightening insights will be used in delineating the sample data in such a way as to depict the characteristic respondent and to uncover the general reaction pattern. The data generated will be broken down utilizing PC supported programs such as Statistical Package for Social Sciences (SPSS) which offers comprehensive data handling capability and various factual investigation routines that can examine small to extremely huge information measurements. The Likert scale will be utilized in analyzing leveraging factors by positioning them in accordance with their weighted means. Tables, charts, and diagrams will be utilized in showing the analyzed data.

The following multiple linear regression will be used:

$Y= \beta o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + e$

Where:

Y= Business decision making

βo = Constant

X_1 = Analytical and intelligent decision support

X_2 = Experiment and integration with environmental information.

X_3 = Reasoning

X_4= Optimization and recommended model

e = error term

β_1, β_2, β_3, β_4 = Model coefficients which are significantly large to have significant influence on the model.

3.5.1 Qualitative Analysis

Qualitative analysis will be analysed using narrative analysis method (Riessman, 1993), while the analysis approach will be inductive, since the researcher knows very little about what the responses might be. Inductive analysis alludes to approaches that basically utilize detailed readings of crude information to infer ideas, topics, or a model through interpretations produced using the crude information by an evaluator or researcher. The reasons for utilizing an inductive methodology are to (a) gather crude literary information into a concise, synopsis group; (b) build-up clear connections between the assessment or research goals and the outlined discoveries got from the raw data; and (c) build up a system of the fundamental structure of experiences or procedures that are obvious in the raw data. Strauss and Corbin's (1998) assert this in their description of inductive analysis: "The researcher begins with an area of study and allows the theory to emerge from the data". We will use open coding to categorize the qualitative data manually. To maintain data anonymity, confidentiality and integrity, the respondents will be coded as required.

3.6 Reliability Analysis

Reliability analysis for this study will be done using Cronbach's Alpha (Cronbach, L. J., 1951). Cronbach's Alpha is utilized to gauge the internal consistency of the research instrument; that is, how closely related a set of items are as a group. According to Borsboom (2009), reliability is defined as the consistency of measurements within an instrument measuring the same thing. For the study to be reliable, the Alpha values must be above 0.6 for all variables under study in the study questionnaire.

3.7 Validity

According to Joppe, (2000), validity determines whether the questionnaire actually elicits the intended information, how truthful the research results are, and whether the research instrument genuinely measures what it is proposed to measure. Survey items are valid on the off chance that they are fruitful in inspiring genuine responses relevant to the information desired. If the response is to be valid, it is fundamental that the respondent comprehends the inquiry as it is comprehended by those conducting the survey, likewise, the respondent must have the capacity to respond; the person must have the data. On the off chance that the respondent does not have the data, a "don’t know" classification could still make the question valid. To measure the validity of the contents of research instrument, the researcher will use experts in this field to assess the concepts and whether they were valid to the research.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This section displays the analyzed data condensed in tables, pie-charts, and graphs in accordance with the research goals with the presentation and elucidation of the findings. Analysis of the data was undertaken with the aid of the Statistical Package for the Social Science (SPSS) version 24. Statistical analysis tests that contained both illustrative and inferential insights were utilized. The elucidations of the findings have been done to respond to the research questions and address the target of the research. The bio-information has likewise been examined and presented to elicit significant attributes of the respondents.

4.2 Response Rate

The research distributed 183 questionnaires in different logistics companies in Kenya presumed to be using BI capabilities in their everyday business making purposes. All 183 questionnaires were returned (100%). 151 (82.5%) respondents indicating that they use BI for their daily decision making in different logistic companies, while 32 respondents indicated they do not have any form of BI systems in their company. Therefore, the 32 questionnaires were not considered for the analysis.

Sample size	Number	Percentage
Total Sample size	183	100
Total Responses	183	100
Total Usable Responses	151	82.5

Table 4.1: Response rate

Source: Author (2019)

4.3 Reasons for using BI Systems

The reasons given by respondents for using the BI systems to support the daily work in the organizations include; management decision making, to enable Data mining that helps the management make more informed decision making by analyzing patterns and trends, for meeting standards requirements, for compliance and continuous improvement, BI assists in costing and revenue optimization, BI enable organizations to measure the level of customer satisfaction based on certain milestones, better business experience, it offers defined corporate reporting structure, help with better decisions, efficient in management of operations and decision making, easier information storage and retrieval, it bridges distance between the company and its clients thus widening market, the system is needed for financial management, fleet management is made easier with intelligent systems, it fastens solving of complex equations and forecasting of pattern, easy in monitoring the cargo, fast preparation of documents and monitoring of flight services, saves time and workload, efficient and convenient in monitoring of information, useful in generating reports and checking company success, better service delivery, help in achieving the daily objective/chores, the system aid the organization in determining future trends using historical data, frequent notification of schedules, it aids in establishing a distributed system thus easy sharing of information with the company, it has to a large extent eliminated the problem of duplication of information, it organizes information in a systematic pattern thus trends can easily be extracted and finally it increases the market share of the company.

4.4 Years in the logistic company

The study wanted to find out the number of years each respondent has spent working in the company in which they are. It was established that the majority 57.6%, have worked in their respective companies for less than 6 years closely followed by 37.1% who have worked between 6 to 10 years. The least represented by 0.7% have worked between 16-20 years and those who have worked for over 25 years. A visual representation of the output is demonstrated in table 4.2 below.

How long have you been in your current organization?

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 6 years	87	57.6	57.6
	6-10 years	56	37.1	37.1
	11-15 years	4	2.6	2.6
	16-20 years	1	.7	0.7
	21-25 years	2	1.3	1.3
	Above 25 years	1	.7	0.7
	Total	151	100.0	100.0

Table 4.2: Years in logistics company

Source: Author (2019)

4.5 Functional Area

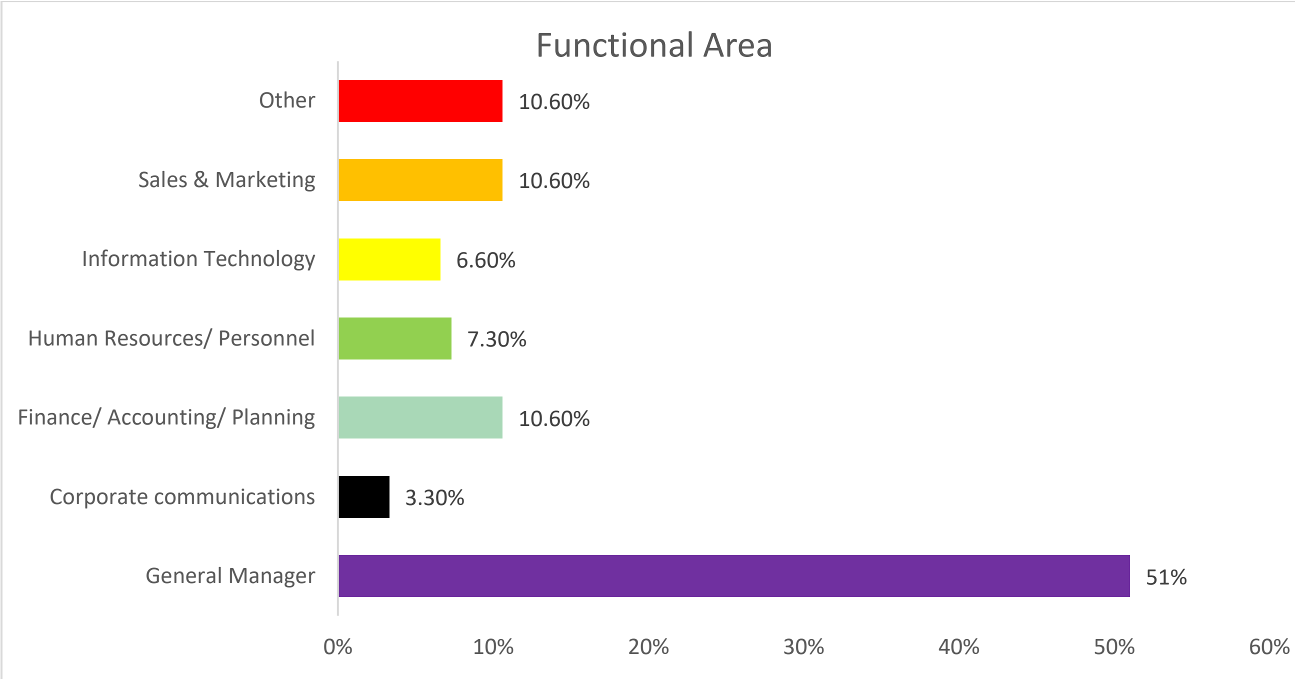

Figure 4.1: Functional Area

Source: Author (2019)

The analysis output on the key functional area of the respondents showed that 51% of the respondents are general managers in their respective organizations, 10% from sales & marketing, finance/ accounting/ planning departments and 10% others came from Strategy, Audit & Risk, Cargo handling, Clearing & Forwarding, Warehouse management, Operational and Fleet management departments. Corporate communications functional area had the least representation of 3.3% which was closely followed by information technology at 6.6% and human resources/personnel at 7.3% as summarized in table 4.3 above.

4.6 Functional area and position in the organization

What is your functional area? * What is your position in the organization? Crosstabulation

Count

		What is your position in the organization?						Total
		Director	Executive Management	Middle Management	Operational Management	Supervisors	Other, Specify	
What is your functional area?	General Management	1.3%	2.7%	6%	35.8%	4.6%	0.6%	**51%**
	Corporate Communications	0	0	1.3%	0.7%	1.3%	0	**3.3%**
	Finance/Accounting/ Planning	0	0	6%	2.6%	0.7%	1.3%	**10.6%**
	Human Resources/Personnel	0	0	4.6%	2.7%	0	0	**7.3%**
	Information Technology	0	0.7%	1.3%	4%	0	0.6%	**6.6%**
	Sales & Marketing	0	2.2%	0.6%	6.6%	1.2%	0	**10.6%**
	Other, Specify	0	0.7%	1.2%	5.3%	1.3%	2.1%	**10.6%**
Total		**1.3%**	**6.3%**	**21%**	**57.7%**	**9.1%**	**4.6%**	**100%**

Table 4.3: Functional area and position

Source: Author (2019)

The study carried out a cross-tabulation analysis was carried out to establish the relationship between the functional area and the position of the respondent in the organization in which they work. As demonstrated in table 4.3 above, operational management had the highest representation of 57.7% out of which 35.8% are from general management functional area, 0.7% from corporate communications, 2.6% from finance/ accounting/ planning, 2.7% from human resources/personnel, 4% from information technology, 6.6% from sales & marketing and finally 5.3% from clearing & forwarding and cargo handling functional areas. Other information on the position and functional area of the respondents are as shown in table 4.3 above.

4.7 Types of Business Intelligence (BI) systems in use.

The study, while seeking to establish the commonly used BI system found out that data warehouse system had the highest number of users at 30.5% followed by information portal at 24.5% and corporate reporting system at 19.9%, 18.5% of the respondents indicated that they are using other types of BI system. The analysis found out that out of this 18.5%, 6.3% use enterprise data input system, another 6.3% use revenue collection system, 1.3% use a combination of Corporate reporting system & Information Portal, 0.7% use a combination of Data-warehouse & Information Portal, 2.6% use a combination of Corporate reporting system & Data-warehouse, 0.7% use a combination of Corporate reporting system, Information Portal, Corporate Dashboard & Decision support system and a final 0.7% use a combination of Corporate reporting system, Information Portal & Decision support system. This is summarized in figure 4.2 below.

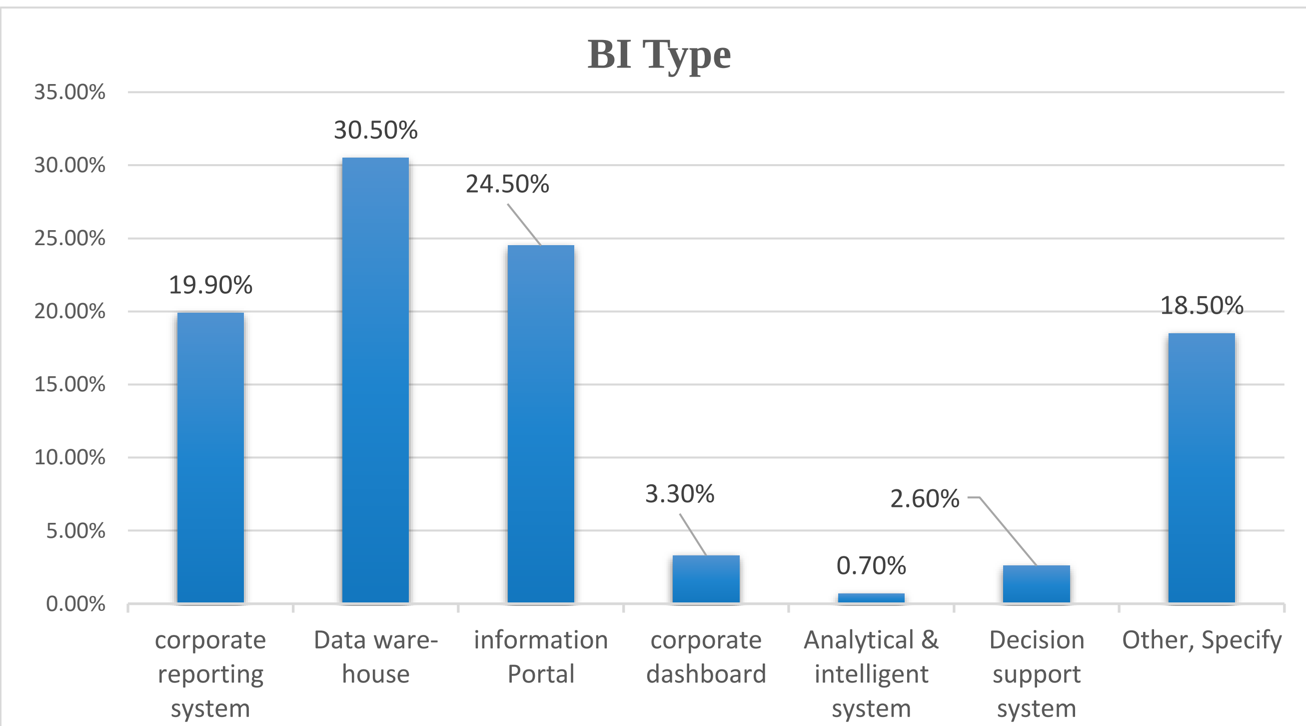

Figure 4.2: BI System Type

Source: Author (2019)

4.8 Evaluation of Analytical and Intelligent decision support (AIDS)

The study sought to find out the percentage response of analytical and intelligent decision support system used within the organizations. The results showed 53.6% of the respondents said that the system they use sometimes evaluates analytical and intelligent decision support, 42.4% indicated that their systems frequently, 2.6% rarely and 1.4% almost always evaluates the analytical and intelligent decision support as shown on figure 4.2 below

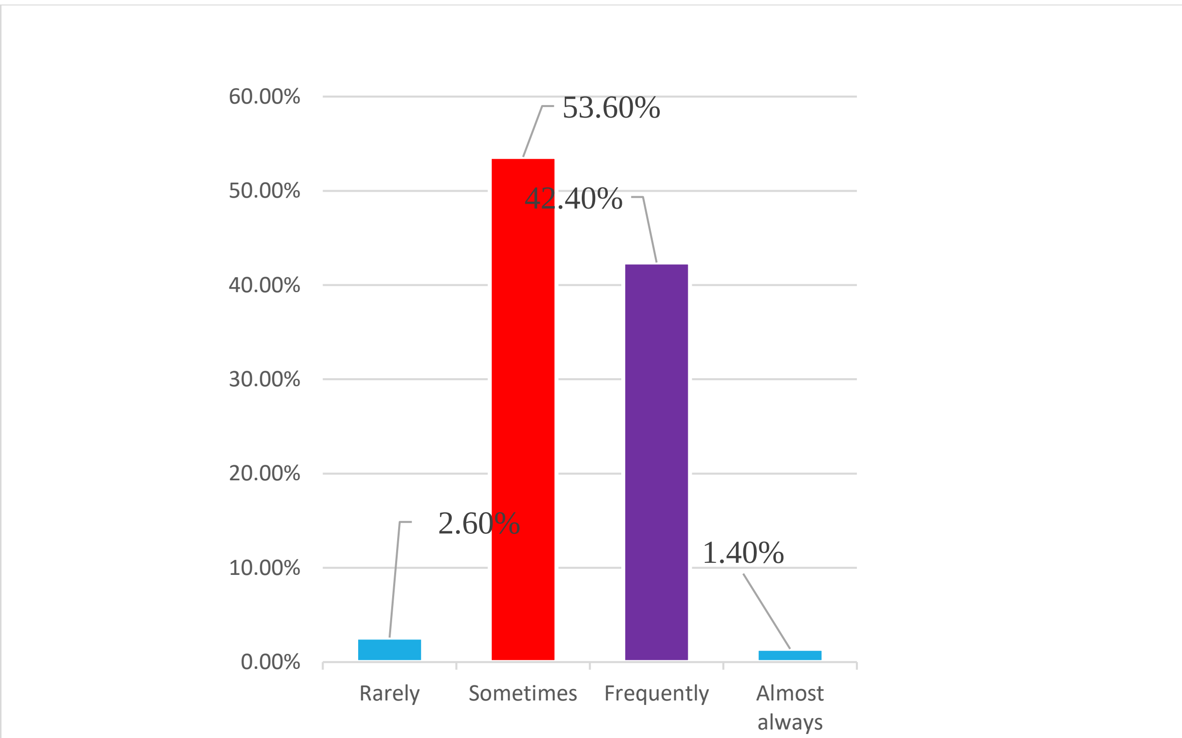

Figure 4.3: Analytical and Intelligent Decision Support (AIDS)

Source: Author (2019)

The study sought to identify the extent at which various indicators assists with the Analytical and Intelligent decision support (AIDS) in BI systems used in the companies under study on the operations of the organizations. For the organizations which use analytical and intelligent decision support, 49% of the users said that the system frequently offers accurate, actionable and timely data, 35.8% said that it sometimes reduces decision making time, 44.4% indicated that it frequently centralizes knowledge base, 46.4% indicated that it frequently leads to discovery of new/hidden knowledge in data, 29.8% said it rarely offers data analysis and decision support tools, 49.7% said that it frequently offers real time notifications of alarms and warnings a final 51% indicated that the system frequently offers multiple channels (email, mobile, web) as shown in table 4.4 below.

		AATD (%)	RDMT (%)	CKB (%)	DNKD (%)	DADST (%)	RNAW (%)	MC (%)
Valid	Almost never (1)	2.6	6.6	2.6	2.0	24.5	7.3	7.3
	Rarely (2)	6.6	15.2	2.6	2.0	29.8	11.9	11.3
	Sometimes (3)	19.2	35.8	35.8	19.2	23.8	9.3	11.9
	Frequently (4)	49.0	31.8	44.4	46.4	15.9	49.7	51.0
	Almost always (5)	22.5	10.6	14.6	30.5	6.0	21.9	18.5
	Total	100	100	100	100	100	100.0	100.0

Table 4.4: Analytical and Intelligent Decision Support (AIDS)

Source: Author (2019)

4.8.1 Challenges

The challenges that lead to low scores among the respondents who scored below 4 sited the following challenges; lack of access to the system, system not customized to my needs, Analysis done at the end, Challenge in data gathering, changing demands not reliable to portal information, changing events according to customer needs, data is captured and entered manually, data manipulation, decisions made are not timely, decision making is not based on the system, decision making is not based on the system, decision support is only tolerated to some extent, difference in markets for instance our challenges in Africa are way different from those of Asia Pacific...the

African market faces challenges in logistical deliverables due to bureaucracy from government making the continent the lowest in penetration of new technology, Different way of interpreting data by decision makers, there is difficulty in using the system, ease in data manipulation, failure to integrate all the data from other sources, feeding of data and analysis takes time, fetching data is not automatic, functionality not as per need, getting the right person with the right information is difficult, historical data misleads some time, inability to handle all business processes hence lack of sufficient information to make informed decision, integration of data with GIS information sometimes is hard, intelligence is missing, it is not user friendly, less automation, the system is less dynamic, limited data discovery, low speed of access to the portal, low speed of operations, mining of data is not enabled, can't work in areas where connectivity is a problem, poor user interphase and lack of proper management of BI in the organization.

4.8.2 Proposed Solutions.

The proposed solutions to the said challenges include providing access, customize to customer data that is not only focused on financials, customize to user needs, automation of data input, restrict data manipulations by use of passwords, secure the system, systems should be secured and not open to manipulation, upgrade of the system to enable easier decisions, understanding case flies from different markets for instance the signing of the African free treaty in 2017 by 44 countries in Africa would be essential in managing Africa's essentials logistical movement of goods, Train staffs on the handling of the system, automate data capture, system should be open to adjustments, employer and employee dialogue, get specialized applications and interface it with the core system, integrate location of cargo and shipment with Portal Geographic Information Systems, review the system for ultimate solution, improve its user friendliness, interface and notifications, upgrade the system to allow prediction, timely upgrade, having a system that can mine data for analyzing trend, backup on other forms of network connection, constant engagement with the service provider, notifications once new versions are generated, do more trainings for managers and supervisors in order to increase uptake, proper IT support, outsourcing should be integrated with the system, upgrade to a more effective systems (underway) and effective user training and monitoring of output, Design have various data can be used meaningful, include data manipulation, harmonization of BI system, have a 24hr emergency number for IT, develop portals that can adopt to congestion, periodic maintenance, incorporate other business demands, there ought to be a system that easily adopts to current trends for better analysis, develop an open system, generate a system that allow offline services, do more training and improve on the current BI and having a stronger and more agile system that is integrated with other platforms.

4.9 Evaluation of Experiment and integration with environmental information (EIEI)

While seeking to know the extent to which experiment and integration with environmental information system supports the various organizations that use it, the study found out that 64.9% of the respondents indicated that the system supports them to some extent, 19.2% said that the system supports them to a great extent, 11.9% to a small extent and 4% indicated that the system doesn’t support them at all. This is demonstrated in figure 4.4 below.

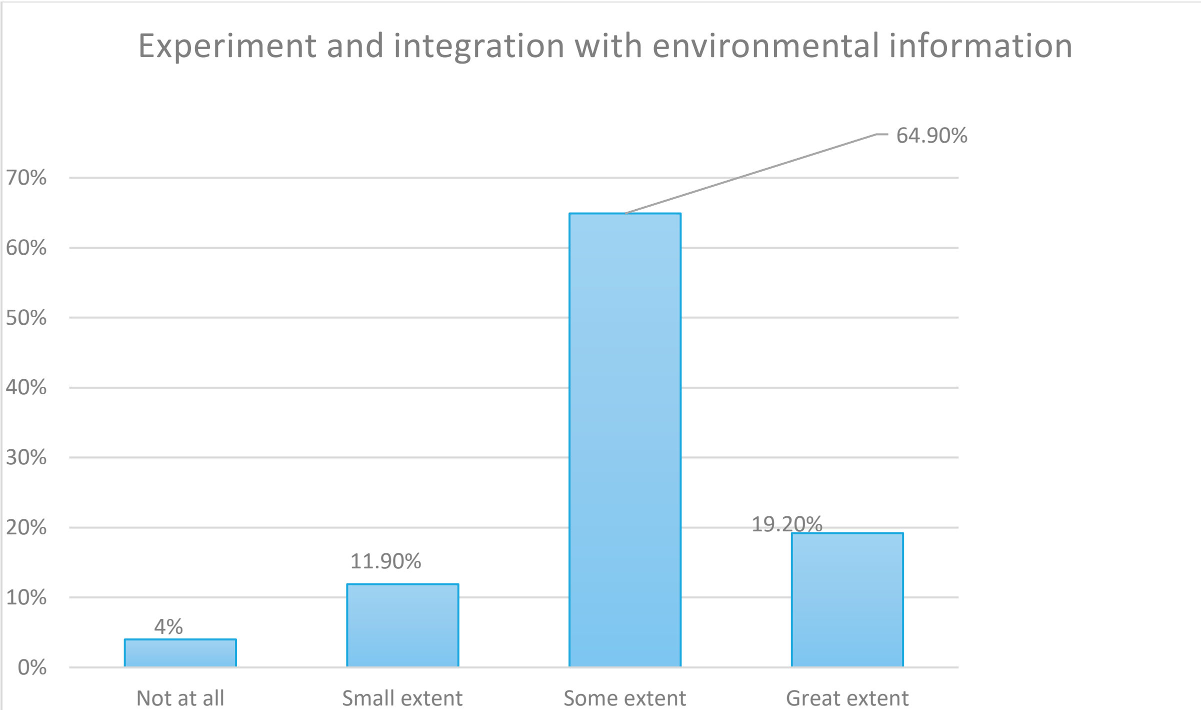

Figure 4.4: Experiment and integration with Environmental Information (EIEI)

Source: Author (2019)

The study sought to identify the extent at which various indicators assists with the Experiment and integration with environmental information (EIEI) in BI systems used in the companies under study on the operations of the organizations, the study found out that 51% of the respondents indicated that the system to a great extent supports corporate environmental awareness, 57% indicated that the system supports data importation from other systems, 58.9% indicated that the system is able to export reports to other systems. On the other hand, 47.7% of the respondents indicated that the system to some extent supports the combination of experiments, 42.4% indicated that the system supports situation awareness modelling and model flexibility to some extent and finally 48.3% indicated that the system supports clustering of problems to some extent as shown in table 4.5 below

		CEA (%)	IDOS (%)	EROS (%)	CE (%)	SAM (%)	FM (%)	CP (%)
Valid	Not at all (1)	7.9	2.6	4.0	10.6	17.9	22.5	17.9
	Small extent (2)	6.6	5.3	6.6	25.2	22.5	25.8	25.8
	Some extent (3)	17.2	23.8	16.6	47.7	42.4	42.4	48.3
	Great extent (4)	51.0	57.0	58.9	14.6	12.6	8.6	3.3
	Very great extent (5)	17.2	11.3	13.2	2.0	4.6	0.7	4.6
	Total	100	100	100	100	100	100	100

Table 4.5: Experiment and Integration with Environmental Information (EIEI)

Source: Author (2019)

4.9.1 Challenges

Some of the challenges faced by respondents on experimental and integration with environmental information system on the operations of the organizations were cited as follows; Integration of major systems is rather low e.g. link of warehouse operations in Nairobi and Mombasa synergize the processes, conversion of the data inherent in the system to information that can be analyzed for decision making, mostly done manually, the data is dependent on what the users key in, no modeling, compromised data compatibility, Government agencies do not compliment the logistics business in Africa, since I haven't been long in the organization at times its challenge to get historical data, poor support, duplication of data, less data integration, Management is not conditioned to the system as per the changing activities, records are generated daily and not timely, not conversant, reporting not easily carried out, a report has to be generated, lack of a clear way of integrating all data from all departments, generating reports takes time, system compromised by situations, report generation aren't real time, decision comes before system, the system does not operate separately, clustering of problems generated under complex scrutiny, data security not guaranteed as well as the inability of the system to generate models.

4.9.2 Proposed Solutions

The possible solutions to the above-mentioned challenges include; implementation of SAP system that can enable integration and mining of data, the system need more improvement in real time data interchange, link the two locations to encourage synergy, upgrade of current system to enable data analysis capability, increase interaction with external sites, have models of parallelizing included, the modern day governments must embrace technological changes and integrate all agencies into a similar platform that would save time and money to business models, include data mining as part of induction, the modern day governments must embrace technological changes and integrate all agencies into a similar platform that would save time and money to business models, address data redundancy, upgrade the system to allow easier reporting and that the system requires comprehensive data automation.

4.10 Reasoning

This shows how BI systems assist the users in reasoning. The study found out that 39.7% of respondents agreed that BI systems assist them to a great extent in reasoning, 39.1% to some extent, 11.9% to a small extent, 3.3% to a very great extent, while 6% “not at all” indicated that their BI systems do not assist them with reasoning. This is shown in figure 4.5 below.

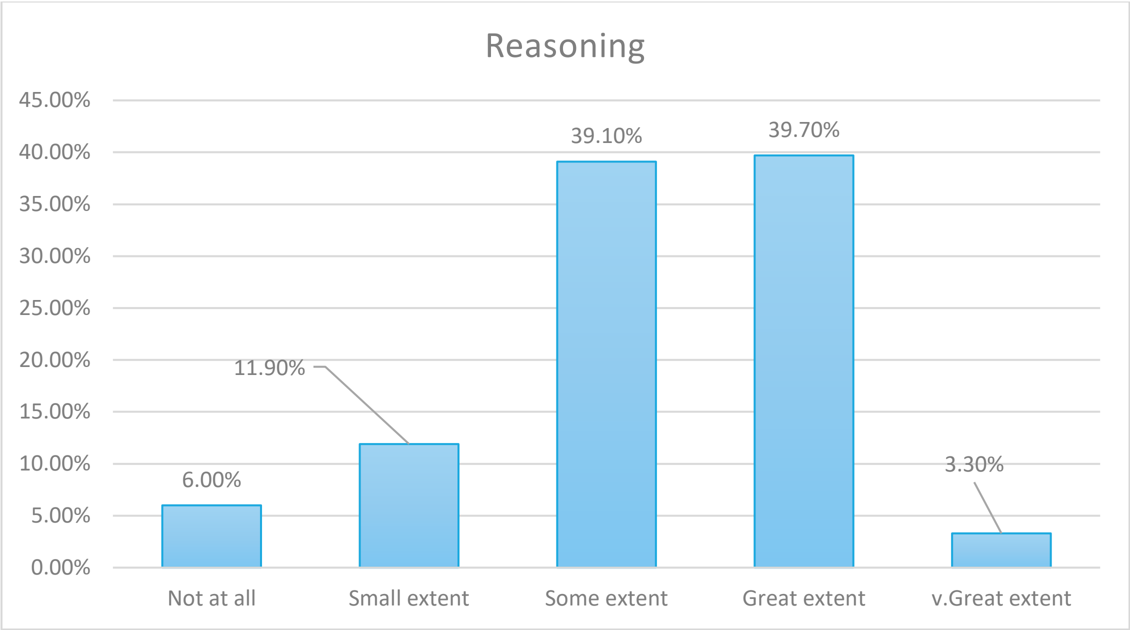

Figure 4.5: Reasoning

Source: Author (2019)

The research sought to discover the percentage response of BI reasoning as used within the organizations under study.

		FA (%)	BIDR (%)	KRGM (%)	KRPDA (%)	KRRI (%)	KRHR (%)
Valid	Not at all (1)	3.3	6.6	9.9	14.6	15.2	19.9
	Small extent (2)	6.0	12.6	12.6	12.6	17.9	17.9
	Some extent (3)	14.6	25.2	27.8	39.1	31.8	44.4
	Great extent (4)	43.0	49.0	44.4	30.5	29.8	15.9
	Very great extent (5)	33.1	6.6	5.3	3.3	5.3	2.0
	Total	100	100	100	100	100	100

Table 4.6: Reasoning

Source: Author (2019)

4.10.1 Challenges

The respondents when asked to explain the challenges they face that make them score less than 4 in the aspects of consideration above cited the following issues; too much raw data, Inferior/ outdated system, the system give information based on the data in the DBs, having division managers to use more available data to forecast future trends, system is too rigid, everything dependent on data keyed, the system doesn't collaborate with others, no forward focus in the system, poor extrapolation, not reliable for making decisions, difficulty in using the system, decisions are made at a managerial level, less analysis is carried out by the system, does not work well with incomplete indicators, reports have to be generated and integrated, less hybrid

Human resource department doesn't rely on model and simulations, it automatically creates a gap, inferences using probability not possible, goal model are generated but it’s hard to integrate with other companies, systems work with available data and finally the system cannot work on data using extrapolation.

4.10.2 Suggested Solutions to the challenges

The proposed solution to the challenges mentioned above include; enable the system analyze data, implement SAP, we need more predictive and also the one which compare the market trends, engage with the general managers to expose them to use of BI systems to improve planning, upgrade of current system as modules that can help achieve desired outputs are available, improve linking, customize the system to Collaborate with other systems, build work plans, upgrade of current system as modules that can help achieve desired outputs are available, upgrade of current system as modules that can help achieve desired outputs are available, better inferences, enable the system to predict, continuous use makes users adapted to the system, incorporate future analysis, make the system hybrid, goals can be made more dynamic, allow extrapolation, and finally allow data sharing, incorporate features in systems that can work with unknown indicators".

4.11 Optimization and recommended models

The study in trying to find out the extent to which BI assists in optimization and recommended models in various organization, 42.4% of the respondents said that the BI system assists to some extent in optimization, 31.1% indicated that the system help to a small extent, 19.9% indicated that the system helps to a great extent and 6.6% others said that the BI system they use does not assist in optimization and recommended models. This is as shown in figure 4.5 below

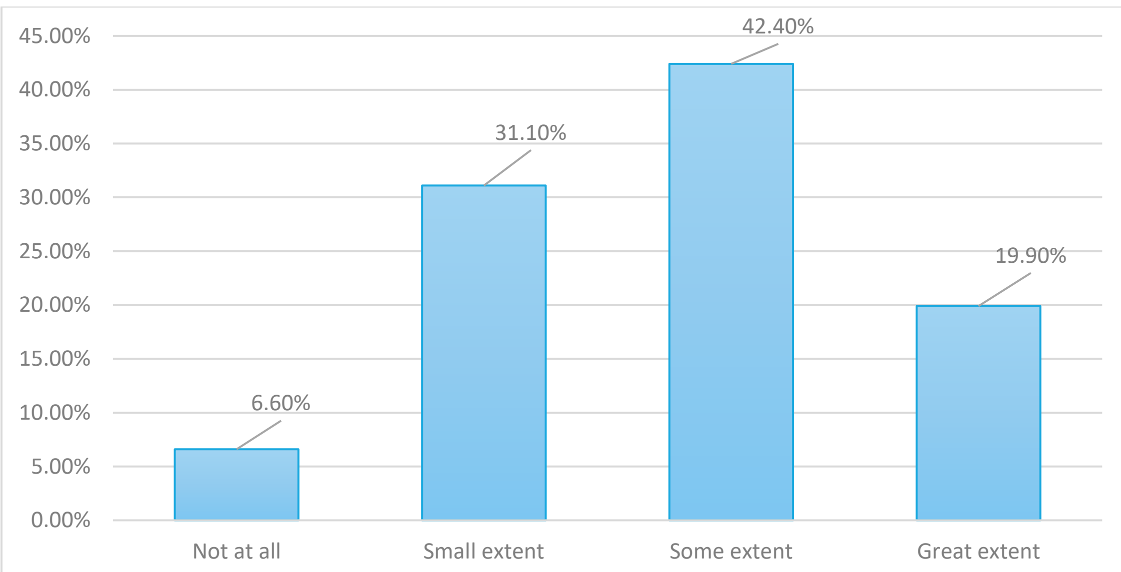

Figure 4.6: Optimization and Recommended Models (ORM)

Source: Author (2019)

The study while looking at the individual aspects that the system ought to assist in decision optimization found out that 43% of the respondents indicated that the system offers simulation models to some extent, 47% said that the system to some extent simulates business and environmental risks, 53% said that the system offers dynamic & evolutionary prototyping models to some extent, 35% indicated that the BI they use to some extent offers dashboards/ recommender platforms, 40% indicated that the system provides optimization techniques for forecasting and predicting the business performance to some extent and a final 37% indicated that the system to some extent provides learning capabilities as shown in table 4.7 below.

		OSM (%)	SBER (%)	ODEPM (%)	ODP (%)	POT (%)	PLC (%)
Valid	Not at all (1)	15.9	15.2	18.5	11.3	19.2	19.2
	Small extent (2)	25.2	19.2	18.5	18.5	21.2	23.8
	Some extent (3)	43.0	47.0	53.0	35.1	40.4	37.1
	Great extent (4)	13.2	18.5	9.3	31.1	13.9	18.5
	Very great extent (5)	2.6		0.7	4.0	5.3	1.3
	Total	100	100	100	100	100	100

Table 4.7: Optimization and Recommended Models (ORM)

Source: Author (2019)

4.11.1 Challenges to Optimization and recommended models

For those who scored below 4 in the analysis demonstrated in table 4.7 above indicated that the scores are as a result of limitation of the system, the current BI doesn’t offer the comparison and predictive analysis, the system is not responsive to change, there is no dynamic reporting, the system lacks learning models, the system allows for customization but has limitations on specialized operations, the system doesn’t have the ability to predict, decision making isn't reliable with this model, the system is confined, the system can’t model, trends in data easily change thus the system plays a small role in decision made by management, the system is not heuristic, simulation is not yet achieved, situations cannot be easily optimized by BI, the system is unable to use historical information in determining future trends, my organization does not execute simulation, business performance can only be determined after integrating data with other departments, some trends are hard to be determined as they are not consistent, simulation and modelling can't be achieved well using information portal, simulation models only generated at the end of a given period, system rigidity and finally, all model generated cannot optimize decision making.

4.11.2 Suggested Solutions

The proposed solutions by the respondents to the challenges listed above include; implement SAP and other systems, advance market analysis tool, carry out training, improve the response to changes, need for a system with dynamic dashboard presentation, have in-build future solutions, upgrade to the latest version or get specialized applications and interface, enable the system to carry out trend analysis, IS systems should be customized, incorporate both situations and business intelligence, the trends do no take a uniform change thus difficulty in modelling, design of a system that will be able to determine trends using uneven distribution, incorporate other business intelligence system, diversify the system to manage all aspects, improve the system to use the historical data to compute future trends and add other BI systems.

4.12 Decision making

The study sought to find out how frequently the respondents make decisions based on the BI system information or reports, it was established that 62.9% of the respondents frequently rely on the system, 18.5% sometimes, 8.7% almost always, 7.9% rarely and 2% almost never make decisions guided by the respective system as shown in figure 4.7 below.

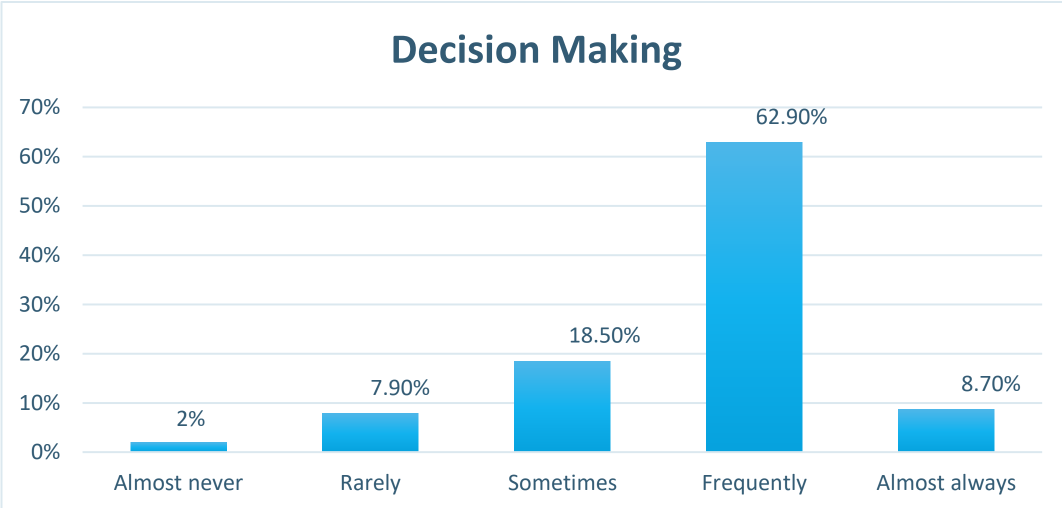

Figure 4.7: *Business Decision Making*

Source: Author (2019)

As shown in table 4.8 below, 51.7% of the respondents make routine, repetitive decisions frequently, 54.4% frequently make decisions without higher level management involvement, 57% frequently make decisions that can be automated, 51% frequently make decisions which require judgement and intuition and finally 49.7% frequently make decisions which require computational complexity and precision as shown in table 4.8 below.

		RRD (%)	DWHLMI (%)	DA (%)	DRJI (%)	DRCC (%)
Valid	Almost never (1)	1.3	1.3	2.0	7.3	7.2
	Rarely (2)	4.0	9.9	4.6	11.3	11.9
	Sometimes (3)	11.2	13.9	17.2	11.9	9.3
	Frequently (4)	51.7	54.4	57.0	51	49.7
	Almost always (5)	31.8	20.5	19.2	18.5	21.9
	Total	100	100	100	100	100

Table 4.8: Decision making

Source: Author (2019)

4.13 Inferential Statistics

4.13.1 Normality Test

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AIDS	.380	151	.0016	.724	151	.0516
EIEI	.345	151	.0037	.769	151	.0637
R	.231	151	.0080	.857	151	.0580
ORM	.236	151	.0024	.867	151	.0724
DM	.334	151	.0053	.742	151	.0553

a. Lilliefors Significance Correction

Table 4.9: Tests of normality

Source: Author (2019)

Parametric tests require that data are normally distributed and therefore we should always check if this assumption is attained before running any analysis. In Shapiro-Wilk tests, the null hypothesis is that the data is normally distributed. Razali, and Wah (2011) states that, small values of the alpha leads to the rejection of normality, and values closer to 1 indicates data comes from a normal distribution. We, therefore, failed to reject the null hypotheses, according to the above results. For datasets smaller than 2000 elements, we considered the Shapiro-Wilk test, otherwise, the Kolmogorov-Smirnov test could be used. In this study, since we had only 151 elements, the Shapiro-Wilk test is used. From table 4.9 above, the p-values for all the variables in the study are higher than .05 ($p>0.05$).

4.13.2 Reliability test

Case Processing Summary

		N	%
Cases	Valid	151	100.0
	Excluded[a]	0	.0
	Total	151	100.0

a. Listwise deletion dependent on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.665	5

Table 4.10: Reliability statistics

Source: Author (2019)

Cronbach's alpha, α (or coefficient alpha), measures reliability, or internal consistency, that is, how firmly related a set of items are as a group. The reliability coefficient ordinarily ranges between 0 and 1 and the closer the coefficient is to 1.0, the greater is the internal consistency of the items (variables) in the scale. Cronbach's alpha will tell you if the test you have designed is accurately measuring the variable of interest. The acceptable values of Cronbach's alpha are 0.7 and 0.6 (Taber, 2018). From the reliability table 4.10 above, the study concludes that there is a good internal consistency in the variables used for the study.

4.13.3 Correlation

The study used Pearson's correlation coefficients to find out how strongly the two pairs of variables are related. Correlation is stronger when the value is closer to -1 or +1. Evans (1996) proposed the r values as: $r < 0.19$ very weak, $r < 0.39$ weak, $r < 0.50$ moderate, $r < 0.79$ strong and finally r < 1 very strong. The correlation analysis shown in table 4.13 below indicates that there is a positive moderate correlation between the dependent variable (Decision making) and EIEI, Strong correlation with "Reasoning" weak correlation with ORM, and a weak negative correlation with AIDS.

A strong relationship was observed between Reasoning and ORM and, between Reasoning and EIEI, there was a moderate relationship between ORM and EIEI. There was a weak negative correlation between AIDS and EIEI, Reasoning, ORM.

	DM	*EIEI*	*R*	*ORM*	*AIDS*
DM	1				
EIEI	0.420968	1			
R	0.547189	0.540874	1		
ORM	0.378235	0.465579	0.568016	1	
AIDS	-0.14185	-0.12862	-0.15793	-0.05945	1

**. Correlation significant at 0.05 level (1-tailed).*

Table 4.11: Correlation results

Source: Author (2019)

4.13.4 Regression Analysis

Regression analysis is a set of statistical processes for estimating the relationships among variables of interest. It is used to estimate the conditional expectation of the dependent variable given the independent variables, and to explore the forms of their relationships.

From Table 4.12 below, the value of R^2 in the model summary is 0.069, which means that 69% percent of the total variance in decision making has been explained. The statistics term R^2 shows how good one can predict another, where 1 shows perfect indication. The model showed a good linear relationship between the independent and dependent variables for the study, with a coefficient (R) of 0.746. The adjusted R-square 69% presents a strong relationship between the variables. This proved that the model used accounts for the 69% of the observations, whilst 31% remains unexplained by the model. Further research should be conducted to investigate the other factors that explain 31% of Business Decision Making.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.746[a]	.069	.067	.569

a. Predictors: (Constant), ORM, AIDS, EIEI, R

Table 4.12: Regression model summary

Source: Author (2019)

Analysis of Variance

The (ANOVA) test developed by Ronald Fisher, is a collection of statistical models and their associated estimation procedures among and between groups. It's used to test the differences among group means samples. From table 4.13 below; the model presented the significance of p-value = 0.0282. This value is less than the alpha level of 0.05, demonstrating that the model is statistically significant in forecasting the impact of; Optimization and Recommended Model, Analytical and Intelligent Decision Support, Experiment and Integration with Environmental Information and Reasoning, on Business Decision Making.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.652	4	.413	1.277	.0282[b]
	Residual	47.222	146	.323		
	Total	48.874	150			

a. **Dependent Variable**: Decision Making

b. **Predictors**: (Constant), Optimization and Recommended Model, Analytical and Intelligent Decision Support, Experiment and Integration with Environmental Information, Reasoning

Table 4.13: Analysis of variance

Source: Author (2019)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.910	.264		14.789	.000
	AIDS	.358	.078	.704	.751	.045
	EIEI	-.529	.084	-.063	.625	.033
	R	.751	.071	-.121	1.056	.029
	ORM	.450	.068	.673	.656	.013

a. Dependent Variable: DM

Table 4.14: Coefficients

Source: Author (2019)

Table 4.14 above shows, taking all factors (AIDS, EIEI, R and ORM) constant at zero, the decision making of transport and logistics companies in Kenya will be 3.910. A unit increase in Analytical and Intelligent Decision Support leads to 0.358 (p=0.045) increase in decision making holding other factors constant. A unit increase in Experiment and Integration with Environmental Information leads to -0.529 (p=.033) decrease in decision making, holding other factors constant. A unit increase in Reasoning leads to 0.751 (p=0.029) increase in decision making, holding all other factors constant. It was also observed that a unit increase in Optimization and Recommended Model leads to 0.450 (p=.013) increase in decision making in transport and logistics companies in Kenya, holding other factors constant. The study model is as shown below:

$Y = C + aX_1 + bX_2 + cX_3 + dX_4$

$Y = C + aX_1 + bX_2 + cX_3 + dX_4$

$Y = 3.9 + 0.358 X_1 – 0.529 X_2 + 0.751 X_3 + 0.450 X_4$

Where

Y= DM = Decision Making

X_1 = AIDS = Analytical and Intelligent Decision Support

X_2 = EIEI = Experiment and Integration with Environment Information

X_3 = R = Reasoning

X_4 = ORM = Optimization and Recommended Models

4.14 Discussion

The findings of this study indicated that 74.9% of the respondents use BI types of corporate reporting, data warehousing and information portals and is consistent with previous research that posits “information management is the key necessity of the decision making and BI is the best conductor of information management” (Citroen, 2011; Chen et al., 2012; Isık et al., 2013).

Analytical and Intelligent decision support achieved a significance of 0.045 on decision making. This confirms its importance in BI systems, with majority of the respondents (96%) agreeing that the BI systems help with analytical and intelligent decision making. The study coincides with Yam et al., (2001) experimental findings, their predictions were useful in enhancing the efficiency of maintenance functions e.g. repairs planning and scheduling, IPDSS (Intelligent Predictive Decision Support System) was able to reduce extra costs by producing remedial actions before an error could occur. Negash (2004), states that, “analytical tools in BI systems can play a remarkable role in preparing essential information for planners and decision makers”.

Reasoning established a significance of 0.029 on decision making. Bankes, Lempert and Popper (2001), suggested an inductive approach termed as Computer-assisted reasoning, where the interactive computer visualizations assisted users produce predictions on the best decisions. CAR improved the capability of dealing with problems from deep uncertainty by joining information from machine-based quantitative mathematics and human knowledge. This study results, also concurs with their work on CAR, they assert that CAR has helped in in a range of difficult decision makings industries e.g. defense force structure, global climate policy, planning decisions and long-range financial planning for public universities.

On the evaluation of experiment and integration with environmental information the study identified significant challenges with the use of BI systems in logistics industry to model and experiment for future predictions. The responses showing a larger percentage (80.8%) feeling the various systems fell short.

Shollo and Kautz, (2010) and Trinh et al., (2012) pointed out that since BI concerns with planning change adaptation in future, it is considered as an early warning system in businesses. This agrees with the findings on reasoning where most of the respondents agreed that the BI systems in use helped with financial analysis, bidirectional reasoning, goal model/oriented reasoning and probabilistic decision analysis. Several gaps were raised especially on the capacity of current systems to provide extrapolation functionalities but some solutions including upgrading of these systems were suggested.

Optimization and recommended models (ORM) obtained a positive significant effect of 0.013, this was in line with the study done by Rouhani Ashrafi, Zare Ravasan, & Afshari, (2016), where ORM had a significant effect of t=3.44 and 51% in reducing decision time.

In general, when organizations must decide in real environment, some tools like risk simulation, prototyping models, optimization, and dashboards can provide instrumental aid in dynamic decision-making process (Bose, 2009; Evers, 2008; Gao and Xu, 2009; Shang et al., 2008). The study affirms this with 62.3% of respondents agreeing that the BI systems in use offer these functionalities, hence improving their decision-making process. There, however, are challenges with some respondents citing especially lack of training and systems that are not holistic in their data capturing.

62.9% of the respondents frequently rely on a BI system for decision making, this proves that the BI system is an important tool to organizations when it comes to decision-making. 51.7% of the respondents make routine, repetitive decisions, while 48.3% don't. Most of the respondents indicated that they were using BI for primarily operational decisions and reporting purposes. This concurs with Watson et al., (2006) posits, it should be considered employing different types of analysis on information would increase analysis latency causing decision latency. Therefore, for more complex decisions, most decision makers shun away from the BI systems due to the complexity in analyzing the information. Cummings (2004), too warns against higher level of automating decisions in times of risks and complexity of systems and inability of automated decisions. In order to eliminate errors while making decisions, BI systems should be designed and developed with human cognitive constraints in mind.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This section gives a quick picture of the study findings and displays the study outcomes in a more understanding manner. The chapter talks about the research study summary findings, recommendations, conclusions and limitations of the study and finally offers suggestions for further research.

5.2 Achievements

The report expands knowledge in the areas of business intelligence and decision making in a logistics and transportation companies. This report will help stakeholders and researchers in this area to conduct trainings, implementations and systems support of business intelligence capability. For a better decision making, organizations must encourage the use of systems intelligence capabilities.

Objective 1: To identify the role of BI to Logistics companies in Kenya

This was attained through a detailed literature reviews on areas of systems and business intelligence, and corporates decision making. The focus was on computer intelligence and how to support efficient and effective decisions in the organization and various BI capabilities supported in the systems. Literature review established that similar work had been discussed, but with an insignificant contribution made in logistics companies especially in Kenya. From the literatures, it was evident that the BI evaluation framework by (Ghazanfari, Jafari, & Rouhani, 2011), had not been discussed in logistics and transport companies when evaluating effective decision making.

Objective 2: To investigate the Impact of BI system capabilities on business decision making

The study successfully analyzes BI capabilities based on the adapted evaluation framework by (Ghazanfari, Jafari, & Rouhani, 2011), where all the tested variables had a significant effect on the companies' decision making.

Objective 3: To propose the model for business decision-making in a BI environment in logistics companies in Kenya

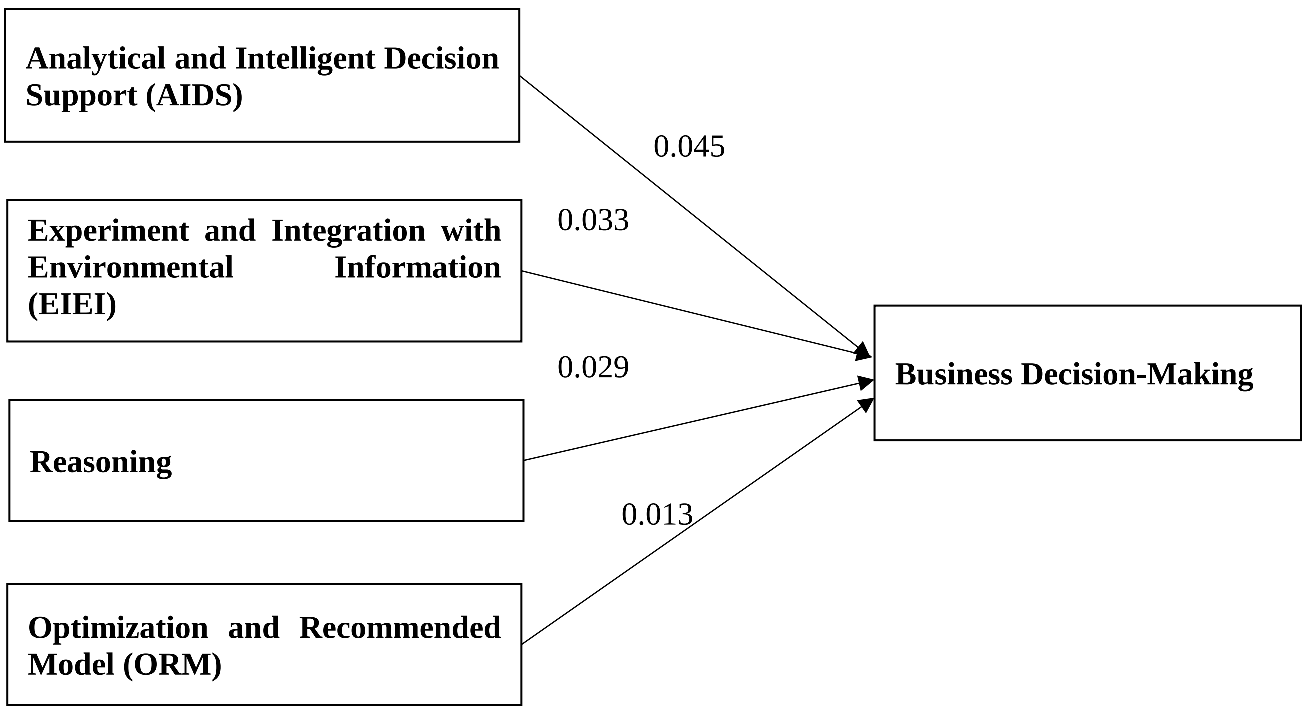

Figure 5.1: Proposed business decision making model

Source: Author (2019)

Figure 5.1 shows the established model from the research findings and their individual impact on decision making. Analytical and intelligent decision making had an impact weight of 0.045 on business decision making, EIEI had an impact weight of 0.033 on decision making, Reasoning had an impact of 0.029 on the decision making, and finally optimization and recommended model variable had an impact of 0.013 on business decision making of the organizations under study. The research found out various solutions on how to solve specific challenges facing users in a BI environment, especially in a logistics and transport companies in Kenya.

5.3 Limitations of the Study

The research faced some challenges and limitations, they include: Primary data collection was the main source of obtaining the relevant information. Not all respondents were comfortable to provide information as they were not very certain how the information they provided was to be used. The framework only tested several logistics and transportation companies in Kenya, hence generalizing results to all the logistics companies and this could not be the case. Due to the limited time and scope of the study, the researcher worked with a few constructs from the derived model. There was also a limitation on the amount of literature for review in this field; a lot of the literature was based on Business Intelligence implementation or adoption and on decision support systems but very little linking the two.

5.4 Conclusion

This research confirmed the importance of Business Intelligence to Business Decision Making in a logistics and transport companies. A conceptual framework model for examining the relationship between BI functions and Business Decision Making is presented. Based on the literature, Analytical and Intelligent Decision Support (AIDS), Experiment and Integration with Environmental Information (EIEI), Optimization and Recommended Model (ORM) and Reasoning, were identified as the main components for this research. After finalizing the components of conceptual model, based on literature, the model was designed, and the expected relationships were confirmed through a descriptive cross-sectional survey research. The findings of this research confirmed all the four independent variables as having a significant influence on decision making. Current research provides an insightful understanding about which functions of

BI have strongest impact on Decision Making. The study also brings out the various bottlenecks in existing BI systems used in the logistics industry in Kenya and offers suggestions on how to deal with various challenges in the BI environment. Further the study also establishes the various challenges that affect the use of BI for business decision making; unreliable data, low confidence in the systems by decision makers; poor utilization of installed systems and lack of integrations especially with environmental information.

5.5 Recommendations

5.5.1 Recommendations for practitioners e.g. Policy makers, logistics sector and actors

The researcher recommends an effective utilization and application of the model in supporting business decision making among logistics companies. Policy makers and management should come-up with rules and ways of eliminating or minimizing challenges sited by the respondents e.g. bureaucracies, and failure to make decisions based on the analysis/reports from the system. The management should also conduct trainings to staff members on how to manipulate and read BI data. The researcher believes that this research will enable Kenyan logistics industry to make better decisions for designing, selecting, evaluating and buying BI systems that offer better decision-support environment.

5.5.2 Recommendations for further research

The study covered logistics and transport companies in Kenya, we recommend the use of same constructs in other organizations in different sectors apart from logistics in order to compare the results. We further recommend the use of other evaluation frameworks e.g. by (Rouhani, Ashrafi, Zare Ravasan, & Afshari, 2016), to be used in logistics and transport companies in establishing an effective business decision making processes.

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APPENDIX I: Questionnaire

Section 1: General Information

Which Logistics Company do you work for? ....

How long have you been in your current organization? __________ years

What is your functional area?

General management ☐

Corporate communications ☐

Finance / Accounting / Planning ☐

Human resources / Personnel ☐

Information technology ☐

Legal ☐

Sales & Marketing ☐

Other (please specify) _____________________________

What is your position in the organization?

Director ☐

Executive management ☐

Middle management ☐

Operational management ☐

Supervisors ☐

Other (please specify) _____________________________

What is your job title? _____________________________

For the purposes of this research, Business Intelligence (BI) is defined as the following;

"BI is a system comprised of both technical and organizational elements that presents historical information to its users for analysis, to enable effective decision making and management support, for the overall purpose of increasing organizational performance."

Please answer the following questions about a specific BI application you use for your everyday business decision making purposes. If you are using more than one BI application, please focus only on one of them and answer the questions only based on that specific application.

Does your organization have any form of BI (Business Intelligence) systems in use?

Yes, ☐ No ☐ Don't know ☐

If the answer is NO; **exit.** If the answer is YES; **proceed.**

What is the type of BI system you use in your organization? Please tick from below list:

Corporate reporting system ☐

Data-warehouse ☐

Information portal ☐

Corporate dashboard ☐

Analytical and intelligent system ☐

Decision support system ☐

Others; specify…………………………………………………………….

Section 2: Evaluation of Analytical and Intelligent decision support

On a scale of 1 to 5 how well does your BI system offer the following?

Items	5 Almost always	4 Frequently	3 Sometimes	2 Rarely	1 Almost never
Accurate, actionable and timely data					
Reduced decision-making time (visual graphs, summarization)					
Centralized knowledge base (data warehousing and aggregation)					

Discovery of new/hidden knowledge in data					
Data analysis and decision support tools (data mining tools)					
Real-time notifications of alarms and warnings					
Multiple channels (email, mobile, web)					

If any of the scores is less than 4 please briefly explain the challenges, you face

…………………………………………………………………………………………………….

…………………………………………………………………………………………………….

Suggested solutions to the challenges

…………………………………………………………………………………………………….

…………………………………………………………………………………………………….

Section 3: Evaluation of Experiment and integration with environmental information

On a scale of 1 to 5, kindly indicate the extent to which your BI system supports the following:

Item	5 Very great extent	4 Great extent	3 Some extent	2 Small extent	1 Not at all
Corporate environmental awareness					
Import data from other systems					
Export reports to other systems					
Combination of experiments (comprehensiveness)					
Situation awareness modelling					
Flexible models					
Clustering of problems					

If any of the scores is less than 4 please briefly explain the challenges, you face

…………………………………………………………………………………………………….

…………………………………………………………………………………………………….

Suggested solutions to the challenges

…………………………………………………………………………………………………….

…………………………………………………………………………………………………….

Section 4: Reasoning

On a scale of 1 to 5, kindly indicate the extent to which your BI system assists in the following:

Item		5 Very great extent	4 Great extent	3 Some extent	2 Small extent	1 Not at all
Financial analysis (profitability, stability, solvency)						
Bi directional reasoning - forward and backward reasoning. (working backwards from a goal /inferring towards a goal)						
Knowledge reasoning	Goal model/oriented reasoning (extrapolation towards a set goal)					
	Probabilistic decision analysis (inference using probability)					
	Reasoning with indicators (extrapolation with defined indicators)					
	Hybrid reasoning (with incomplete indicators)					

If any of the scores is less than 4 please briefly explain the challenges, you face

……………………………………………………………………………………………….

……………………………………………………………………………………………….

Suggested solutions to the challenges

……………………………………………………………………………………………….

……………………………………………………………………………………………….

Section 5: Optimization and recommended models

On a scale of 1 to 5, kindly indicate the extent to which your BI assists in optimizing decision making in your organization by:

Item	5 Very great extent	4 Great extent	3 Some extent	2 Small extent	1 Not at all
Offering simulation models					
Simulating business and environmental risks					
Offering dynamic & evolutionary prototyping models (easily modified in response to user feedback/needs.)					
Offering dashboards/recommender platforms					
Providing optimization techniques for forecasting and predicting the business performance					
Providing learning capabilities (heuristics)					

If any of the scores is less than 4 please briefly explain the challenges, you face

……………………………………………………………………………………………….

……………………………………………………………………………………………….

Suggested solutions to the challenges

……………………………………………………………………………………………….

……………………………………………………………………………………………….

Section 6: Decision making

Please indicate how well each statement below describes the decisions you make:

Items	5 Almost always	4 Freque ntly	3 Somet imes	2 Rarely	1 Almost never
I make routine, repetitive decisions					
I make decisions without higher level manager involvement					
The decisions I make could be automated					
The decisions I make require judgment and intuition					
The decisions I make require computational complexity and precision					

Please give reasons why you use BI systems to support your daily work

……………………………………………………………………………………………….

……………………………………………………………………………………………….

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APPENDIX II: Logistics Companies Studied in Kenya

Transport and Logistics Companies Studied					
NO.	-		NO.		
1	Acceler Global Logistics	6	27	Lush exports	1
2	Agility Logistics	2	28	Mardav logistics	3
3	Aircom Cargo Logistics	2	29	Mitchell Cotts Logistics	3
4	A-Z	1	30	Morgan Cargo Logistics	4
5	Biju Freight and Logistics	2	31	Panalpina Logistics	4
6	Bollore Logistics Kenya	1	32	Polygon logistics	4
7	Cisco superior Cargo and Supply	1	33	Quick start freight logistics	4
8	CMA CGM	3	34	Rapid Logistics Center	1
9	Comrade Logistics	2	35	Regional Logistics	3
10	DB Schenker	2	36	Sharid Shipping Cargo	1
11	Eyelink Logistics	3	37	Sheffield Cargo Logistics	3
12	Fantashi Freighters Logistics	3	38	Shreeji Logistics	3
13	Fastline Logistics Services	3	39	Siginon Group	18
14	Fox Logistics	3	40	Skyland Logistics	2
15	Freight in Time	4	41	Skyline logistics	2
16	Freight wings Ltd	4	42	Spedag Inter freight logistics	3
17	Global Freight Logistics	1	43	Speedex Logistics	2
18	Jaspa Logistics	1	44	Superior logistics services	4
19	Kencont Logistics Services	3	45	Swift cargo logistics	1
20	Kenfreight	3	46	Swissport Cargo Limited	2
21	Kuehne + Nagel Ltd	5	47	TNT Worldwide Express	3
22	Lambval logistics	1	48	Tradewinds Logistics	3
23	Logistics Link	4	49	Trans Meridian logistics	3
24	Logistics Link Kenya	2	50	Transglobal Cargo Centre	4
25	Lolling Logistics	2	51	Union Logistics	4
26	Lupha Exports	3			

APPENDIX III: Variable Indicators

The significance of Variable Indicators on the dependent variable (Decision making)

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1.1 Accurate, actionable and timely data	.223	.050	.258	4.464	.022
1.2 Reduced decision-making time (visual graphs, summarization)	.122	.039	.153	3.123	.002
1.3Centralized knowledge base (data warehousing and aggregation)	.093	.042	.108	2.212	.029
1.4Discovery of new/hidden knowledge in data	.129	.029	.187	4.513	.000
1.5Data analysis and decision support tools (data mining tools)	.122	.032	.167	3.803	.000
1.6Real-time notifications of alarms and warnings	.099	.032	.153	3.069	.003
1.7Multiple channels (email, mobile, web)	.171	.028	.273	6.081	.000
2.1Corporate environmental awareness	-.022	.036	-.033	-.619	.037
2.2Import data from other systems	.003	.052	.003	.054	.057
2.3Export reports to other systems	.036	.045	.047	.797	.127
2.4Combination of experiments (comprehensiveness)	.026	.034	.032	.765	.046
2.5Situation awareness modelling	.004	.033	.006	.121	.004
2.6Flexible models	-.068	.042	-.088	-1.623	.107

2.7Clustering of problems	.041	.034	.056	1.209	.029
3.1Financial analysis (profitability, stability, solvency)	.015	.033	.021	.469	.040
3.2Bi directional reasoning - forward and backward reasoning.	-.034	.041	-.047	-.819	.115
3.3Knowledge reasoning-Goal model/oriented reasoning	.027	.046	.040	.586	.049
3.4Knowledge reasoning- Probabilistic decision analysis	.009	.042	.014	.225	.022
3.5Knowledge reasoning- Reasoning with indicators	-.027	.049	-.043	-.553	.041
3.6Knowledge reasoning- Hybrid reasoning	.024	.045	.034	.532	.596
4.1Offering simulation models	-.017	.038	-.023	-.450	.013
4.2Simulating business and environmental risks	.040	.047	.052	.846	.049
4.3Offering dynamic & evolutionary prototyping models	.016	.041	.020	.385	.001
4.4Offering dashboards/recommender platforms	.051	.033	.074	1.558	.022
4.5Providing optimization techniques for forecasting and predicting the business performance	-.007	.091	-.011	-.078	.038
4.6Providing learning capabilities	-.064	.093	-.091	-.685	.095

a. Dependent Variable: Decision Making
b. Significant value at 0.05

Source: Author (2019)