Decision-Support System in Select Fast-Moving Consumer Goods Firms in South West Nigeria

Oluwatoyin S. Ayanlade, PhD; Gbonjubola O. Binuyo, PhD; Oyetola A. Oyeleye & Titilayo O. Olaposi, PhD
African Institute for Science Policy and Innovation (AISPI)
Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria
osayanlade@oauife.edu.ng gobinuyo@gmail.com
oyeleyetola29@gmail.com; olaposititi@googlemail.com

Abstract
This study seeks to identify the types of Decision-Support System (DSS) used in fast moving consumer goods and the extent and level of adoption in select firms. The study was carried out in thirteen (13) Fast Moving Consumer Goods firms in three towns of two states where there is high concentration of headquarters of FMCG firms' in South Western Nigeria. In the two select states, all the thirteen (13) Fast Moving Consumer Goods firms were sampled. Three (3) departments were chosen from each of the select firms and 195 copies of questionnaire were administered to wholesalers and members of the departments. The findings showed that majority of the organisations use data-driven DSS and majority of the firms also adopted only one type of the DSS. Moreover, most of the organisations use their adopted DSS weekly, with adoption duration within two years. Therefore, it was recommended that governments and policy makers should encourage public and private manufacturing organisations, especially Fast Moving Goods sector, to continually deploy and use decision-support system because it is an assistive tool that will enhance good and accurate decision making.

Keywords: Decision Support System, Manufacturing, Fast Moving Consumer Goods, Consumer Packaged Goods, Industry 4.0, South Western Nigeria

Introduction
Manufacturing organisations which engage in transforming raw materials to final products, operate in an environment that is dynamic, driven by so many factors such as demands of customers, market conditions, consumers' taste, among others (ElMaraghy, AlGeddawy, Samy & Espinoza, 2014; Marques, Agostinho, Zacharewicz & Jardim-Gonçalves, 2017). Therefore, local and global competitiveness have made the organisations to be under pressure to adopt different strategies to enhance their competitiveness (Ogunlela, 2018). Fast Moving Consumer Goods (FMCG) industry, also known as Consumer Packaged Goods (CPG), cuts across manufacturing value chain which includes production, wholesale, distribution and retail of short shelf life, frequently updated, rapid obsolescence and highly perishable products such as beverages, soft drinks, processed foods, canned goods, meats, chocolates, snacks, among others (Tarallo, Akabane, Shimabukuro, Mello, & Amancio, 2019). Therefore, Angeles-Martinez, Theodoropoulos, Lopez-Quiroga, Fryer, and Bakalis (2018) noted that globally, the industry is one of the most essential and largest industrial sector because it cuts across so many product variants.

Manufacturing industries generally, especially fast moving goods sector, involve so many risks and challenges. For instance, Agigi, Niemann & Kotzé (2016) majorly categorised the risks in Fast Moving Consumer Goods industry into three; namely: Supply, Demand and Macro-Environmental risks. Moreover, there are some challenges associated with Fast Moving Consumer Goods, which are very crucial to the sustainability of the industry such as low profit margins (Birhanu, Krishnanand & Rao, 2017). Low inventory and numerous deliveries of small-batches; high product diversity; improving and maintaining high quality, despite the low-income nature of their consumers (Diehl & Spinler, 2013; Colicchia, Creazza, & Dallari, 2017; Pourhejazy, Sarkis & Zhu, 2019).

Table 1: Risk Categories in Fast Moving Consumer Goods

Risk Category	Examples
Supply Risks- High frequency and Moderate impact	Delivery delays/failures; Quality issues; Inflexibility of suppliers to react to macro-environmental risks
Demand Risks- Moderate frequency and High impact	Delivery delays/failures; Quality issues; Inflexibility of suppliers to react to macro-environmental risks
Macro-environmental risks- Low frequency and High impact	Power outages; Natural disasters; Strikes

(Agigi *et al* 2016)

In view of these challenges and risks facing the Fast Moving Consumer Goods industry, Kasie, Bright & Walker (2017) state that the role of right decision-making in fast consumer goods industry cannot be overemphasised. Therefore, decision making in Fast Moving Consumer Goods becomes so complicated and difficult and needs to be made effective as much as possible (Bennet & Bennet, 2008). This made Karim Suhag, Solangi, Larik, Lakh & Tagar (2017) to note that FMCGs would need right innovation (such as in terms of technologies) to remain competitive and remain in business. This is because technology, for instance, aims at better data storage and conceptualisation to make shared sense of collected data and information (Arica & Powell, 2017). This could be related to the role of decision support system in making use of available information to enhance decision making. Several researchers (such as Pourhejazy *et al* (2019) have confirmed the fierce competitions in the fast moving consumer goods (FMCG) sector because of the peculiar nature of the sector (such as the products' short shelf-lives, high perishability, obsolete, etc.). Decision-support system plays an assistive role in promoting right and effective decision-making (such as correct demand and sales forecast) that would prevent wastages; thus, low inventory and stock-outs. Therefore, there is the need to identify the types of Decision Support System used to meet these challenges in these firms, to maintain competitive advantage.

Conceptual Review and Review of Related Literature

Decision Support System (DSS) has so many definitions by several scholars viewing from different perspectives. For instance, Silva & Rupasinghe (2017) state that DSS is any computer infrastructure that assists in determining and evaluating alternative courses of action. Moreover, Arnott & Pervan (2008) simply define DSS as different ways of developing and deploying Information systems to enhance decision making. Similarly, Yazdani, Zarate, Coulibaly & Zavadskas (2017) categorised Decision-Support System to

be a precise and detailed class of information system that assists managers with strategic decision making. Therefore, they explained further that the concept of decision support system is a balance between having a human judgment and also having an information process with a computer system.

Decision-Support Systems can be used to enhance decisions in various aspects of life and in various sectors of the economy. Therefore, several scholars have conducted researches on Decision Support System in various Fields. For example, in the field of manufacturing generally, Plitsos, Repoussis, Mourtos & Tarantilis (2017) designed an energy-aware decision-support system, using Iterated Local Search algorithm for production scheduling in manufacturing. Also, Marques *et al* (2017) developed a decentralised decision-support system for intelligent manufacturing in Industry 4.0. Moreover, Accorsi, Manzini & Maranesi (2014) designed a decision support system using Database Management System (DBMS) architecture to design, manage and control the production warehouse system. In addition, Liu, Wang & Liu (2012) structured a decision support system to support the social, economic and environmental aspects of supply chain management. Kostovski, Bojadjiev & Lokvenec (2017) designed a decision support system for new project development in Fast Moving Consumer Goods. Also, Pourhejazy *et al* (2019) used a Fuzzy-based decision support system for product deletion of Fast Moving Consumer Goods. Moreover, Tarallo *et al* (2019) presented machine learning, a form of decision support system, to predict demand and thus forecast sales for highly-perishable and short shelf-life products. Furthermore, Dellino, Laudadio, Mari, Mastronardi & Meloni (2018) designed a decision support system for the supply chain of fresh and packaged highly perishable products.

Equally, researches on decision support system in other areas of national sector are not lagging such as in health (Chatterjee, Cymberknop & Armentano, 2017; Singh, 2017; Ayanlade, Oyebisi & Kolawole, 2018;Enaizan, Zaidan, Alwi, Zaidan, Alsalem, Albahri & Albahri, 2020); Finances (Al-augby, Majewski, Nermend & Majewska, 2016; Ignatius, Hatami-Marbini, Rahman, Dhamotharan & Khoshnevis, 2018); Agriculture (Yazdani *et al* 2017); Climate studies (Kazak, Van Hoof & Szewranski, 2017); Waste management (de Souza Melaré, González, Faceli & Casadei, 2017); Tourism (Yoo, Goo, Huang, Nam & Woo, 2017); Ecosystem service (Zulian, Stange, Woods, Carvalho, Dick, Andrews, Baró, Vizcaino, Barton & Nowel, 2018); Education (Akinwole, Oyebisi & Ayanlade, 2019); Knowledge management (Ivarsson & Gorschek, 2012; Wang, Ding, Liu, & Li, 2016; Centobelli, Cerchione & Esposito, 2018) and Facility management (Cheng, Chen, Tan & Wang, 2016).

Decision-support system is classified into five; namely: document-driven decision support system, knowledge-driven decision support system, model -driven decision support system, data/database-driven decision support system and communications-driven decision support system. Document-driven decision support system makes use of documents to provide relevant and timely information needed for decision making (Yazdani *et al* 2017). Some of the documents involved in this type of decision support system includes the feedback of customers on the product websites, the emails of customers, product twitter feeds and the reviews of customers (Alkahtani, Choudhary, De & Harding, 2019). Felsberger, Oberegger & Reiner (2016) also noted some kinds of stored images, videos, sounds, correspondence, hypertext documents, scanned documents and so on that are important to organisations in having efficient and effective decision-making. There are many ways in which these documents could aid decision-making, for

example, in linking the document-driven DSS to search engines. Also, information retrieval that is text-based could help to find relevant documents for organisational data mining. Such accessible documents could also include product specifications, procedures and policies, catalogues, historical corporate documents e.g. correspondence and minutes of meetings. Therefore, search engines are very important tools for document-driven decision support system (Power, 2002; Bumblauskas, Gemmill, Igou & Anzengruber, 2017).

Similarly, to emphasise the significance of knowledge-driven decision support systems, Janssen, Porter, Moore, Athanasiadis, Foster, Jones & Antle (2017) defined decision support system generally from knowledge point of view, simply to be a computerised system in which knowledge to assist in decision-making is embedded. In the same line and specifically, knowledge-driven decision support system is, therefore, a type of decision-support system that has intelligent capability and can act like a human consultant (Turban, Liang & Aronson, 2005; Kasie *et al* 2017). Thus, the knowledge-driven decision-support system entails converting data into information and information into knowledge by reasoning, facts, rules, procedures and so on (Alkahtani *et al* 2019). Therefore, knowledge-driven decision support systems are connected to artificial intelligence (AI) or expert system by providing information and methodological knowledge through analytical decision models (Zhao, Hwang & Low, 2016). Model-driven decision support system entails data manipulation and analysis techniques through quantitative or mathematical methods such as simulation and optimisation (Lei & Moon, 2015). Therefore, the term 'model' in a model-driven decision support system signifies simplification of reality, and the statistical methods and tools involved include decision tree analysis (Pourabdollahi, Karimi, Mohammadian & Kawamura, 2014), analytical hierarchy process, multi-criteria decision analysis (Saha, Aqlan, Lam & Boldrin, 2016) and probabilistic forecasting (Hanlon, Stefik, Small, Verlinde & Young, 2013). Example of the application of model-driven decision support system is obvious in sales and demand forecasting, especially considering the short shelf life of Fast Moving Consumer Goods (Arunraj & Ahrens, 2015).

Data or Database-driven Decision Support System assists in decision-making by providing access, storage (and possibly manipulation) for data bank through database management system, DBMS (Yazdani *et al* 2017). Several technologies like text/data mining, big data, cloud computing, internet, etc. have allowed these access and storage for instant updating (Yang, Page, Zhang & Zhao, 2020) and not to be location-dependent (Singh, 2017). The data/database stored in the database management system serves as input to the decision support system (Alkahtani *et al* 2019). Examples of the application of Data/Database Decision Support System are Business Intelligence Systems and Online Analytical Processing, whose major aim is to enhance the quality of data or information available for decision making (Munhoz & Morabito, 2014).

The efficient and effective real-time communications needed by decision support systems are provided in communication-driven Decision Support System (Basheer, Siam, Awn, & Hassan, 2019). These are made possible by various digital technologies that allow the connection of people at high speeds and across the globe (Janssen *et al* 2017) through telephone; internet (Danes, Jellema, Janssen & Janssen, 2014); satellite (Capolupo, Kooistra, Berendonk, Boccia, & Suomalainen, 2015). Therefore, a communication-driven decision support system allows working on a task that is shared real time by receiving and sending of data amongst groups of decision makers(Yazdani *et*

al 2017). Baumeister & Striffler (2015) state that Model-driven DSSs are mostly for one user, while data-driven DSSs could be used by multiple users across the organisations. Similarly, a document driven DSSs concentrate more on the manipulation and management of data available in several electronic formats and knowledge-driven DSSs are just communication modules having application controller, controlling function, user update and communication manager modules as elements. Similarly, in showing the relationship between the DSS components, with a view to providing individual or team decision makers, the information and analytical capabilities needed for the decision process; for example, data, information and documents gathered from a large database (document and data/database driven) could be analysed based on the appropriate model (model-driven) or available expertise (knowledge-driven) and the results be presented and communicated (communication-driven) in an interactive way (user interface) using the applied format (Zhang, Hu, Yin, Kashem, Li, Cai, Perkins, & Wang, 2018).

The targeted users, purpose and enabling technology with examples of each of the components of decision support framework are illustrated in table 2 below:

Table 2: A Table showing the detailed components of Decision Support Framework

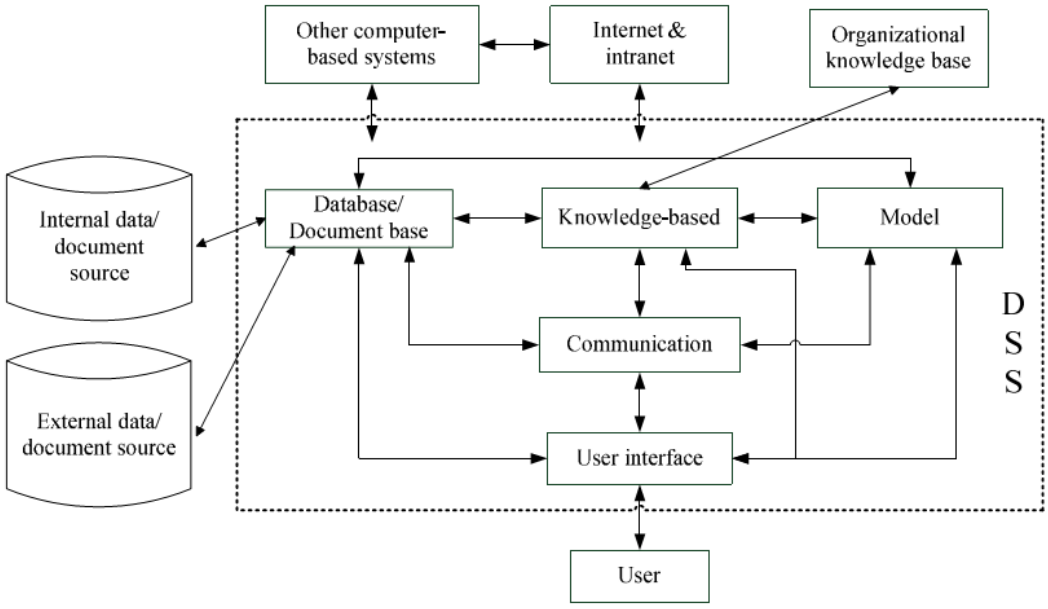
DSS Type	**Dominant DSS component**	**Targeted Users (examples)**	**Purpose (examples)**	**Enabling Technology (examples)**
Communication-Driven DSS	Communications	Internal teams, supply chain partners	Conduct a meeting, help users collaborate, Chats and instant messaging software; Online collaboration; Net-meeting Software, etc.	Bulletin Board, Videoconferencing
Data-Driven DSS	Database	Managers and staff now suppliers	Query a data warehouse	Relational databases, Multidimensional databases
Document-driven DSS	Document storage and management	Specialists and user group is expanding	Search Web Pages	Search engines, HTML
Knowledge-driven DSS	Knowledge base, AI	Internal users, new customers	Management advice	Expert Systems

Model-Driven DSS	Quantitative models	Managers and Staff, new customers	Scheduling, Forecasting	Linear Programming, Excel

Modified from Power (2009), cited in Power, Sharda & Burstein (2015)

Theoretical Framework

The theoretical framework of this study is based on the works of Power *et al* (2015) which categorised Decision Support System into document-driven, knowledge-driven, model-driven, database-driven and communication-driven decision support systems, depending on the driving technology, as illustrated in Figure 1.



Thus**,** the theory identified five types of decision support system in manufacturing organisations namely and illustrates their relationship with a diagram as shown in Figure 1 above. Therefore, the figure showed that these different types of decision systems in use in manufacturing organisations like fast moving consumer goods, are interrelated and thus these organisations can use more than one type of DSS at a time, so that their combined benefits would be achieved.

Materials and Methods

Both primary and secondary data were used for the study. The primary data were collected through structured questionnaire in the headquarters of the Fast-moving consumer goods (FMCG) firms in South Western Nigeria, which were based in the select states. The population of the study is made up of the staff of thirteen fast moving consumer goods firms in select towns of South West Nigeria. Three copies of questionnaire were administered each to members of the select units, including the

Manager of the unit. This study used multi-stage sampling techniques. Firstly, out of the six geopolitical regions of Nigeria, the study was purposively carried out in South Western geopolitical region for detailed assessment, which comprises six states. Also, out of these six states again, only three towns in Oyo and Lagos states were also purposively chosen for this study because of the high concentration of South Western FMCG firms' headquarters based in these states and towns. Moreover, in the two states selected, all the thirteen (13) Fast Moving Consumer Goods firms (or organisations) were sampled.

Furthermore, three (3) units were purposively chosen from each of the select firms based on the relevance of the units to the study. The sampled units were Information and Communications (ICT) unit, Marketing unit and Sales unit in each of the Fast Moving Consumer Goods, FMCG, firm in the study area. Lastly, twelve (12) wholesalers/distributors from each firm were randomly selected, making a total of one hundred and ninety five (195) copies of questionnaire administered. Therefore, using purposive sampling, all the headquarters of FMCG firms residing in Lagos, Ibadan and Oyo towns were selected.

Data Presentation and Analysis

The data from the study were analysed statistically, using Statistical Package for Social Sciences (SPSS) version 20.0.

Table 3: Types of Decision Support System adopted

Types of Decision Support System Adopted	Frequency (%)	
	In Use (%)	Not In Use (%)
Communication-Driven DSS	38 (20.8)	145 (79.2)
Data-Driven DSS	87 (44.6)	96 (52.5)
Document-Driven DSS	51 (27.9)	132 (72.1)
Model-Driven DSS	25 (13.7)	158 (86.3)
Knowledge-Driven DSS	26 (13.3)	157 (85.8)

Table 3 shows the percentage distribution of the types of decision support system in use by the firms. The data show that all types of Decision Support System which includes Data-driven DSS, Communication-driven DSS, Knowledge-driven DSS, Document-driven DSS, Model-driven DSS and User Interface were adopted by either one or more of the firms under study, but the most adopted DSS was Data-driven DSS with the percentage rate of 44.6%. This might be because Data-driven DSS is very fundamental to the accuracy of all types of decision support system.

Table 4: Number of Decision Support System adopted in FMCG firms

Number of types of Decision Support System adopted	Frequency	Percentage
One type	147	80.3
Two types	25	13.7
Three types	11	6.0
Total	195	100

The data in table 4 show that the organisations use more than one type of Decision - Support System to maintain competitive advantage. This is based on the fact that majority of the respondents answered to that effect (80.3%).

Table 5: Level of Adoption of Decision Support Systems in the Select FMCG firms

Extent and level of DSS Adoption	Frequency	Percent (%)
Duration of Usage		
Below 2 yrs.	78	42.6
2-3yrs.	72	39.4
4-5yrs.	30	16.4
5-6yrs.	0	0
Above 6 yrs.	3	1.6
Total	**183**	**100**

Table 5 presents the percentage distributions of duration and period of usage of the different types of decision support system in the select firms. These results showed that those that had been using it between 4-5 years (16.4%) were more than those that had used it for 6 years and above (1.6%). Therefore, the period of use by each firm differs. The data also show that majority of the respondents use it on weekly basis (49.1%).

Discussion of Findings

The high values recorded for data/database-driven followed by document-driven decision support systems showed the significance of data (or database) and documents with respect to having an accurate decision-support system. Moreover, the lowest values recorded by knowledge-driven decision support system could be because most of the times, users do not know that they are using knowledge DSS as data and information they have are converted to knowledge either directly or indirectly. This is in line with the findings of Alkahtani *et al* (2019).

The findings further showed that some users of decision-support system use more than one type of decision support system. This is in line with the theoretical framework which proposes an interrelationship between all the different categories of decision support system, thus making organisations to be using multi-DSS at the same time. Therefore, using more than one type of decision-support system had been noted by several researchers such as (Zhang *et al* 2018). This will bring to work the advantages of using each of them; thus, leading to a standardised decision support system.

The findings further showed that most of the organisations have just started using the decision-support system in two years. This could then be drawn that decision support system is just penetrating into the Fast Moving Consumer Goods sector and the impact is being felt gradually as the technology is being accepted and adopted. Also, the organisations mostly use the decision-support system weekly, which would enhance easy integration into the workflow of the organisation and thus, be conversant with the technology. This finding is in line with that of Ayanlade, Oyebisi & Kolawole (2019).

Conclusion and Policy Recommendations

The findings revealed that data and document-driven DSSs are commonly in use in the select firms and that knowledge-driven is rarely in use. Thus, the researchers conclude that the organisations use more than one type of decision support system. Based on the findings, the following policy recommendations are given:

1. Governments and policy makers should encourage public and private manufacturing organisations, especially Fast Moving Goods sector, to continually deploy and use decision support system because it is an assistive tool that will enhance good and accurate decision making.
2. There are different types of decision-support system, but they work together to achieve the same goal of accurate decision making. Thus, manufacturing organisations should be encouraged to use many types in one DSS to achieve competitive advantage.
3. The extent and level of use of these decision support systems are very critical in maximising the benefits they bring. Therefore, organisations should integrate the use of decision support system in their workflow for effective decision-making.

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