

https://dspace.org/

Analytics and data science business systems in the automotive industry in South Africa

Simango, Nancy Ntombizodwa

2018

https://hdl.handle.net/10539/30503

Downloaded from a DSpace repository. https://dspace.org/

Analytics and data science business systems in the automotive industry in South Africa

Student

Nancy Simango

Student Number: 1138684

Supervisor

Jane Nelisa Freitas

A research article submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Business Administration

Johannesburg, July 2018

Protocol number: WBS/BA1138684/345

DECLARATION

I, Nancy Simango, declare that this research article is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.



Nancy Simango

Signed at JOHANNESBURG

On the 27TH day of AUGUST 2018

ABSTRACT

The research project sought to establish the use and effectiveness of analytics and data science in the automotive industry in South Africa. According to Chen, Chiang, and Storey (2012), effectiveness and competitive advantage are said to be the expected basis for the use of analytics. To experience the full benefits, the analytical tools investigated had to satisfy the requirements of leveraging efficiency; objectifying decisions; disclosing assumptions; testing strategy impacts and required the capability to see and learn from changes. The underlying and critical support towards the effectiveness of the tools is data and it was required to establish whether data and the management thereof, was freely available. Probable causes to the uptake of the tools were reviewed and this included ease of use of the tools, training and support towards daily management.

The study was done using the qualitative method. Qualitative methods were found suitable for this investigation because the researcher needed to understand the reasoning behind the use or lack thereof, of analytics in the automotive industry in South Africa from a user perspective. The participants in this approach were directly sought for responses that would aid the study, which would elicit responses and ensure that deeper understanding into the operations was obtained. The research established that some of the industry, mostly the premium brands, had adopted the use of analytics. Some organisations have implemented some analytical tools and practice, but this applies to only some departments and is not widely spread across the organisation. Therefore, there is a misalignment with regard to the use of data within the organisation. Some of the industry still relied on many manual processes, and working in silos where the organisation could benefit from an integrated approach.

The cross-value analytics chain that was presented proposes an approach that the participants felt would benefit all. The interpretation therefore concludes that the use of the cross-value analytics chain would need to be adopted, as a start, to building a journey towards common processes. This would drastically improve the efficiencies of operations within the organisations as there would be interdepartmental integration. A common approach would also allow for room for expansion into improving the already available tools with a quicker turnaround time for growth and expansion.

INTRODUCTION

Business intelligence and analytics systems in businesses are perceived to contribute positively to an organisation's effectiveness (Chen et al., 2012; Negash, 2004). However, it has become necessary to quantify this for the automotive industry in South Africa. The principle driver to attaining effective decision making through analytics is data, and there has been a rise of ubiquitous data (Klatt, Schlaefke, & Moeller, 2011; Walker, 2015). Some organisations in the automotive industry are moving away from a Business-to-Business (B2B) model and aligning to a Business-to-Customer (B2C) model due to the reach towards the customer and therefore, this model of operation is moving toward a service oriented function, which entails that the usefulness of data has become vital (Tannou & Westerman, 2012). With this B2C approach, alignment among the key pillars that contribute to organisation effectiveness is critical. The contributors to the automotive industry's bottom line are the customer, product (which is the vehicle) and the organisation. Customer data is derived from the customer interactions through many channels, and product data from manufacturing and organisational operations. Walker (2015) suggests that the rapid transition of technologies force businesses to face the challenge of implementing immediate decision-making capabilities in order to remain competitive and sustainable.

Research purpose

This study sought to review the use of analytics and their effectiveness in the automotive industry. The availability of data in business systems is key to providing adequate analytics and this study indicates whether the data is available and if it is being used effectively to provide business direction in making business decisions (Bumblauskas, Bumblauskas, Igou, & Nold, 2017). Technologies are continuously improving and the drive towards effectiveness is being influenced by the uptake and use of data for daily operations which are key in preparation for the fourth industrial revolution. Intelligence will become paramount to handling the incoming technologies (Klaus, 2016; Oosthuizen, 2016). The study therefore provides a guide as to whether the available analytics are being utilised adequately to contribute towards effectiveness and competitiveness in the organisation.

Background and context of the study

Competitiveness in the automotive industry is measured by the National Association of Automobile Manufacturers of South Africa (NAAMSA) index. NAAMSA represents franchise holders marketing vehicles in South Africa (*NAAMSA*, 2017). It is the custodian of detailed information with regard to the automobile's retail information and competitiveness and it is these statistics that enable the organisations to gauge their position and review their strategies to remain effective and competitive. There are seven major Original Equipment Manufacturers (OEM) that subscribe to NAAMSA, namely; BMW, Ford, General Motors (GM), Mercedes Benz, Nissan/Renault, Toyota and Volkswagen (VW). It is these OEM's that aid in the contribution to the country's exports and ultimately, contribute to the country's Gross Domestic Product (GDP). The automotive industry contributes about 10% to the South African manufacturing exports and contributes 7.5% to the GDP (Muller, 2009).

Customer preferences are captured through a variety of systems. Data from the customer and organisation is captured via multiple channels, such as email, Short Messaging Service (SMS), social media, online applications, organisational Enterprise Resource Planning (ERP) and production systems (Zhan, Tan, Ji, Chung, & Tseng, 2017). The evolution of technology has thus made data abundant. The deluge of data that is captured by the industry falls under the ambit of structured and unstructured data (Negash, 2004). The researcher is of the view that intelligence needs to be applied to the data that is derived from the multiplicity of systems in the automotive industry. The accuracy of information and the speed of making decisions will assist the automotive organisations to either remain uncompetitive or progress to effectiveness and competitiveness (Deloitte, 2017). Management in organisations needs to make sense of the structured and unstructured data that is available. This study reveals whether the automotive industry uses the available analytical tools and whether they are effective in assisting the industry in making the right business decisions with regard to their strategies based on the information derived from analytics.

Problem Statement

Decision making has become critical in creating efficient operations to improve business performance. In the automotive industry, this ability is not readily available due to multiple manual processes, the multiplicity of data sources and a dependency on the use of Excel data. The use of analytics in other industries has demonstrated the benefits of adopting analytical tools to create faster and more accurate decision-making. Data, which is key to analytics, has become abundantly available due to the development of technology. However, the multitude of platforms of data intake leads to an abundance of data which requires management that will lead to quick, efficient and effective decisions. The customer in the automotive industry has emerged as a critical role player in the profitability model, where information from the data that influences the customer positively, can be derived from an informed model of efficient and effective decision-making. The research problem thus presents a research question which is further extended into two sub-questions. The purpose of the first sub-question is to establish whether organisations have any analytical tools in the organisation and efficient data modelling in order to effectively use analytics in their organisations. The second sub-question determines if the use thereof improves business performance by enabling them to effectively make decisions. The next section deals with the research question and subsequent sub-questions.

Research Question

Three research questions drove this investigation. The main research question asked how the automotive industry in South Africa has adopted the use of analytical tools to aid in decision-making to increase their effectiveness and profitability. The objective for asking this research question was to establish if the automotive industry in South Africa has adopted the use of analytical tools, identify which ones were adopted, and then establish the effect of the adoption of the tools. Sub-question one asked what the evidence was that the automotive industry in South Africa uses analytical tools and data science modelling techniques. The objective for asking this question was to delve deeper into understanding if indeed, the industry had taken up the analytical tools and to what extent they were utilising them. Finally, sub-question two asked how the analytical

tools are enabling the organisation to add value and drive effectiveness, competitiveness and profitability in their operations. The objective for asking this research question was to ascertain if the tools were adding value to the organisation, as perceived by users in other industries.

Proposition

The proposition for this investigation is that organisations that are using analytics and data science in their business systems are more effective in their operations and the performance is considerably better than the performance of the competition (Kache & Seuring, 2017).

Study objectives

The objective of this research was to establish the adoption of analytics and data science in organisations in the South African (SA) automotive industry. This investigation further sought to establish whether there are data management strategies to aid the effectiveness of the analytical tools, whether they are adopted and to evaluate the value of the contributions towards competitiveness and profitability (Müller & Jensen, 2017). To achieve the objective of this study, a literature search was conducted using the keywords, automotive, analytics, business intelligence, data science and competitiveness. The literature review was conducted to search for authors who mentioned the above terms in the databases using search fields like title, keywords, abstract, etc. The required restrictions specified that the journals be peer reviewed.

Significance of the knowledge

The study sought to influence management within the SA's automotive industry by emphasising the advantages of adopting an analytics strategy which is supported by a full data management strategy. The organisations in the industry provided with relevant key performance indicators (KPI's), will allow it to easily analyse trends, accurately predict performance influences with ease and draw immediate reports, compare variables and make timely decisions that benefit the organisation.

LITERATURE REVIEW

This section reviews the literature on the challenges that face the automotive industry with regard to their operations. It then reviews the theory on analytics in view of the effect on operations and the influence of data as enablers to the effective use of analytics. It then reviews customer influence on effective organisational performance with the effective use of analytics. Themes that came out from the literature reviewing process are used to present the literature reviewed in the next section.

Challenges in the automotive industry

Traditionally, the automotive industry modus operandi is to manufacture and provide vehicles, based on forecasting. Holweg and Pil (2001) suggest that organisations could be more effective if they understood the customer voice instead of basing production decisions based on forecasting. The traditional model of basing decisions pertaining to forecast demand has been due to organisations working in silos and the traditional model of operations. The communication barriers do not portray a unified picture of optimum organisational performance. Organisational interactivity is important because it promotes co-ordination which impacts on the productivity cycle. Interactivity requires co-ordination between various stakeholders, including customers, dealers and the vehicle manufacturer (Howard, Vidgen, & Powell, 2003). The vehicle manufacturing organisation itself needs to operate interactively. The effect of organisational performance is largely measured from the impact of operations on the three key elements; the customer, the product (which is the vehicle) and the organisation.

Theory on the use of analytics

According to Kache and Seuring (2017), organisations apply analytics to business data in order to find meaningful patterns in data and thereby make decisions to improve business performance. This intelligence is transcribed into Business Intelligence. Business intelligence is about knowing one's position, customers and competitors which serves as a tactical input to strategic and tactical decision making. Klatt et al. (2011) support the notion that it is about providing the ability to engage intelligently with customers for better performance. Intelligent engagement requires a voice. This voice is derived from accurate information in the data. Analytics aids in the integration of this

intelligence. Analytics provide knowledge management of data across every aspect of the business. In the automotive industry, this operational knowledge spans demand planning, product design, production, inventory sourcing and logistics. According to Klie (2015), the business stands to benefit from a single view of the customer which is derived from the customer journey. The customer journey begins from pre-sales, to sales and thereafter aftersales. This means that the ultimate product that the customer owns would have to be processed with a touch from each organisational department. Optimum organisational performance should ultimately benefit from the successful production of the vehicle to the successful sale and maintenance of the customer. The intelligence derived from the inter-relatedness of this information will ultimately drive business performance positively.

According to Seidel, Müller-Wienbergen, and Rosemann (2010), the capability of business intelligence (BI) has evolved and the need for powerful computational and analytical needs has increased as enterprises have become more sophisticated in their operations. Knowledge, which is derived from analytics, has become a key differentiator and determinant to success for organisations. Furthermore, Müller and Jensen (2017) add that the ability to create reports and status updates with speed and ease has become critical. Personalised experiences, optimised data for different uses, provide real-time on-demand data for decision making which is critical to enhance competitiveness (Uden & He, 2017). Several industries have demonstrated the benefits of using analytics to make business decisions to improve effectiveness and competitiveness. Klatt et al. (2011) support the use of analytics and state that the five primary advantages to applying analytics are to leverage efficiency; objectify decisions; disclose assumptions; test strategy impacts and to see and learn from changes. This is seen in the Swedish environment where Tannou and Westerman (2012) illustrate the recent implementation of analytics which enabled success and improvement on efficiencies at Volvo.

Data as an enabler to analytics

Analytics cannot be effective on their own, instead they need an enabler and that enabler is data. In the organisation, it is useful to know the extent to which the data that is obtained is utilised in the analytical process. According to Jacoby, Speller, and

Berning (1974), the increase in the amount of available data has progressed since the 1970's, presenting a challenge in its capability to provide adequate relevant information. With the increase in data, information overload during the 1970's was a problem in decision making. The evolution of advanced computing during the mid-1980's to mid-1990's made data available across the organisation and led to the evolution of material requirements planning (MRP) and enterprise resource planning (ERP) systems. However, Anderson (2008) emphasises that this data without a model is just noise . A deeper study of data required for analytics, led to the philosophy that data is composed of structured and unstructured data (Negash, 2004). The structured data takes the form of online analytical processing (OLAP), data warehouse data, enterprise information system data and ERP. Negash further explains that collected semi-structured data takes the form of chats, emails, image files, marketing materials presentations and reports.

Currently, Zhan et al. (2017) highlight that the automotive industry gathers data through multiple media, inter alia, social media, email, connected car (through applications like GPS location information, sensor data), information from dealers through the dealer management systems, online data from websites and various customer relationship management (CRM) solutions, to say the least. The advent of all this data leads to big data, and the estimated amount of growth is 100 zettabytes of data by 2020 (Wong, 2012). However, big data has some characteristics associated with it that is valuable once quantified, namely; volume, velocity, variety, veracity and value (Villanueva, Aguirre, Villa, Santofimia, & López, 2014).

With the advent of big data, the volume of data in the automotive industry that is derived in various forms from customers and organisational operations makes the extent of velocity in analysis critical. This data is not helpful unless converted into useful information with speed and ease. The question arises on how to transfer this data that is received in the organisation into actionable knowledge. It is necessary to translate the barrage of data, timeously, to make the organisation a differentiator (Anderson, 2008; Bumblauskas et al., 2017; Fosso Wamba, 2017). Hence, datafication and its digitisation thereof has become key in the aid of analytics to driving business decisions (Newell & Marabelli, 2015).

Customer at the forefront of competitiveness

According to Muller (2009), leaders with regard to analytics in the automotive industry have accepted that their main core function is no longer a standalone function, but needs to satisfy the whole value chain. Volvo goes on to state that it "sells an experience" (Tannou & Westerman, 2012). The drive for market share in the automotive industry in South Africa has become challenging and the rising costs of the economy has put a strain on businesses across the board. At the forefront of every bottom line of the organisation is the Customer. However, the need to understand the customer and his/her needs is very limited in the automotive industry. Holweg and Pil (2001) believe that the manufacturing industry must first understand what the customer prefers with regard to which product they want. In addition, Holweg (2003) states that as far back as 1999, only 32% of new vehicles that were sold in the United Kingdom were made to customer order.

Holweg believes that the root cause of the inability to provide responsive order fulfilment was as a result of a strategic misalignment on the internal order process to the external requirements. Eisenstein (2000) points out that not only can industries improve customer satisfaction, but they can also increase profits, by increasing efficiency and providing the exact vehicle that the customer wants, at the right time, due to the abundance of data. Information such as customer behaviour, patterns, expectations can be realised from the deluge of data. Volvo in Sweden alludes to the fact that information on the customers is owned by the dealerships that sell their vehicles (Tannou & Westerman, 2012). This information is in the underlying data that is expected to be in the OEM's data files. It has been established further that there is a lot of information that resides in pockets of unrelated databases.

From the literature review, the researcher has established that analytical tools have the ability to plug into the multiple sources of data and make sense of a singular story, be it of the organisation and its trends, vehicle information and the customer. Ultimately, a retail sale requires a present customer. The data that is available in the organisation and speaking volumes can aid in ensuring that the organisations are aware of cues on the latest trends and the preferences of customer. The understanding of the data requires intelligence, and this is where analytical tools become crucial. Intelligence into

preferences provides advantages over the competitor. A seminar held at DecisionINC in Johannesburg in July 2017 on the available tools that are used for analytics revealed that a lot of commercial organisations are still using tools like Excel for analysis. Recently, consulting companies have introduced SAS, Qlikview and Tableau with SAS and Qlikview topping usage in the industry. The use of Tableau has been gradually increasing and might soon be a leader in the automotive space due to its aggressive marketing campaigns. The research was therefore done considering the analytical tools listed in Table 1. From the table, the two companies, Accenture and Deloitte, are consulting firms that service the automotive industry in South Africa and hence the introduction of the two tools SAS and Qlikview into the automobile organisations.

Table 1 - Top Companies Using the Most Popular Analytics Tools

Popular Analytics Tools	Top Companies Using Them
Open Source	
R	Accenture, Cognizant, Google, Facebook, Citibank, Genpact, MuSigma, Fractal Analytics
Python	Alibaba, Google, Cognizant, TCS, Genpact, Gramener
Apache Spark	Uber, Pinterest, Ola, Facebook, Infosys, Wipro, Netflix
Apache Storm	Groupon, Twitter, Yahoo, Alibaba, Spotify, Flipboard
PIG & HIVE	Yahoo, Facebook, Twitter, Baidu, Uber, Flipkart
Commercial	
SAS	HSBC, Citibank, Google, Netflix, WNS, Genpact, Accenture, HDFC
Tableau	Barclays, Citibank, Gallup, Ogilvy, LA Times, Toyota, AOL, Dell, HP, Marico, Ashok Leyland
Excel	Almost every company known to mankind
Qlikview	TCS, Capgemini, Accenture, Cisco, Deloitte, Citibank
Splunk	Adobe, Nasdaq, Coca-Cola, Cognizant, Groupon, First Data, GoodData, ING, Intuit

Table 1 demonstrates the top 10 companies that use open source and commercial analytical tools. The automotive industry in South Africa operates at a commercial level. The industry utilises the services of consultancy firms such as Accenture and Deloitte, to manage analytics therefore, it is important to review the use of SAS and Qlikview. Although Toyota as an OEM is listed as using Tableau, it was expected that the research would highlight this as an optional analytical tool used. The use of Excel

was excluded from the research because the extent of its effectiveness would need to be established as a separate investigation.

RESEARCH METHODOLOGY

The qualitative approach was found suitable for the needs of this investigation because it allowed an holistic perspective from participants' reflections about the current methods of managing data in their business environments. Jacoby, et al., (1974) argue that there has been a progressive increase of the amount of data generated which hinders decision making in the automotive industry. Therefore, this study delves into a deeper perspective of the participants to obtain a broader view into the topic under study (Creswell, 2013; Leedy & Ormrod, 2015; Merriam, 2009). Neuman (2014) suggests that the qualitative methodology enables a thorough understanding of phenomena experienced in a particular setting. Neuman's notion gave this study a practical approach which opened up a channel for contributing to the solution of problems.

Other authors argued that data that is required in the qualitative approach is obtained by asking individuals open-ended questions (Percy, Kostere, & Kostere, 2015). Despite these ideas, Willig (2013) states that the qualitative approach is seen to have limitations in that it leaves the study open to various interpretations. However, based on the notions gained from the various authors, I sought to find answers to the research questions that guided this investigation through the qualitative methods strategy. Ethics clearance approval letter was obtained from the University of the Witwatersrand Business School, Johannesburg, South Africa. Thereafter, a standard generated letter from the same university was sent to the respective participants to request their participation. Creswell (2015) denotes that permission is required before any qualitative process can be valid. After the participants consented to the study, a mutually convenient time and date was established and set. The interviews took place between January and February 2018.

Research Method

Semi-structured interviews were chosen and used as a research instrument for data collection. The research instrument consisted of several open-ended questions. This stance was adopted in line with Sutton and Austin (2015) who suggest that this method

allowed for lengthy discussions on the analytics and data science use within the automotive industry. Moreover, the interview guide was designed such that it established the effect of the analytical tools, ease of use, availability of support, decision making enablement and measure of effectiveness towards the contribution to organisational performance. It was hoped that the outcome of the data analysis process would provide guidance to the automotive industry on whether they should or should not adopt analytical tools to operate effectively and efficiently, if such tools are not in use already. Abusabha and Woelfel (2003) denote that currently there are reporting challenges with the massive uptake of data in the automotive industry.

Data Collection

Merriam (2009) suggests that interviewing is necessary to collect data from a number of people where a broad understanding of a phenomenon is required. A pilot study was conducted with five managers in a Johannesburg automotive office. The managers were randomly selected. The pilot study was used to test the validity of the research instrument. According to Leedy and Ormrod (2015), a pilot study is used to formulate an understanding of how the research might develop and to gauge how long the real research might take to complete. The pilot study was therefore used on a smaller scale and it did not apply laborious standards. It also did not form part of the research. The semi-structured interviews were conducted, and open-ended interview questions were asked to collect data from the research participants. Information around data science management and use of analytics was key to the successful investigation of analytics usage. The researcher collected pre-screening criteria which were used to select participants. Techniques and experience derived from coaching sessions to conduct the interviews were applied during the interviews. The techniques included skills on how to conduct open-ended questions in an interview. The researcher also used the experience from the field testing to prepare for any complications that could arise during the interviews.

Seven participants were sourced and interviewed. Patton (2015) advises that to have an effective interview, the number of participants interviewed should allow for effective in-depth information to be obtained and thus, anything between 5-20 participants is allowed. The venue for the one-to-one interviews was communicated to the research

participants. Time and dates were confirmed with all participants. Before each interview session, the participant was briefed on the interview process. The brief included seeking permission from the participants to use an audio machine. The audio machine allowed the researcher to listen fully to the participants. Following the disclaimer, permission was obtained from the participants to proceed. Five managers were interviewed in person, while the remaining two managers were interviewed telephonically, using Skype due to their geographic location. Each applicant was interviewed for an hour (Merriam, 2009). The interviews were done until the researcher was satisfied with regard to data saturation (Guest, Bunce, & Johnson, 2006). The data gathered included participants' demographic background, eight pages of reflective journaling and over six hours of recording. During the interview, the researcher scribbled notes to direct guided thoughts. Participants' personal details were not included in the transcripts.

Research Instruments

The semi-structured interviewing strategy was the primary instrument in this qualitative research and was used for the collection and interpretation of data (Creswell, 2015). An interview guide containing seven open-ended questions was used to gather information from the participants. The questions were designed by the researcher and based on the outcome of the pilot study responses. A purposeful sampling strategy is used when a research consists of participants with similar experiences (Guest et al., 2006). According to Leedy and Ormrod (2015), a research project which requires the researcher to establish people's perceptions and perspectives and also tries to understand a particular situation, needs lengthy interviews. The interviews were semi-structured and semi-formal. Questions were formulated in an easy manner so that they were easy to understand.

The nature of the questions was based on gaining insight into the use of analytical tools and the level of data management in the automotive industry. Questions on the interview guide were tested on colleagues before being used on respondents. This was done to gauge their difficulty or simplicity and clarity. Pre-testing the interview questions also allowed for the modification of the questions before data collection began. Merriam (2009) advises that one does a pilot telephone call, gathers feedback then feeds information to the research study, so that the purpose of the pilot study is

understood. She also advises that the latter should be a brief discussion on the research and it should not take away the main data that is acquired from the core observations to the study. However, for the purposes of this study, the results of the pilot study were not included nor referred to during this study, so that there is a clear understanding of how analytics affect organisations. The interview questions consisted of questions that forced responses from the participants aligned to their experiences of managing the data, the effort it took to draw reports and intelligence from the available data. It allowed the respondents to review the available tools, if any, that were available in the extrapolation of the reports.

Data analysis

Creswell (2015) suggests that data that are stored in a software program are easier to manage as the process has grown since the 1980's. Various data analysis tools were explored as per recommendations. However, the software that was available freely because it was on a trial basis was NVivo version 11. This was downloaded; the code function was used to align the information. NVivo11, a computer program that is used for analysing qualitative data, was selected to aid in the thematic analysis of the data because it improves the accuracy and speed of the analysis (Rowley, 2012). The tool also aided in the storing of data, making it easier to search for codes and themes. The NVivo11 tool enabled the retrieval of codes and associated links between categories and themes which allowed the researcher a means of conducting an in-depth analysis. This data was compared on a constant basis by constantly updating codes, patterns and themes through the analysis process (Percy et al., 2015). Transcription of each interview was done immediately after the interview in order not to lose data and to understand the interviewee's point of view. This was double checked with the researcher re-reading the transcript while listening to the recordings.

The themes and patterns included quotes from the transcripts to provide supporting evidence. Audio recorded data were transcribed after each interview session and were compared against a reflective journal that the researcher kept. Any data that was thought to be useful was highlighted with NVivo11. The highlighted data was coded, utilising the coding function of the NVivo11 tool. As the data analysis continued, the categories

that emerged were assigned direct quotes from the interviews. The different categories that further emerged were grouped into clusters based on pattern codes and commonalities. Coding was complete when categories and themes were fully described and defined. The relevant data was then loaded into a software program, NVivo11, for further analysis.

Other functions used were word cloud and word frequency to view the most used words. Tree maps were also used to view the associated information and largely coded using the coding function. I used the transcribed data to load onto the software. It saves all the loaded information as a database. The inductive thematic analysis was used for analysing the data. This was conducted because it was found to be the most relevant for analysing data gathered from open-ended interview questions. An inductive thematic analysis approach allows for the categorisation of the data (Percy et al., 2015). An interpretative approach was used to identify patterns from the responses of the participants (Smith & Firth, 2011). It was required to compare data from the different participants constantly which allowed for the production and extrapolation of patterns and themes collected during the interview.

Research Design

A research design that suited the needs of this investigation was chosen after the approval for conducting this study was received from WITS Business Schools' ethics committee. Creswell (2013) advises that the research design should be determined in the early stages of the study so that there is a clear path of the way in which data was to be collected. As a start, an effective organisation requires that all the data that is stored and is pertinent to a department is shared across all departments. The use of analytics aids this inter-relatedness. In support of this phenomenon, Deloitte (2017) illustrates a model from the United Kingdom that shows a value chain that uses analytical models to ensure success from the production of the vehicle to the sale of the vehicle. The underlying source of the analysis is the data that is shared cross functionally. Figure 1 illustrates the research design that shows the importance of inter-relatedness and the proposed analytics required to achieve value and success.

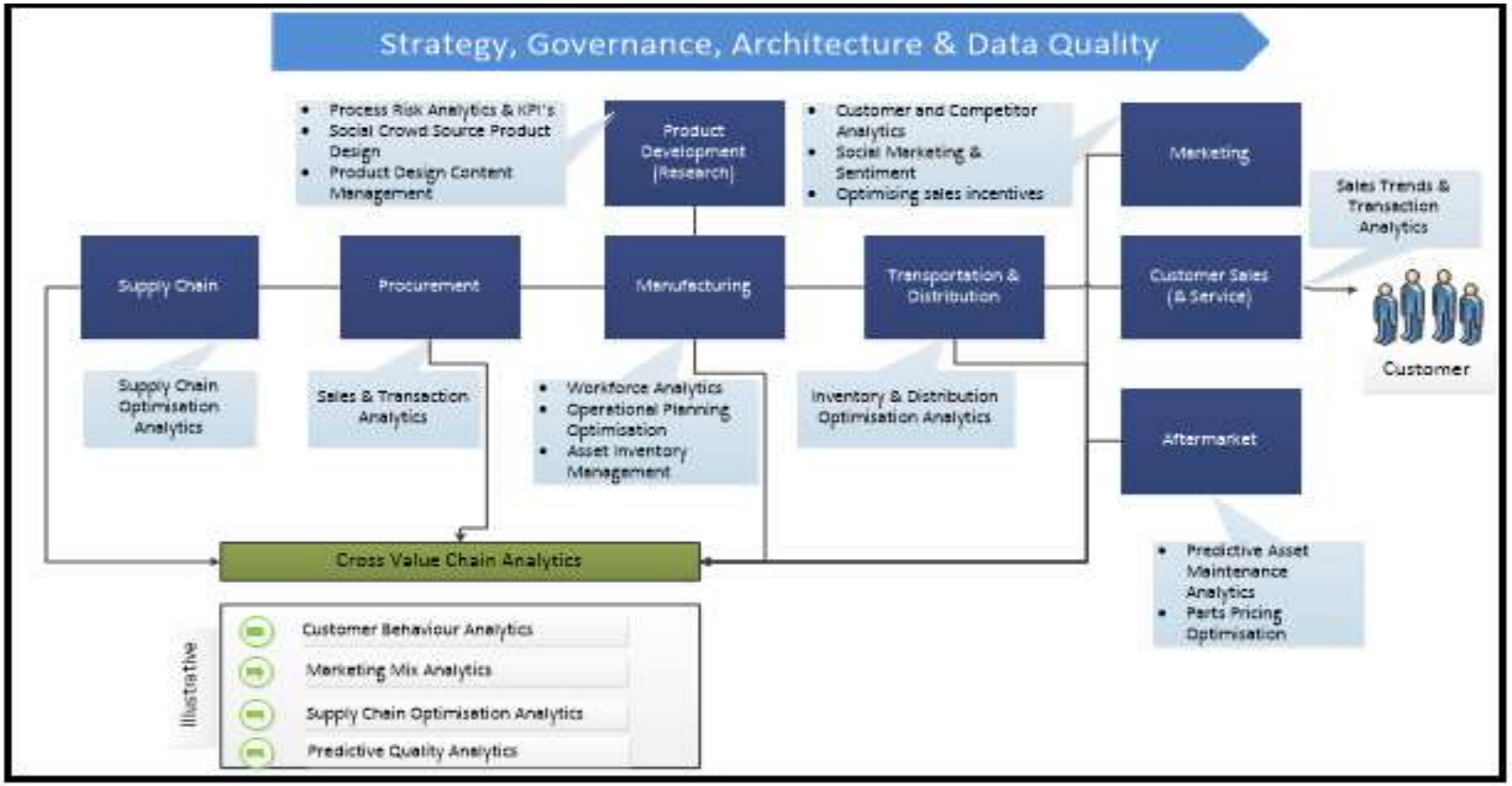

Figure 1 - Automotive value chain (Source – Manufacturing analytics value chain) (Deloitte, 2017))

Figure 1 displays the research design that drove this study. A pictorial demonstration of the research design showcases the inter-relatedness of the departments in a typical automotive organisation. It highlights examples of relevant analytics per department and the importance of understanding the full organisational cycle to get to the benefit of the ultimate consumer who is the customer. The overall success of the organisation lies in its strategy, governance, architecture and data quality. Organisational competitiveness is derived from the implementation of a successful strategy and therefore, cohesion within the organisation needs to be clearly determined from inter-related operations. The model illustrates that the different analytics in the different departments have an effect on the key decision-making capabilities throughout the organisation. The governance, architecture and the quality of the data are influential to the cross-value chain. Analytics feed off data which is deemed to be available in the organisation. From the different departments, clear outlines of expected analytics are laid out which influence the success of the overall strategy.

Population

The sample came from the target population of middle, senior and higher level managers who worked in the Automotive Industry in South Africa. The total numbers of the population from which the sample of managers was drawn is unknown to the researcher. Purposeful sampling was done with this research because one is required to strategically sample key informants who have knowledge, influence and can shed light on the inquiry issues (Patton, 2015). The target group needed to be in a position to have the ability to make quick decisions that impact the operations and final strategic outcome of the organisation. The target group was deemed to be in a position to explain the effectiveness of analytics in a given environment as they would be aware of the operations and challenges facing the industry with regards to data and the management thereof. The ability to explain the effectiveness could only be derived from the experience of the respondents, therefore, the minimum years of working experience was limited to not less than five years. Gentles, Charles, Ploeg, and McKibbon (2015) suggest that identifying detailed characteristics of the population ensures that the responses that are derived from the respondents align with the study objectives. The characteristics identified required participants who had no less than five years working experience and the type of work that they performed required the use of the analysis of

data to a certain degree. The population thus was made up of the management level who were required to provide some level of reporting to organisations. The reporting thereof was deemed to assist executives of the organisation to make decisions.

Sample

Seven managers were deemed to be able to generate enough data that would allow data analysis that could be generalised back to the population from which the sample was taken. The target sample size for the research was five to 20 participants as Patton (2015) suggests that enough in-depth interviews to get an accurate representation of views is required. Gentles et al. (2015) emphasises that the selected sample size must be able to provide in-depth description of the ideals behind the research purpose. However, it was required to ensure that adequate information and representation of the research purpose was attained. Guest et al. (2006) describe saturation as the process by which interviewing any more participants would not produce any new codes. The participants on the list were interviewed until the researcher was satisfied that no new codes would be attained from further interviews.

Fusch and Ness (2015) state that the sample size needed to provide data saturation and if the selected sample size did not provide that, the plan was to include further participants. Criterion based purposeful sampling was used because the researcher needed to find and select participants who would answer the research questions for this study. The appropriateness of the data, therefore, is key in determining the sample as the participants needed to provide enough rich data to a point of data saturation. Saturation, in this instance, was achieved by the completion of the fifth interview. Most of the identified participants were sought on LinkedIn. Some were contacted via email or a personal call to request them to attend the interview. The participants received information about the study which included a short synopsis that described the study.

Participants' Demographics

The participants who were interviewed, each had at least five years of motor industry experience. The participants' ages ranged from 35 to 55 years. All the participants had worked in one or more companies in the automotive industry and were fully conversant with the operations of the organisations. The companies they had worked for included

Volvo, Volkswagen Group (VW), Mercedes Benz, Nissan, BMW, Ford and T-Systems. Table 2 illustrates the profile of the participants.

Table 2 - Demographics

No of Participants	Management Level	Type of Service Offered	Gender	Tenure in Years
1	Senior Level	OEM[1]	Male	More than 15
2	Middle Level	OEM	Female	More than 8
3	Higher Level	ASS[2]	Male	More than 20
4	Middle Level	OEM	Male	More than 7
5	Middle Level	OEM	Male	More than 8
6	Higher Level	OEM	Male	More than 20
7	Middle Level	OEM	Female	More than 5

Table 2 demonstrates the level of experience that includes many years when one adds all the years of working experience possessed by the research participants. Figure 2 shows the gender demographics of the research participants

[1] Original Equipment Manufacturer (OEM)

[2] Automotive Solution Supplier (ASS)

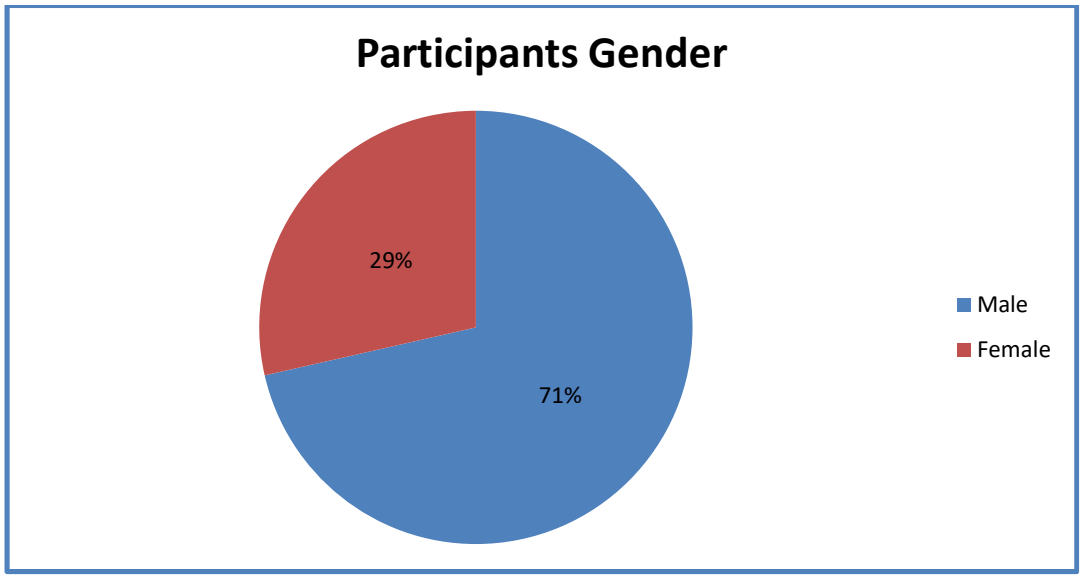

Figure 2: The participants' demographics by gender

Figure 2 shows the participants' gender demographics. The gender demographics were important in the selection of participants so that there is a representation of management views across all genders that make management decisions. Moreover, the gender allocation of the participants is pivotal to assess whether the gender influenced the views on the usage of analytics and data management. The strategy that was used for the systematic approach to data analysis of the interviews obtained from the seven participants, was recorded interview data.

Data Triangulation

Merriam (2009) and Creswell (2013) contend that data triangulation ensures that the information that has been gathered is congruent with the responses from the participants and confirms emerging findings. Examining the quality of the collected data against converged data sources provides dependability. The researcher outlined the data collections actions and data analysis activities to ensure dependability of the study, and in turn, the reliability. The steps describing how data collection and analysis occurred provides for a systematic methodology that other researchers may follow. Therefore, the data that was triangulated was used as a final stage in the data analysis as a quality control measure.

Validity, reliability, credibility

There is an expectation that the participants are honest and open when answering questions (Baxter & Eyles, 1997). As such, the participants were further approached to verify the data that was captured by the researcher as a means of triangulation. A reflective journal was used throughout the interviewing process to capture the researcher's preconceived notions and understanding provided through previous experiences. In the process of transcribing the interviews, the reflective journal was used to capture bracketed feelings and thoughts, thus mitigating the risk of potential bias and thus, establishing credibility for the results (Lincoln & Guba, 1985).

Ethical considerations

Conducting research with human subjects requires adherence to guidelines. Hanson, Balmer, and Giardino (2011) suggest that ethical considerations are key and these include informed consent, privacy, confidentiality and anonymity. Dissemination of the findings and ensuring protection of the individuals through respect of the information provided is important. The American Psychological Association guidelines were thus maintained to ensure that the participants were respected. Hanson et.al states that a researcher ensures that the data is stored and secured effectively and that that personal insights that are shared by participants could lead to adverse effects and therefore these need to be securely protected. Informed consent was obtained before each interview. A full disclosure of the purpose of the study, the interview process and the confidential nature of the data collection process was shared with the participants. The participants were briefed that they could withdraw at any time from the study. To ensure the participants' right to privacy and maintain anonymity, the data did not contain participants' names.

RESULTS

The purpose of this study was to establish the adoption of analytical tools in the automotive industry and if the organisations that had adopted analytics and data science strategies, were effective and competitive. There was a lack of study examining the usage of analytical tools in the automotive industry. Competitiveness was believed to be

based on traditional methods of assumptions due to accurate forecasting, and the aim of this study was to establish if there was a joint effort between operations and available data in the organisation. Three main themes emerged from the data analysis process. These were: (a) analytical tools in the automotive industry, (b) available data science modelling techniques, and (c) factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa. The first theme that emerged indicated that the participants were aware of analytical tools in general; and that they were aware of the capabilities of the tools. The second theme that emerged indicated that the participants were aware of the deluge of data in the industry and due to the magnitude of the data, were seeking solutions to its management. The third theme that emerged indicated that there were key success factors that if implemented, would affect the effectiveness, competitiveness and profitability of the organisations in the industry.

Analytical tools in the automotive industry

Results of the data collection indicated each of the respondents' views on the analytical tools in the automotive industry in South Africa. Two categories emerged from knowledge of analytical tools. The categories associated were: (a) availability of the tools and (b) use of the tools. With regards to the availability of the tools, most of the participants felt that analytical tools were not readily available, as yet. Whilst one OEM had a custom-built solution, the participants from the premium brands felt that the tools had advanced fairly, although they were not where they should be. There were different levels of the tool sets discussed. These included the graphical presentation layer and the underlying engine that churned the data.

The experience of the participants with regard to the use of the tools varied across the OEMs. Whilst some tools were developed to ease the workload of the users, the up-take was seen to be low. Participant 6 indicated that adopting analytics required a mind-set change, whilst Participant 4 believed that there were a number of reasons why the tools for those that had them, were not being utilised. He alluded this to that the person that built the tool or had vested interest in the tool was not the same person using it, or there was lack of use in his organisation due to lack of knowledge on how to use the tools.

Available data science modelling techniques

All of the participants conceded that there was a lot of data in the automotive industry which exist in various sources. There was data that was internal to the organisations whilst a large amount of data was contracted to external sources. The four categories that emerged from this theme were: (a) data availability, (b) employment of data scientists, (c) support, and (d) training options for ease of use. All the participants acknowledged the massive amount of data that was all over from multiple data sources. Participant 2 alluded to the multiple sources of data which included fleet data, warranty information, service data from the dealers, finance house data and information from the parent companies.

The participant also shared that although they were partners, the databases are external that are eventually linked back to the OEM. When asked what the data was like in their organisation, Participant 4 advised that one of the data houses, Lightstone, had developed a data management tool which houses a lot of manufacturer vehicles from the licencing department, from a vehicle licencing system called ENATIS. This was a huge database with vital OEM data. He also stated there were huge amounts of data from social media which had not been contained in the information provided in the interview as part of the organisation's data. Within the organisation, there was external and internal data, of which internal data had its own challenges. Participant 5 also stated that he collected data from several departments which included Human Resources (HR), such as employee recruitment and training information, finance information, which is inclusive of supplier information.

All this information was requested via emails from the various sources to aid him in the decision-making process. Participant 4 also states that there is a growth need to go into the Sub-Saharan markets as part of the organisation's strategy, but the challenge is that a lot of the time, they cannot find adequate information to make those decisions. They have dealerships in those markets but the process of acquiring that information is manual. Participant 1 also concedes that there is no limit to the amount of data that one can have, the challenge is in having it all together.

Most of the participants expressed frustration at the thought of having to manipulate the data themselves in order to get insights into the data. Participant 2 clearly stated that she was a highly credible Customer Relationship Manager specialising in CRM and was not an “analytical tool expert”. This sentiment was supported by Participant 4 who stated that he was a marketing manager and therefore his use of analytics is limited to the extent where he had been exposed. He raises concern that due to lack of the required analytical skills, he is not able to “do the magic” that BI tools have the capacity to generate. What came out strongly is that data needed to be managed by the experts in order to build a story that the organisation could use. Participant 3 emphasised the importance of data and referred to it as the “new oil”. He continued to state, “data is the ones and zeros which was the language of the machine and useless for someone ordinary to understand. You need to take that data and turn it into information and that only a machine can do”.

Participant 6 supports this notion that you need a person that is passionate about data, someone that has the skills to turn, “quite deep analytical insights into looking for trending data, using the scientific tools. You can’t just give it to someone who's not really qualified to, to understand the information.” The deluge of data therefore calls for the employment of data scientists who can interpret the data, translate it into English and if not, as Participant 3 says, the gathering of data “is pointless”. The only two participants who did not share frustration with the manipulation of the data using analytical tools were Participants 1 and 6 as they had extensive experience in Information Technology. Only a small fraction of the participants expressed the opinion that support on the tool was not adequate. This is aligned to the level of expertise that was in question with regard to the analytical tool ease of use.

While the two participants felt that the solution providers needed to be aligned as business partners, and offer advice on trending evolution of the tools, one of the participants felt that the tools should be intuitive enough to not warrant support. The view was that costs should begin to decrease as the tools are beginning to be adopted widely in other industries as well. The other view from Participant 6 was that the tool should be able to “provide us independence and we don't have to rely on a consultant all the time. Happy to pay more for that”. The notion was that it would be better and more convenient to talk to someone online, when one had a query.

It was required to determine what the reason for the lack of use of the tools was. The researcher sought to establish if this was due to complexity in the solution itself. The lesser fraction of the participants responded to the availability of the training once the solution was implemented in the organisation. Participant 4 believed that the tool was too technical, and the use required training if one had to adopt the "robotic skill set". The risk of drawing unreliable data was also raised as non-competent staff were required to draw the reports. Participant 2 expressed frustration that the only training that was provided was that received on implementation. Training was also required to make sense of the data that was readily available and transformed into reports. Ultimately, Participant 4 stressed that uptake of the tools was required so that the system did not become a white elephant which was costly to implement and yet remain unused. He believed that comfort created through training would alleviate this problem.

Factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa.

Organisational effectiveness with the use of data science analytical tools is measured by the effectiveness, competitiveness and profitability of the organisation. The four categories that emerged with this theme were: (a) the benefits of the tools, (b) value of reporting, (c) measure of competitiveness and (d) profitability. All the participants shared common knowledge on the value of implementing analytical tools in the organisation. The participants believed that speed and accuracy of data representation was key in the implementation of the analytics solutions. Participant 3 believed that the tools had evolved to be so agile and states, "Qlikview is great because the bosses get to walk around with iPads and it shows very nicely what's happening in some matrix". The participants believed that the tools help to portray one picture with the ability to provide insights that drive quick business decisions. Participant 6 explains the power behind these tools that have the ability to delve into large unstructured amounts of data.

He states that Qlikview is just the graphical representation of the tool. He stresses that there are other tools beneath the surface that expose the information that is unknown within the business, and provides direction regarding logistics, marketing or production as examples, but the more transactional information is derived from looking back at the

trends in that information that can expose opportunities for the organisation. The participant highlights the massive sources of data such as social media data which is derived from the internet, Twitter and Facebook and expresses the advantage of tools that can trawl through millions and trillions of pieces of information and package the results together. Participant 6 views' illustrates that the disparity of data does not matter and that the amount of data is not a challenge for analytical tools. The other issue that arose from the participant was that time was saved due to the speed at which the analytical tools would provide insights and trends. Participant 5 stated that manually managing the data was not ideal. He stated "It takes forever! Just to generate a gap analysis, it can take me about a month". This led to challenges because sometimes, by the time the user who required the information, it would have been received too late, therefore resulting in wastage of time and resources. The benefits of the available tools in the industry at large include speed, and the ability to go through a variety of data with sophistication and ease.

The major advantage that the participants shared was the speed with which the tools provide reports. A lot of reporting is required in the industry and most of this, in the volume brands, is done manually. The reporting is done monthly whereas some departments required more frequent reporting items. When asked how much reporting was required, "millions, millions and trillions. Tt is crazy the amount of reports", says participant 2. The value of reporting also spans the immediate response. Participant 5 supports the use of analytical tools as reporting tool and states, "The parameter and the information is there…making these processes quite quick". On demand reporting empowers the user to report in real time. "There's not an overview of everything in one. You have to review each and every report and then try and build a picture yourself of what's happening in the business", says participant 2.

The main driver behind every analytical tool is the urge of competitiveness that it gives. With the amount of reporting and business operations that is currently in play, the resources do not have the time to be creative and competitive. Participant 2 states "to be honest I have barely time to analyse what we are doing to go out and evaluate against a competitor". Participant 5 alludes to this and adds, "you don't have to struggle to collect data for decision making. It should generally be available, you know, and real time available and that makes life, your decisions are much quicker, your behaviour and your

reaction is quite speed and that's what you want." The other school of thought that emerged was that the data was available, and the tools were available. The challenge was that the two were not matched and the ability to make decisions was compromised. Use of the tools was believed to alleviate a lot of frustration on lack of foresight. Participant 1 illustrates the proper use of analytical tools. He illustrates that valuable information can be derived from service records due to the unique identifier of the vehicle known as the VIN number. All information can be available when a vehicle goes into a dealership at the service intervals. As this is a regular pattern, predicting types of parts or service is easily achievable with analytics. The organisation is then able to pre-order the relevant parts and prepare a forecast on the business plan accordingly. Making timely decisions was another competitive advantage raised by the participants. It was required that reports were so new and relevant that the decisions to outsmart the customer could enable benefits to be realised.

Ultimately, Participant 3 pulls it together with a reflection on the optimum performance of the organisation. He states, "I always talk about the highway. Everybody's on the highway. All going more or less the same direction. Everybody wants to make their customers happy. They want to make more cars at cheaper prices and sell more than they ever have, that's the ultimate goal. Some organisations are only getting on the highway, others, they are almost at the finish line and others will never make it, but I think that's that all manufacturers in the automotive space struggle with the fact that their production environments are centrally managed and controlled so that the global board orders instructions to build" The participant believes that the main aim of analytical tools is to add value by making information relevant. He believes that insight should be achieved at a glance of the performance indicators of the organisation. It is from these insights that higher management should make quick decisions, for example, with regard to price positioning based on warranty information and geographical location of the vehicle in question.

Summary of the presentation of the results

The results of the data collection and analysis as they related to the research question and sub-questions are provided in this section. The objective of the study was to

establish if there was an adoption of analytics and data science in organisations in the South African (SA) automotive industry, the data management strategies and the value of contribution towards competitiveness and profitability. The results indicated that there were similar characteristics that affected the use of data science and analytics in the SA automotive industry. Three main themes emerged: (a) analytical tools in the automotive industry, (b) available data science modelling techniques, and (c) factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa.

The first theme that emerged, required the researcher to review the level of *participation and knowledge of the tools* available in the automotive industry. The emergence of the first theme indicated that the participants were aware of analytical tools in general; and were aware of the capabilities of the tools. The second theme that emerged, *available data science modelling techniques*, provided the researcher with evidence of the availability of the data and its level of usage. The evidence indicated that the participants were aware of the deluge of data in the industry and due to the magnitude of the data, were seeking solutions to its management. The third theme that emerged, *factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa*, guided the researcher in determining the correlation between availability of tools and data with the effectiveness and competitiveness of the organisation. The evidence indicated that there were key success factors that if implemented, would affect the effectiveness, competitiveness and profitability of the organisations in the industry.

The first theme, *analytical tools in the automotive industry,* involved participants' views with more than five years working experience in the automotive industry. Two categories emerged from knowledge of analytical tools. The categories associated were: (a) availability of the tools and (b) use of the tools. These categories guided the researcher to review the level of participation in the use of analytics. The second theme that emerged was *available data science modelling techniques.* Four categories that emerged from this theme were: (a) data availability, (b) employment of data scientists, (c) support, and (d) training options for ease of use. This helped the researcher to delve deeper to understand the users' level of engagement. Participants described what data

was available, from what sources and how this was being incorporated into the organisation. The third and final theme described by the participants was *factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa*. The four categories that emerged with this theme were: (a) the benefits of the tools, (b) value of reporting, (c) measure of competitiveness and (d) profitability. The participants therefore provided evidence on the reality of the operations within the organisations which allowed the researcher to delve deeper into the four categories that emerged with this theme. As lack of management of analytical tools and data science modelling was not incorporated into the organisations, the effectiveness, competitiveness and profitability of the organisation was compromised. A discussion of the themes in the research with relation to the literature follows.

Analytical tools in the automotive industry

The availability of analytical tools, as described by the participants, influences the daily decision-making capabilities within the organisation. Analytical tools were invented to ease the burden of individuals and this is largely being accepted in other industries. The participants shared frustrations with regard to the progress of the uptake of analytical tools in the volume brands. Whilst the premium brands had made some progress, they were still behind, in comparison to the industry standards. Implementation of analytics and data science techniques is seen to create value. With analytics, organisations are able to read the available data and transition that into meaningful insights. Figure 3 shows the transition of this intelligence into meaningful insights using proper data science techniques:

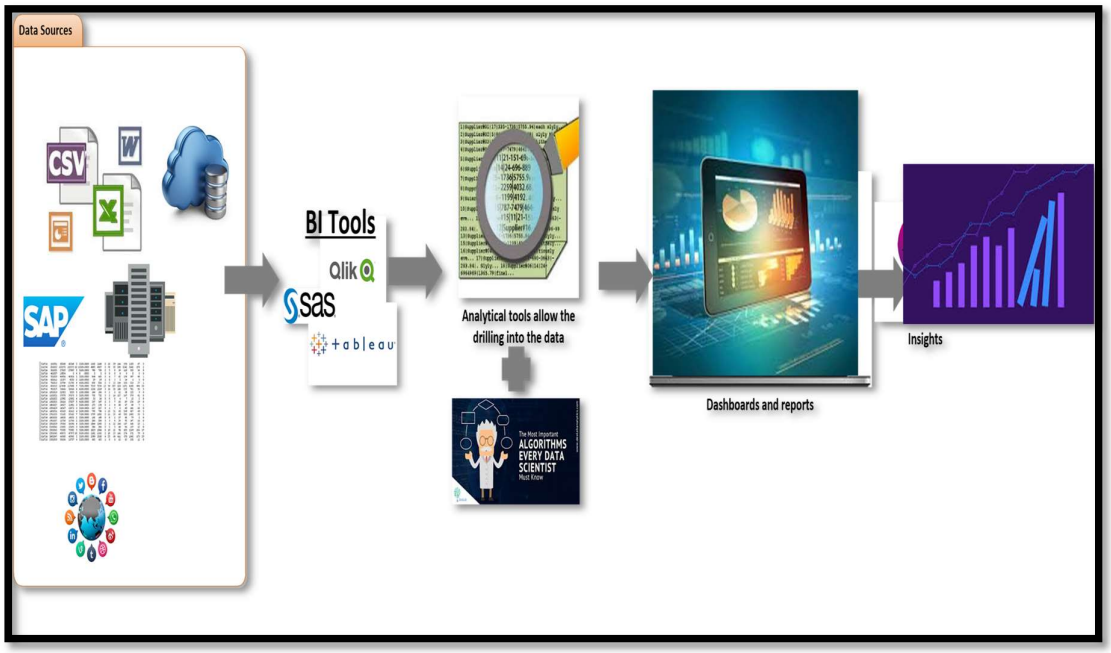

Figure 3 -Transition of data into meaningful insights

Figure 3 is critical because it demonstrates how data should and can be turned into meaningful insights with the use of analytical tools. Kache and Seuring (2017) suggest that meaningful patterns to data are required if the organisation is to improve business performance. From the discussions with the participants, there are analytical tools available, but these are either not taken up at all and where successful organisations have adopted these, the uptake has been implemented in small pockets. The uptake or lack thereof, defeats the purpose of the analytical process illustrated in figure 3.

The tools that are readily available in the industry to aid this process include Qlik, SAS and Tableau, as ascribed to by some participants. There are two layers of the analytical engines, the front-end that provides dashboard reporting and the back-end that churns the data into information. Whilst the back-end is managed by the suppliers of such products, the front-end which enables dashboard reporting, needs to be managed by the front-end user. With the evolution of the dashboard and reporting requirements, there have been two set-ups that have revolutionised. The two set-ups include static reporting and agile reporting. The static reporting is created for individuals who are not comfortable with manipulation of the dashboards. Agile reporting subscribes to the techno-savvy users. The reluctance to utilise the front-end part of the tools implies that

the users have not been adequately trained into analysing the information that is displayed on the dashboards.

Available data science modelling techniques

To provide a real picture of operations in the organisation using analytical tools, there is a dependency on data. The amount of data has been increasing from as far back as 1974 as supported by Jacoby et al. (1974). The participants indicated that data was everywhere in large masses. This is also supported by Wong (2012), in that the growth of data would grow into 100 zettabytes by 2020. The level of growth of this data can be attributed to the various media capturing this data. Zhan et al. (2017) indicate the various media of data capture, such as social media, traditional emails; and applications which have led to the advent of big data. The various sources of data as indicated by the participants in the industry include both internal sources such as ERP systems, email and other sources. External sources include Dealership data, Lightstone, fleet data such as AVIS, and finance house data as examples. There is no end to the amount of data that is available.

This leads to a drive towards the management of this data as Anderson (2008) states that data without a model is just noise. Figure 4 indicates a possible management process for this data which could lead to its optimum use.

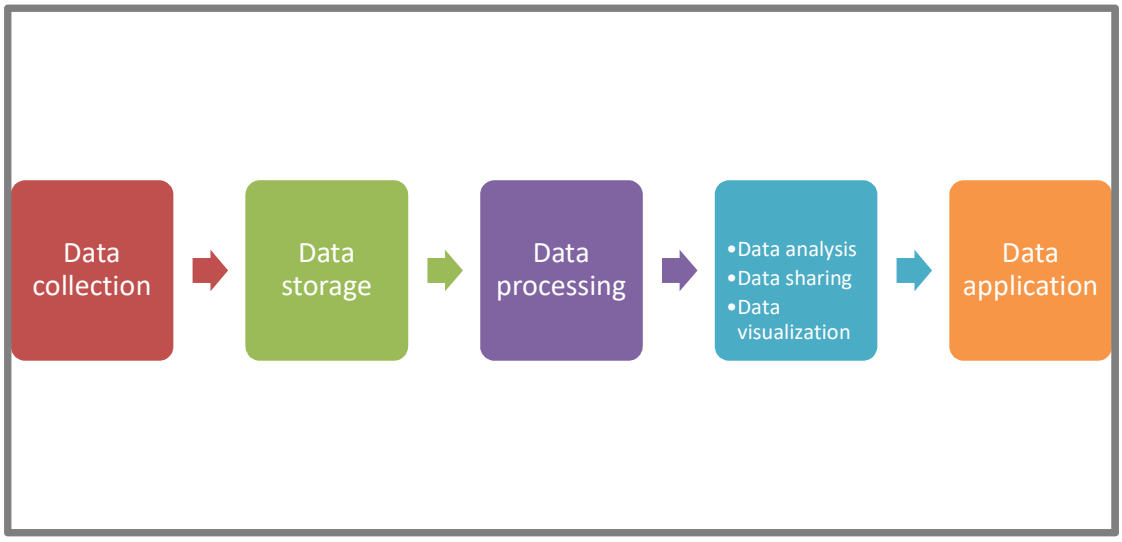

Figure 4: Data Value Chain

Figure 4 indicates that the process from the point where data is collected needs to be managed to the successful point of its application. 66% of the participants found this data management process frustrating as the data was too much. For this reason, it was required to determine if the employment of data scientists was required to manage the transition process from storage to its application. The application of the data would have to follow a process as depicted in figure 3, where the data would be transitioned into meaningful insights. Due to the skills of the data scientist, this would be achievable in preparation for further growth of data with the advent of the fourth industrial revolution. The employment of relevant skills and tools to manage data is a viable option to release skills that are required to perform other functions within the organisation. As supported by some participants, making the tools intuitive enough was aligned with the move towards future developments of analytical tools. The development of more intelligence will demand on-line support which should be available all the time. Training was discussed as an option to up-skill the workforce. The participants expressed concern that the growth of this intelligence was increasing rapidly and therefore training an unnecessary skill set would be costly and of very little value.

Factors that influence effectiveness, competitiveness and profitability in the automotive industry in South Africa

Analytical tools allow the process to turn data into green, which is meaningful data. The advent of intelligence which is applied to analytical growth refers to this as machine learning. It allows one to make strategic decisions based on the real data within the organisation. Analytics allows the decision-maker to make different relevant assumptions. In the example of Eskom, generator trends are relevant, because the generators that worked for one year does not mean they will work for the following year. There could have been underlying issues, that are present in the data, that led to the uptake of generators in that period.

Figure 3, which illustrates the transition of data to meaningful insights is a big advantage of analytical tools. Klaus (2016) states that with the increase in technologies, intelligence that is required to be applied to data, is key. One participant shared the view that the disparity of the data did not matter if a tool would be placed on top of the data to transition that data into information with speed and ease. The shared view was

that analytical tools have this capability and should therefore definitely be employed. Bumblauskas et al. (2017) and Fosso Wamba (2017) state that managing the transition of data into insights with speed and ease is paramount to making an organisation a differentiator. The speed and ease with which analytics are deployed allows for operational efficiency and productivity. They allow for firstly understanding organisational performance based on actual data, and understanding customer behaviour and patterns, which are key to organisational growth. Analytical tools allow for reporting efficiently and timeously. It is critical to understand that clean data is key to providing accurate output. The data management process as depicted in figure 4,shows the data value chain is key. The organisation needs to ensure that data is managed adequately otherwise the voice behind the data will not be valid.

Reporting with analytical tools shows the key performance indicator's (KPI) of the organisation. This can be illustrated for any division of the organisation and with speed and ease. This metric enables real time strategic decision making which is relevant to the organisation. As the customer has become a key variable in the competitive game, the participants, especially in the CRM space, find the speed with which to respond to customers is key in the customer journey. To satisfy the "experience" of the customer as expressed by Tannou and Westerman (2012), having the relevant information in the right format at the right time would manage this experience. Not only will customer management be exceptional, but operational efficiency would be achieved with the relevant reports.

Analytical tools lead to reporting that enables management to make the relevant assumptions. The assumptions that are made, lead to competitive advantage. The industry is fortunate to have data from NAAMSA which includes information from the manufacturers and is indicative of the performance in that sector. This entails that the industries are able to draw the competitive curve and create strategies to steer ahead of this curve. Reporting, which has been discussed above, allows management to make timely decisions based on information that is available within the organisation and compare this with the industry information. Klatt et al. (2011) are of the view that when intelligence is applied, it increases the chance of competitiveness in the organisation because competitiveness is about knowing one's position, customer and competitors.

The successful competitive nature of the organisation leads to its profitability. Frei (2006) states that there is a direct correlation between the customer, product and service. The model further illustrates that there needs to be alignment between the three if the organisation is to operate successfully and not trade off service. As service is largely applicable to the customer, it is critical that the customer remains satisfied. Employment of analytical tools and data science modelling techniques is therefore relevant in ensuring the profitability model. Eisenstein (2000) points out that employing these techniques not only increases efficiency, but also the profits, as by understanding the customer and their preferences, the organisation is able to satisfy their clients.

Implication of the study results

The study highlighted that the industry had started warming to the idea of analytics. However, the use of analytics and data science modelling techniques was still in its infancy. The maturity of the organisations had a huge impact on the change required to make the required move with speed towards the fourth industrial revolution. In the analytics space in general industries, technologies have advanced rapidly, which includes usage of cognitive engines to increase performance. The advances in the endless deluge of data have moved to cloud solutions which provides for an increase in storage space. The emergence of disruptors such as these, requires critical data and analytics management strategies in these organisations. This also requires that at the very basic level, basic data management practices should be implemented with the relevant right analytical skill set.

Limitations of the study

Due to time limitations, the research was limited to top management of the OEM's in the majority of the industry. Further investigation into the use of analytics at a lower level than management level would benefit the study on the capability of the tools at operational level. Although the qualitative method allowed for deeper insights into the capabilities of analytical tools, the tools were generalised, therefore understanding the differences between the available analytical tools would require further research. The size of the industry in South Africa created a reservation of the participants to provide much more intense information due to the retention of competitive strategies.

CONCLUSION

The research sought to establish how the automotive industry in South Africa has adopted the use of analytical tools to aid in decision-making in an attempt to increase their effectiveness and profitability. The advent of data brought huge challenges in the automotive industry. Computational power has been growing exponentially over the last couple of years. While there is the perception that the use of analytics and data science exists in business systems in the automotive industry, the interviews with the participants indicates that these have not been fully adopted for use. Mostly, the implementation has been adoption of CRM information which is largely used in a part of the organisation and specific to the organisation. Furthermore, unanimous agreement among the participants reveals that an agreed management of data does not exist. The data is there, but it resides within the different divisions and external sources and therefore a data management strategy is key.

Despite that none of the participants were aware of the cross-value chain analytics model developed in the United Kingdom, the idea of adopting a similar process was plausible to every participant as a way to begin the process-thinking approach in the industry. A structured approach with predetermined analytical models that are defined for the different departments was a more organised way of starting to achieve a lot of objectives. From the participants' responses, some organisations, which are largely known as the premium brands, have adopted the use of analytics. Although some of the organisations have adopted the use, there are only specific departments that have adopted and implemented the said tools. It has been found that some brands like BMW, Mercedes Benz, Volvo and Audi/VW has made progress on the adoption of these tools. In some OEMs like Nissan, the attempt has emerged, but the situation is a far cry from where it should be.

By and large, industry-wide, there is advanced progress being made towards artificial intelligence and this will require additional computational power over what the use of analytics requires currently. In effect, the organisations should be fully on-boarded. The OEM's that have adopted these tools enable the organisation to make quick and timely decisions. Benefits that have been provided include the competitiveness which is

evident in the sales figures as provided by NAAMSA. The research has realised that while organisations work in silos to achieve objectives, they would achieve more competitiveness by having a structured methodology to reporting in order to engage, inter alia, within the organisation and speak the voice of competitiveness. It is clear from the participants' feedback that the idea of the cross-value analytics model can be adopted because there is a need for a defined process within the organisation in the industry and the model would be a ground-breaking good example.

Based on the above, this investigation has concluded that "not all the organisations in the automotive industry have adopted the use of analytics to increase their effectiveness and profitability".

Recommendations

From the research, it has been established that some OEM's like Nissan, require a structured strategy to implementing analytics and data science techniques in their organisation. The organisations that are lagging need to review the model of having a dedicated team where possible. These dedicated resources would assist the organisation in that it would engage with the current resources to fully understand the data that resides in the organisation. Data is an integral part of the real story behind an organisations' operation, therefore analytics can aid in the transition of their data into information as the data would highlight the problem areas in the organisational operations.

In view of this scenario and in order to advance the desired idea of complete adoption of analytics, or a process model further, the recommendations from this research are to understand the following:

- Why the executives in some OEM's are not adopting analytical tools for their organisations in the automotive industry.
- Is there room to adopt a standard process for analytical tool usage in the automotive industry?

REFERENCES

Abusabha, R., & Woelfel, M. L. (2003). Qualitative vs quantitative methods: Two opposites that make a perfect match. *Journal of the Academy of Nutrition and Dietetics, 103*(5), 566-569.

Anderson, C. (2008). The end of theory: The data deluge makes the scientific method obsolete. *Wired magazine, 16*(7), 16-07.

Baxter, J., & Eyles, J. (1997). Evaluating qualitative research in social geography: establishing 'rigour'in interview analysis. *Transactions of the Institute of British geographers, 22*(4), 505-525.

Bumblauskas, D., Bumblauskas, P., Igou, A., & Nold, H. (2017). Big data analytics: transforming data to action. *Business Process Management Journal, 23*(3), 703-720.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *Mis Quarterly, 36*(4).

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches.* Thusand Oaksm CA: Sage publications.

Creswell, J. W. (2015). *30 essential skills for the qualitative researcher.* Thusand Oaks, CA.: Sage Publications.

Deloitte. (2017). Big Data analytics in the automotive industry. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/manufacturing/deloitte-uk-automotive-analytics.pdf

Eisenstein, P. (2000). Just what the customer ordered. *Professional Engineering, 13*(14), 36-36.

Fosso Wamba, P. S. (2017). Big data analytics and business process innovation. *Business Process Management Journal, 23*(3), 470-476. doi:10.1108/bpmj-02-2017-0046

Frei, F. X. (2006). Breaking the trade-off between efficiency and service. *Harvard business review, 84*(11), 92.

Fusch, P. I., & Ness, L. R. (2015). Are we there yet? Data saturation in qualitative research. *The Qualitative Report, 20*(9), 1408.

Gentles, S. J., Charles, C., Ploeg, J., & McKibbon, K. A. (2015). Sampling in qualitative research: Insights from an overview of the methods literature. *The Qualitative Report, 20*(11), 1772.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field methods, 18*(1), 59-82.

Hanson, J. L., Balmer, D. F., & Giardino, A. P. (2011). Qualitative research methods for medical educators. *Academic pediatrics, 11*(5), 375-386.

Holweg, M. (2003). The three-day car challenge: Investigating the inhibitors of responsive order fulfilment in new vehicle supply systems. *International Journal of Logistics Research and Applications, 6*(3), 165-183. doi:10.1080/1367556031000123106

Holweg, M., & Pil, K. F. (2001). Successful build to order strategies: Start with the Customer. *MIT Sloan Management Review, 43*(1), 74-83.

Howard, M., Vidgen, R., & Powell, P. (2003). Overcoming stakeholder barriers in the automotive industry: building to order with extra-organizational systems. *Journal of Information Technology, 18*(1), 27-43. doi:10.1080/0268396031000077431

Jacoby, J., Speller, D. E., & Berning, C. K. (1974). Brand choice behavior as a function of information load: Replication and extension. *Journal of consumer research, 1*(1), 33-42.

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management, 37*(1), 10-36. doi:10.1108/ijopm-02-2015-0078

Klatt, T., Schlaefke, M., & Moeller, K. (2011). Integrating business analytics into strategic planning for better performance. *Journal of Business Strategy, 32*(6), 30-39. doi:10.1108/02756661111180113

Klaus, S. (2016). *The Fourth Industrial Revolution.* Paper presented at the World Economic Forum. Davos: The Forum.

Klie, L. (2015). Integrate CRM and ERP for Better Intelligence. *CRM Magazine*.

Leedy, P. D., & Ormrod, J. (2015). *Practical Research: Planning and Design* (Eleventh Edition ed.) Boston: Pearson Education Limited.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry* (Vol. 75). Thoousand Oaks, CA: Sage.

Merriam, S. B. (2009). *Qualitative Research: a guide to design and interpretation* (Revised edition ed.). San Francisco: Jossey-Bass.

Muller, M.-L. (2009). Current automotive industry: how one leader practices CI. *SA Journal of Information Management, 11*(3), 6 pages.

Müller, S., & Jensen, P. (2017). Big data in the Danish industry: application and value creation. *Business Process Management Journal, 23*(3).

NAAMSA. (2017). Retrieved from http://www.naamsa.co.za/papers/2017_2ndQuarter/index.html

Negash, S. (2004). Business intelligence. *The communications of the Association for Information Systems, 13*(1), 54.

Neuman, D. (2014). Qualitative research in educational communications and technology: a brief introduction to principles and procedures. *Journal of Computing in Higher Education, 26*(1), 69-86. doi:10.1007/s12528-014-9078-x

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. *The Journal of Strategic Information Systems, 24*(1), 3-14.

Oosthuizen, J. (2016). *Entrepreneurial Intelligence: Expanding Schwab's Four-Type Intelligence Proposition To Meaningfully Address The Challenges Of The Fourth Industrial Revolution.* Paper presented at the proceedings of 28th Annual Conference of the Southern African Institute of Management Scientists, University of Pretoria, South Africa (ISBN: 978-0-620-71797-7).

Patton, M. Q. (2015). *Qualitative Research and Evaluation Methods*. Thousand Oaksm CA.: Sage.

Percy, W. H., Kostere, K., & Kostere, S. (2015). Generic qualitative research in psychology. *The Qualitative Report, 20*(2), 76.

Rowley, J. (2012). Conducting research interviews. *Management Research Review, 35*(3/4), 260-271.

Seidel, S., Müller-Wienbergen, F. M., & Rosemann, M. (2010). Pockets of creativity in business processes. *Communications of the association for information systems, 27 (1).*

Smith, J., & Firth, J. (2011). Qualitative data analysis: the framework approach. *Nurse researcher, 18*(2), 52-62.

Sutton, J., & Austin, Z. (2015). Qualitative research: data collection, analysis, and management. *The Canadian journal of hospital pharmacy, 68*(3), 226.

Tannou, M., & Westerman, G. (2012). Volvo Cars Corporation: Shifting From a B2B to a "B2B+ B2C" Business Model. *The MIT Center for Digital Business. Retrieved November, 10*, 2015.

Uden, L., & He, W. (2017). How the Internet of Things can help knowledge management: a case study from the automotive domain. *Journal of Knowledge Management, 21*(1), 57-70. doi:10.1108/jkm-07-2015-0291

Villanueva, F. J., Aguirre, C., Villa, D., Santofimia, M. J., & López, J. C. (2014). *Smart City data stream visualization using Glyphs.* Paper presented at the Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS), 2014 Eighth International Conference.

Walker, R. (2015). *From Big Data to Big Profits: Success with Data and Analytics*. New York: Oxford University Press.

Willig, C. (2013). *Introducing qualitative research in psychology.* London: McGraw-Hill Education (UK).

Wong, D. (2012). Data is the Next Frontier, Analytics the New Tool. In: London: Big Innovation Centre, November. Available at: http://www.biginnovationcentre. com/Publications/21/Data-is-the-nextfrontier-Analytics-the-new-tool.

Zhan, Y., Tan, K. H., Ji, G., Chung, L., & Tseng, M. (2017). A big data framework for facilitating product innovation processes. *Business Process Management Journal, 23*(3), 518-536.