NELSON MANDELA UNIVERSITY

A MODEL FOR SMART FACTORIES IN THE PHARMACEUTICAL MANUFACTURING SECTOR

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In accordance with Rule G5.6.3, I hereby declare that the above-mentioned thesis is my own work and that it has not previously been submitted for assessment to another University or for another qualification.

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DATE

DEDICATION

To my son Anesu Charles for teaching me love, patience and hope.

It is better to have loved and lost than never to have loved at all.

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ABSTRACT

Since the turn of the century, the manufacturing industry has metamorphosed from manually driven systems to digitalisation. Product life cycles have shortened and customer demands have become more intense. Globalisation has brought about challenges that drive the need for smart manufacturing. Industry 4.0 has emerged as a response to these demands. The integration of various processes, facilities and systems throughout the value chain and digitalisation of physical systems is promoted in Industry 4.0.

Due to increased competitive pressures, organisations are strategically looking at automation to deliver competitive advantage in delivering products at the right cost, quality, time and volumes to the customers. Organisations are therefore looking for manufacturing solutions that are technology driven, such as cyber-physical systems, big data, collaborative robots and the Internet of Things. This allows autonomous communication throughout the value chain between machine-to-machine and human-to-machine.

The smart factory, a component of Industry 4.0, is a self-organised, modular, highly flexible and reconfigurable factory that enables the production of customised products at low cost, therefore maximising profitability. Smart manufacturing can bring about competitive advantages for an organisation. Labour concerns have been raised against automation and smart manufacturing, citing potential job losses, workforce redundancy and potential employee lay-offs. This unease, in turn, influences the employees' attitude towards technology, which could lead either to its acceptance or refusal.

The purpose of this research is to enhance the understanding of smart factories in the pharmaceutical industry by conducting a systematic analysis of the factors which influence the attitude of those involved towards a smart factory implementation. This study focuses on the perceptions among employees and management. The research is a quantitative study consisting of a literature review of the key concepts related to Industry 4.0, smart factories and technology-acceptance theories.

The empirical study consisted of surveys completed by management and employees of one of the pharmaceutical manufacturers in South Africa. The questionnaire used in this research consists of questions regarding demographic data and questions regarding the perception of change and factors influencing attitudes towards the acceptance of technology, within the pharmaceutical manufacturing company. Descriptive statistics were used to summarise the data into a more condensed form, which could simplify the identification of patterns in the data. Inferential statistics were used to validate if the conclusions made from the sample data could be inferred to a larger population.

Various factors influence perceptions about ease of use and usefulness, which then, in turn, influence attitudes and the intention to use technology. These factors have been examined by numerous authors in the technology acceptance literature. Recommended factors based on the statistical analysis of the questionnaire results were identified. A model, supported by Exploratory Factor Analysis, Correlations and ANOVA Testing identified the following factors as having an influence on the Attitude towards the Positive Impact of Smart Factories, within the pharmaceutical manufacturing company: Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs and Job Security. The importance of each factor was identified to understand its function how to improve the implementation of smart factories.

The research results indicated that the perception of management and employees is different on factors like such as Training, Individual Characteristics, Trust, Resources and Costs, Automation and Support and Parent Company in relation to technology acceptance. There was however no difference in perception between managers and employees on Security, Government Laws and Regulations, Organisational Culture, Peer Support and Organisational Support in relation to technology acceptance. The research study contributed to the identification and understanding of the factors influencing the implementation of smart factories in the pharmaceutical industry.

Keywords: Industry 4.0, Smart Factories, Cyber-physical systems, Cloud Computing, Big Data, Internet of Things, Technology Acceptance Model.

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CHAPTER 1

INTRODUCTION AND PROBLEM STATEMENT

1.1 INTRODUCTION

Since the turn of the 20th century, technological advancements have been rapid and the manufacturing landscape has not been spared (Fulton & Hon, 2010). Industry 4.0, Internet of Things (IoT), Big Data Analytics and Smart Factories have brought the world to unprecedented levels of information availability, processing and accelerated levels of efficiency to those who can leverage this phenomenon (Prinza, et al., 2016).

The manufacturing industry is going through transformation, with smart factories and the emphasis on digitalisation at the forefront (Govindan, 2014; Schwab, 2016). The transformation in manufacturing is characterised by a fusion of technologies that are blurring the lines between the physical, digital and biological spheres (Schwab, 2016). The manufacturing sector has embraced smart manufacturing especially in the automotive sector, however, the pharmaceutical sector has been slow in adopting the same until now (Hess & Rothaermel, 2011; Anastasi, 2018).

Germany holds the enviable position of being a world-leading manufacturing hub and is naturally at the forefront of leading the 4th Generation Industrial Revolution (Industry 4.0), based on Cyber-Physical System-enabled manufacturing and service innovation (Lee, Hung-An & Yang, 2014). The Industry 4.0 concept has phenomenally pushed for advancement and adoption of information technology in manufacturing to deliver product innovation, quality, variety and speed of delivery (Lee, Hung-An & Yang, 2014). To garner the requisite competitive capabilities, smart factories are offering self-awareness, self-prediction, self-comparison, self-reconfiguration and self-maintenance as part of service innovation and manufacturing efficiency (Lee, Hung-An & Yang, 2014).

The manufacturing space has become highly competitive to such an extent that the integration of systems is key, resulting in smart factory set-ups (Govindan, 2014). One of the key facets of a smart factory, is real time monitoring, which allows for the synchronisation of manufacturing and market requirements to reduce waste and improve on efficiency and cost (Ranky, 2004). Systems that have the capability of offering consistency in quality with real-time process risk analysis combining the knowledge to prevent and reduce failure, offer an attractive opportunity to investors (Ranky, 2004).

Technology is one of the main drivers of manufacturing in present day factories (Frambach & Schiellawaert, 2002). Being willing and able to acquire technology and taking risks in technology form part of the characteristics of most successful organisations (Orr, 1999; Bloss, 2016). Advanced production technology leads to companies gaining strategic competitive advantage (Fulton & Hon, 2010). Central to the adoption of technology lies the human factor. According to Zhang, Nyheim and Mattila (2014), new technology systems might not be fully accepted if human factor barriers were overlooked. It is important for management teams to understand the impact of how individuals perceive technology and their attitude and acceptance of technology in the workplace.

“The African proverb states that when there are no enemies within, the enemies without cannot hurt you.” This proverb hints at trust and collaboration, as well as the quality of relationships within a team (De Bruyn, 2017, p. 401). Acceptance of new technology in an organisation is therefore dependent on the trust and collaboration within the teams.

Figure 1.1: Chapter Layout

1.2 PROBLEM STATEMENT

The competitive landscape for manufacturing organisations has been altered drastically in the past three decades. Product complexity has brought about new competitive pressure in flexibility, quality, speed of delivery, innovativeness, as well as cost (Costa & de Lima, 2008). Firms have to innovate to stay in business hence the need to harness technology to boost competitiveness and remain relevant in business.

Automated manufacturing systems have become the best available alternative for companies to be able to compete in the new reality of severe competitiveness (Erumban & de Jong, 2006; Bloss, 2016). Investment in technology is no longer a decision an organisation can take lightly but needs to be central to an organisation's strategic decision making (Aloini, Farina, Lazzarotti & Pellegrini, 2017). The onus is on an organisation to understand the technology landscape as it applies to its industry in order to make correct technology decisions.

Most organisations have looked at the management aspect of firms and the type of technology to choose from the myriad of available technologies and this poses a dilemma for the modern day executive (Farooq & O'Brien, 2009). The implementation of technology solutions has not been without failures due to the complexity of decisions in so far as technical alignment, human behaviour, structural processes and capabilities are concerned (Scannell, Calantone & Melnyk, 2012).

There is still limited research on factors affecting the implementation of a smart factory. In their study of assessing readiness and maturity of organisations, Schumacher, Erol and Sihn (2016) identified different dimensions, namely Strategy, Leadership, Customers, Products, Operations, Culture, People, Governance and Technology. In their study of smart-factory implementation, Wang, Wan, Li and Zhang, (2016) considered three factors, namely, horizontal integration through value networks, vertical integration and networked manufacturing systems and finally end-to-end digital integration of engineering across the entire value chain.

Since the advent of the smart factory, employees with low-level skills have been made redundant (Maseko, 2018). This has made employees not be receptive to the idea of smart manufacturing, as there is always of fear of being laid off. A total of 5.7 million jobs are forecasted to be lost from total automation in South Africa (Maseko, 2018). Innovation and technology acceptance in organisations need to be looked at in two models, i.e. the organisational and the individual levels (Frambach & Schiellawaert, 2002).

1.2.1 Smart Manufacturing in the Pharmaceutical Sector

The term smart manufacturing refers to a future-state of manufacturing, where the real-time transmission and analysis of data from across the factory creates manufacturing intelligence, which can be used to have a positive impact across all aspects of operations (O'Donovan, Leahy, Bruton & O'Sullivan, 2015).

The pharmaceutical industry is one such highly regulated and costly industry where the gains from smart manufacturing can have a positive impact. Due to the complexity of pharmaceutical manufacturing, the benefits of smart manufacturing will assist in providing a scalable and fault-tolerant big data pipeline for integrating, processing and analysing industrial equipment data (Clemons, 2016). Commercial losses due to product losses will be potentially avoided in smart manufacturing due to the self-correcting mechanisms of the systems. In most instances product is quarantined and eventually disposed of due to lack of data availability or data integrity.

Blockchain technology, if correctly used, can be of very high value in the pharmaceutical space where the origins of each ingredient especially the active ingredients are traced and their authenticity recorded on the database. These contributions are considered in the context of highly regulated large-scale manufacturing environments, where legacy (automation controllers) and emerging instrumentation like internet-aware smart sensors must be supported to facilitate initial smart manufacturing efforts. This background results in the research problem for this treatise.

Problem Statement: The factors influencing employees and managers' attitudes towards a smart factory have not been adequately researched in the pharmaceutical sector in South Africa.

1.3 RESEARCH OBJECTIVES

The Main Research Objective **(RO_m)**of the study will be as follows:

- **RQ_m**: To identify the factors which influence technology adoption and measure the perception of employees and management regarding smart factories in the pharmaceutical manufacturing industry.

In order to achieve the above-mentioned primary objective, the following secondary research objectives will be pursued:

- **RQ_1**: Identify the characteristics of smart factories;

- **RQ$_2$**: Identify the factors influencing attitudes towards smart factories within the pharmaceutical manufacturing sector;
- **RQ$_3$**: Develop a conceptual model for a smart factory adoption;
- **RQ$_4$**: Justify and explain the research design and methodology used for this treatise with sufficient information for future reproduction;
- **RQ$_5$**: Evaluate the conceptual model for the attitudes towards smart factories in the pharmaceutical manufacturing sector; and
- **RQ$_6$**: Interpret empirical results of the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing company and provide managerial conclusions.

1.4 RESEARCH QUESTIONS

The Main Research Question (**RQ$_M$**) of this study was formulated based on the main research objective and is as follows:

- **RQ$_M$**: What are the differences between the perceptions of management and employees of the factors which influence attitudes towards smart factories within the pharmaceutical manufacturing sector?

In order to evaluate the main research problem effectively, the following secondary research questions need to be worked on:

- **RQ$_1$**: What are the characteristics of smart factories in the manufacturing industry?
- **RQ$_2$**: What factors need to be included in the proposed model to measure the perceptions of employees and management on the factors influencing attitudes towards smart factories within the pharmaceutical manufacturing sector?
- **RQ$_3$**: What research design and methodology can be followed to better understand and reproduce this research study in future?

- **RQ$_4$**: What factors influence attitudes towards smart factories at the pharmaceutical manufacturing factories?
- **RQ$_5$**: What is the importance of the identified factors that are important in technology acceptance as perceived by employees and management at the pharmaceutical manufacturing factory?

The research objectives, research questions and the different chapters in which each will be addressed are illustrated in Table 1.1.

Table 1.1: Research Question, Research Objective and Chapter Outline

Research Question	**Research Objective**	**Chapter**
RQ$_1$: What are the components and characteristics of smart factories?	RO$_1$: Establish the components and characteristics of smart factories.	Chapter 2: Defining smart factories
RQ$_2$: What factors influence the adoption of smart factories in developing countries?	RO$_2$: Identify the factors that influence the adoption of a smart factory by conducting a literature review.	Chapter 3: Factors influencing smart factories
RQ$_3$: What are the factors to be included in the proposed model to measure the perceptions of employees and management on the factors which influence the adoption of smart factories in developing countries?	RO$_{3:}$ Develop a hypothesised model in order to determine the factors that influence the adoption of smart factories in developing countries.	Chapter 3: Factors influencing smart factories
RQ$_4$: What research methodology can be followed to better understand and reproduce this research study in future?	RO$_{4:}$ To establish the appropriate research design and methodology this will be used so that the study can be replicated in future.	Chapter 4: Research and design methodology

Research Question	Research Objective	Chapter
RQ_5: What factors influence the adoption of smart factory at Aspen Pharmacare?	RO_5: Evaluate the hypothesised model for adopting smart factories in developing countries and establish the correlation of the identified factors in the proposed smart factory model.	Chapter 5: Results and analysis of empirical study
RQ_6: What is the perceived importance of the factors identified by employees and management?	$RO_{6:}$ Compare the perceived importance of the identified factors by employees and management at Aspen Pharmacare.	Chapter 5: Results and analysis of empirical study

1.5 RESEARCH DELIMITATION

This research will be limited to the management and employees of one of the pharmaceutical manufacturing factories in South Africa. For this study, management includes middle and senior management. Shop floor and general workers are referred to as employees. The difference in perceptions of management and employees will be analysed.

1.6 RESEARCH SIGNIFICANCE

This research seeks to gain an insight into the perceptions of employees and management regarding the factors which influence attitudes towards a smart factory.

The treatise is significant for the following reasons:

- A greater knowledge and better understanding of a smart factory in the pharmaceutical manufacturing factory will be determined;
- The study will identify the significant factors which influence attitudes towards a smart factory;
- The study will identify the factors which are significant for a conceptual model of a smart factory;

- An understanding of the misalignment of views of employees and management on the factors which influence attitudes towards a smart factory will be determined; and
- The information gained from this research study could assist other manufacturers in the pharmaceutical manufacturing sector to better understand the attitude of employees and management towards smart factories.

1.7 RESEARCH DESIGN AND METHODOLOGY

The research design and methodology will address the research approach, data collection and data analysis.

1.7.1 Research Design and Methodology

The research will be located in the Positivist Paradigm using the quantitative methodology. Collis and Hussey (2014) describe a research paradigm as a philosophical framework guiding how research must be conducted which usually describes the way data are produced in the process of research. Collis and Hussey (2014) stated that positivistic research was the only research paradigm used throughout the past centuries.

Natural sciences were the main focus of research until the 19th century. In this paradigm, positive information is the foundation of knowledge. The aim of the research is to clarify cause-and-affect relations concerning variables. A positivistic approach measures social phenomena and follows a logical approach to ensure that an objective methodology is supported. Therefore, a positivistic study is associated with quantitative analysis as variables are measurable, objective, scientific and experimental in nature (Collis & Hussey, 2014).

1.7.2 Literature Review

In order to get a better understanding of the Industry 4.0, smart factories and their components, a literature review will be undertaken. Smart factories' characteristics and components will be reviewed in developed and developing countries. Factors influencing attitudes towards smart factories will be established. Secondary sources including Journals, Publications, Conference Papers, Text books and Student papers which are related to the research topic will be used.

1.7.3 Data Collection

There are various sources of data and the researcher needs to decide which to use. These sources can further be classified as primary data and secondary data (Collis & Hussey, 2014). Original data collected for a study by the researcher is referred to as primary data and existing data are referred to as secondary data available through resources such as previous research, official statistics and historical data (Babbie, 1998).

The way in which the research questions are approached by the researcher will normally determine the data collection techniques used in order to gather the necessary data (Maree, 2016). The selection of the techniques to be used must be suitable for the research and must also be practical in considering the quality of the data, the costs involved, the possible responses, errors and collection parameters (Collis & Hussey, 2014).

Primary data will be collected and used in this study. The primary data will be collected by using two methods, namely a physical hand-out of the questionnaire and an on-line survey questionnaire (Annexure C). A physical hand-out of the printed hardcopies will be used to distribute the questionnaire and collect responses from the sample group of employees. This approach will be taken for employees who do not have access to a personal computer or the Internet. It is also a timely and effective way to receive responses rather than through an online survey.

A total of 500 questionnaires will be distributed to employees. These prospective respondents will be requested to complete the questionnaire and return it to the team manager within the area. An on-line survey questionnaire will be used to collect responses from management and other employees who have access to personal computers. An email containing a Universal Resource Link (URL) to the questionnaire will be sent to the global list of email addresses within the organisation which contains approximately 700 employees, middle and senior managers.

The potential respondents will be reminded to respond after a week of the initial email being sent in order to capture as many respondents as is possible. As an employee of the organisation, it is fairly easy to access respondents, explain, discuss and clarify potential issues, distribute the questionnaire and collect the data once completed.

1.7.4 Data Analysis

This sub-section will explore the concept of data analysis, validity, reliability and the techniques that will be employed in the study. Data analysis, as one of the stages in the research process, refers to the process of evaluating data by using both analytical and logical reasoning (Maree, 2016). Data will be analysed using a STATISTICA computer software package and the services of a statistician will be sought to sort, categorise and clean the data. Data will be analysed by using descriptive statistics such as measures of central tendency being the mean, median and the mode and inferential statistics specifically by using the ANOVA analysis.

Exploratory Factor Analysis (EFA) will be used to ensure the construct validity of the instrument and to identify items which should be removed. EFA will be used to identify the items which are not suitable for use in the instrument. On the other hand, factor analysis is used to determine which items belong together in the sense that they are answered similarly and therefore measure the same dimension or factor (Maree et al., 2016).

1.8 DEFINITIONS

In order to provide a more comprehensive understanding of the key concepts contained within this treatise, the following definitions and their meanings are provided.

The following terms and concepts will be discussed in this chapter:

Advanced Manufacturing Technology

Computer- and numerical-based apparatus (software and hardware) designed to accomplish or support manufacturing tasks (Costa & de Lima, 2008).

Augmented Reality (AR)

A highly promising technology that allows for the visualisation of computer graphics placed in the real environment and is commonly used in the description, planning and real-time operation monitoring, fault diagnostic and recovery and training related to industrial products and processes (Yew et al., 2016; Doshi et al., 2016).

Big Data Technology

Big Data technology refers to a new generation of technology and architectures that enable organisations to economically extract value through discovering, capturing and analysing very large volumes of a wide variety of data (Ghobakhloo, 2018).

Blockchain

A distributed ledger technology is the foundation of cryptocurrencies such as Bitcoin and Ethereum, but its capabilities extend far beyond that. Blockchain is immutable, transparent and redefines trust, as it enables transparent, secure, trustworthy and swift public or private solutions (Underwood, 2016; Ghobakhloo, 2018).

Cyber-Physical Systems

Cyber-physical systems are integrations of computations and physical processes whereby embedded computers and networks are used to monitor and control the physical processes and interact with humans (Lee, 2008; Schuh, Pitsch, Rudolf, Karmann & Sommer, 2014).

Industry 4.0

Industry 4.0 is a new manufacturing paradigm which promotes and describes a production oriented Cyber-Physical System that integrates production facilities, warehousing systems, logistics and even social requirements to establish the global value-creation networks (PwC, 2016a; Wang, Li & Zhang 2016).

Internet of Things

The Internet of Things (IoT) is defined as the interconnection of intellectual devices and management platforms that, with little to no human involvement, jointly facilitate a smart, connected world (Mumtaz, et al., 2017).

Smart Factory

A smart factory is a factory that unlocks several capabilities through horizontal and vertical integration and a myriad of operational and manufacturing systems that power the organisation and end-to-end, holistic integration through the entire value chain (Deloitte University Press, 2017; Robert, Daniel & Bilal, 2016).

Technology Acceptance Model

A Technology Acceptance Model is used to establish a theoretical explanation of why users choose to accept or reject technology. It provides the theory behind the influence of external variables, beliefs, attitude and intention to use technology (Davis, et al., 1989; King & He, 2006; Small & Yasin, 2003).

1.9 ETHICS

The Ethics Clearance approval documentation was submitted to the NMU Business School. Partial ethics clearance was requested for this study as no vulnerable groups will be involved.

1.10 TREATISE STRUCTURE

The research objectives, research questions and the overview of the chapters of the treatise are illustrated in Figure 1.2.

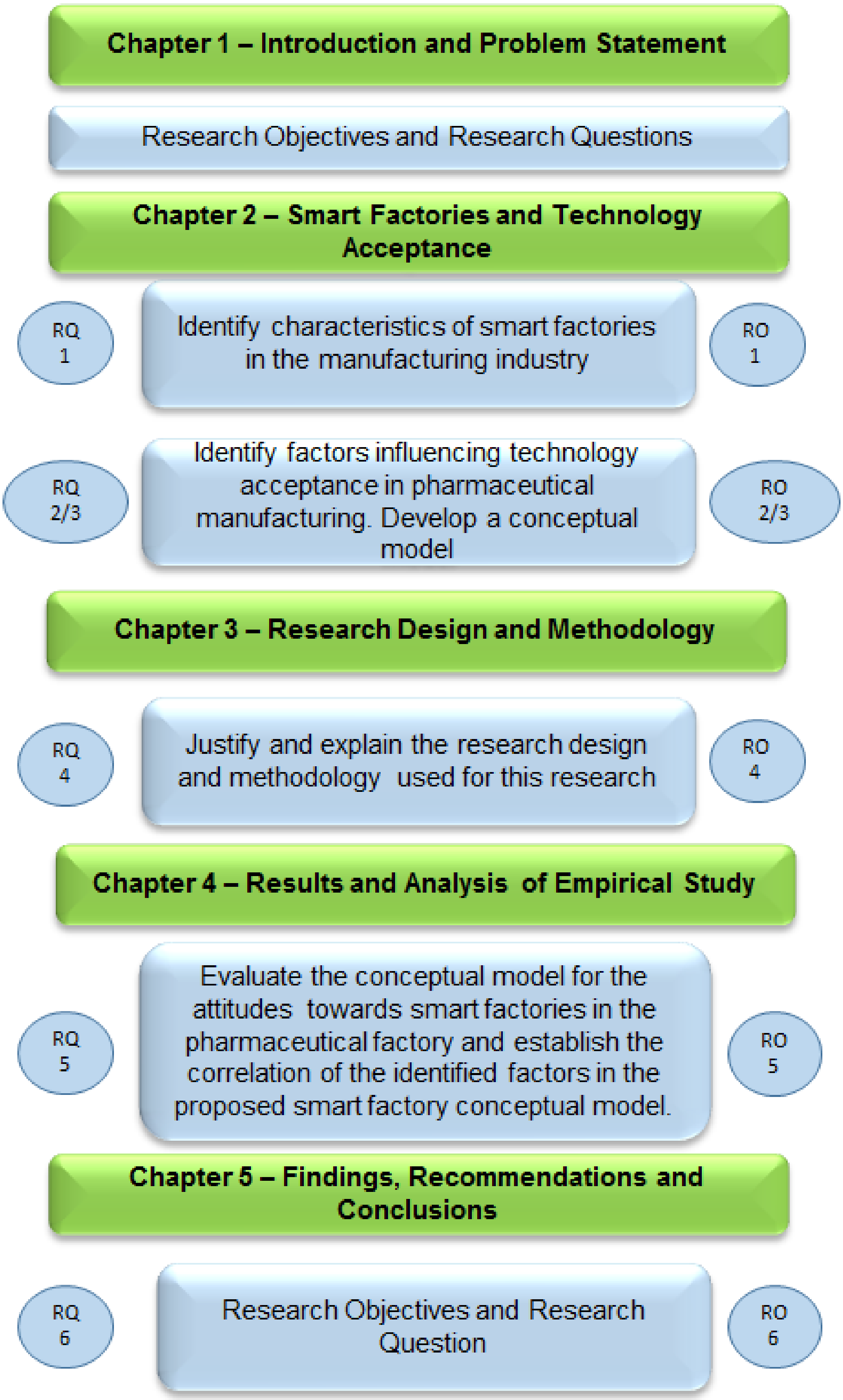

Figure 1.2: Research Map

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Chapter 1 provided an outline of this study that introduced the research problem, research objectives and research questions. This chapter presents the various factors affecting implementation of a smart factory. The factors affecting technology acceptance are identified from literature and proposed in the model. A proposed conceptual model is presented for statistical evaluation in Chapter 4. This will form the basis of the research design. The chapter then presents a review of factors affecting technology acceptance in smart manufacturing.

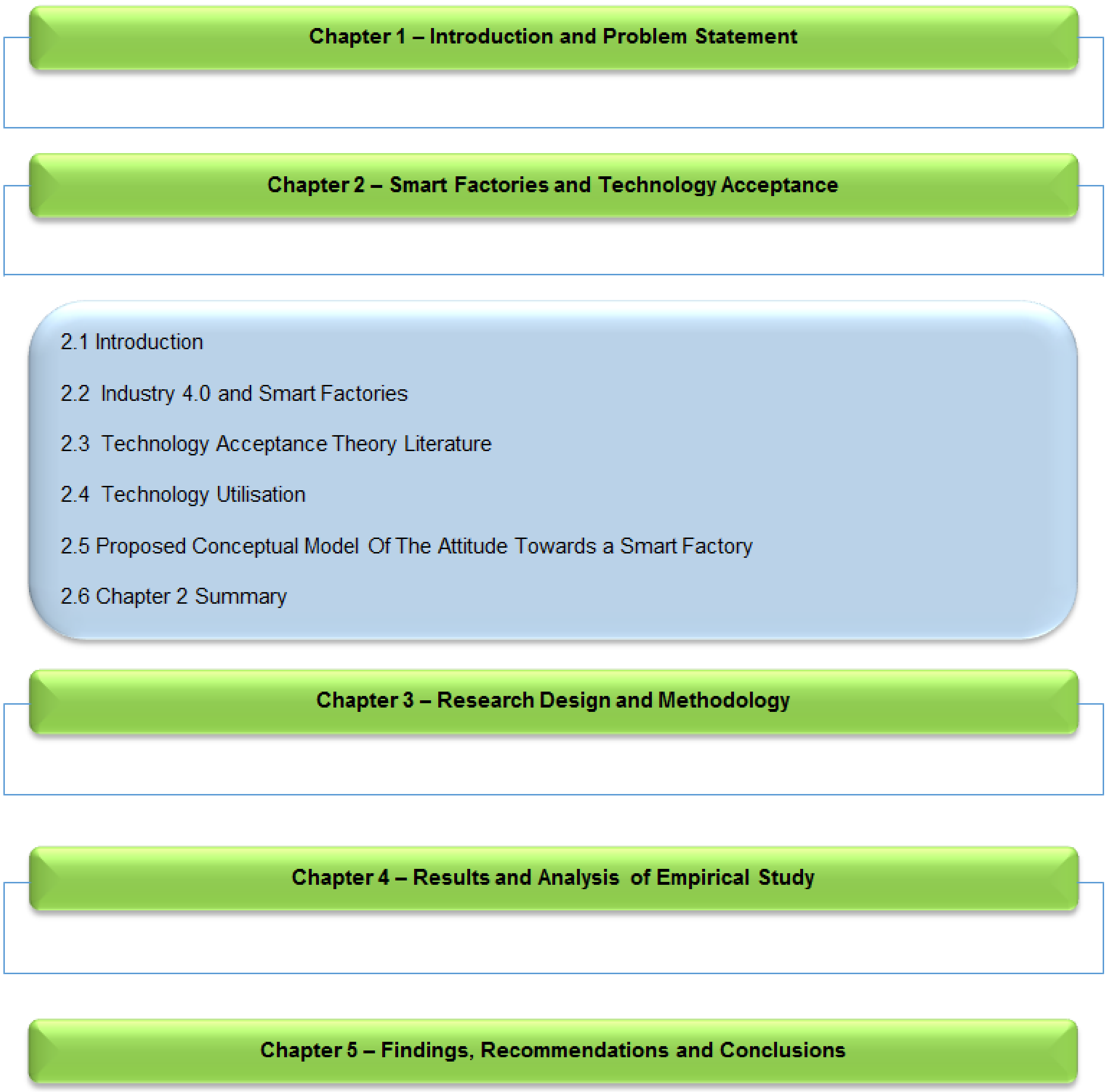

Figure 2.1: A schematic overview of Chapter 2

2.2 INDUSTRY 4.0 AND SMART FACTORIES

The business environment has become highly competitive with new players joining the foray daily. Companies in the manufacturing space are facing tough challenges, not only in terms of competition but also with ever-rising costs of production (Russwurm, 2014). A company needs to innovate, harness continuous improvement, acquire and apply technology to remain competitive and profitable (Luca, Pisano, Pironti & Papa, 2018). Present day products, processes and technologies are becoming more complex and highly individualised (Russwurm, 2014; Luca et al., 2018).

Pressure on businesses has never been greater than it is now to transform operations to provide greater product variety and mass customisation through flexibility and quick responsiveness (Tu, Lim & Yang, 2018). There is a demand on firms to remove data latency, analysis latency, as well as decision latency as much as possible (Tu et al., 2018).

Resource scarcity is at its peak with raw materials and use of energy receiving the most attention. Industry 4.0 offers the solution to manufacturing challenges through flexibly organised production systems and integrated networking at all stages of the value chain (Russwurm, 2014). The philosophy behind smart manufacturing is anchored in the basis belief that human society desires a progressive improvement in the quality of life, however the current production paradigm is not sustainable (Wang, Wan, Li & Zhang, 2016). The continuous drive towards achieving better products and services daily at competitive prices is the main driver towards smart manufacturing implementation.

Flexibility and changeability are two of the major factors to achieve present day production demands (Fasth-Berglund & Stahre, 2013). The smart factory concept is intended to enable extremely flexible production and self-adaptable production processes with machines and products that act both intelligently and autonomously (Syberfeldt, Danielsson & Gustavsson, 2017; Liu, 2016). It is imperative that companies gain the required level of competitiveness in order to survive and grow. On the other hand, companies should be aware that the move towards smart manufacturing is not without risk (Dellermann, Fliaster & Kolloch, 2017).

Apart from the technology and innovation-management tools found in the market, companies need to deal with human resource knowledge acceptance issues human issues about the acceptance of resource knowledge (Aloini, Farina, Lazzarotti & Pellegrini, 2017). Flexibility and adaptability of equipment allow firms to realise benefit from the full lifetime and potential of their productive systems by supporting sustainability on both the economic and ecological fronts (Järvenpää, Luostarinen, Lanz & Tuokko, 2012).

Despite being regarded as a catastrophe which desecrated the English landscape and brought social oppression as characterised by appalling physical hardship to the workers, the industrial revolution is presented as an important and beneficial mark of progress in the material living standards of most of the British people (Ashton, 1997). The industrial revolution improved standards of living by means of technical innovations that brought about economic rewards and provoked greater intellectual ingenuity (Ashton, 1997). In this quest to continually improve the lives of people, innovation is therefore not just an economic course but a social and cultural process that is ever evolving and has seen its boundaries being pushed to new limits (Ashton, 1997; Aloini, et al., 2017; Dezi, et al., 2018).

The Industrial Revolution brought about a major shift in the lives of human beings as the discovery of steam revolutionised the world of work and change the existing work patterns (Slabbert, 1996). The steam engine turned both man and horse into less-marketable commodities. This was a major turning point of the first industrial revolution. Slabbert (1996) avers that oil and electricity were the driving forces behind the second industrial revolution and the focus was more on profitability on an economic level as opposed to a direct contribution to humans.

Advanced computers and numerically controlled machines marked the third industrial revolution (Slabbert, 1996). According to Slabbert (1996) there has been a different focus throughout the stages of industrial revolution. Human input has been the focus area in the agricultural sector while the manufacturing sector has focussed on the mechanical input. The service sector has focussed on the quality of personal service and it is the knowledge sector that has given attention to artificial intelligence (Slabbert, 1996; Russwurm, 2014; Dawson, 1996).

The world has seen so many changes with dramatic shrinking of product and market life cycles. For example, the growth of the global market has led to a shock to the traditionally government-protected and inefficient Australian manufacturing industry (Haynes & Frost, 1994). This status quo was mainly challenged by the rise of highly mechanised and industrialised manufacturing factories of the West and Japan which led to the realisation of a need by the Australian industry to open up to smart manufacturing principles (Haynes & Frost, 1994). The world demands are becoming more varied against the backdrop of ever-diminishing world resources (Pham, Pham & Thomas, 2008). Figure 2.2 below shows the various components that make up a smart factory.

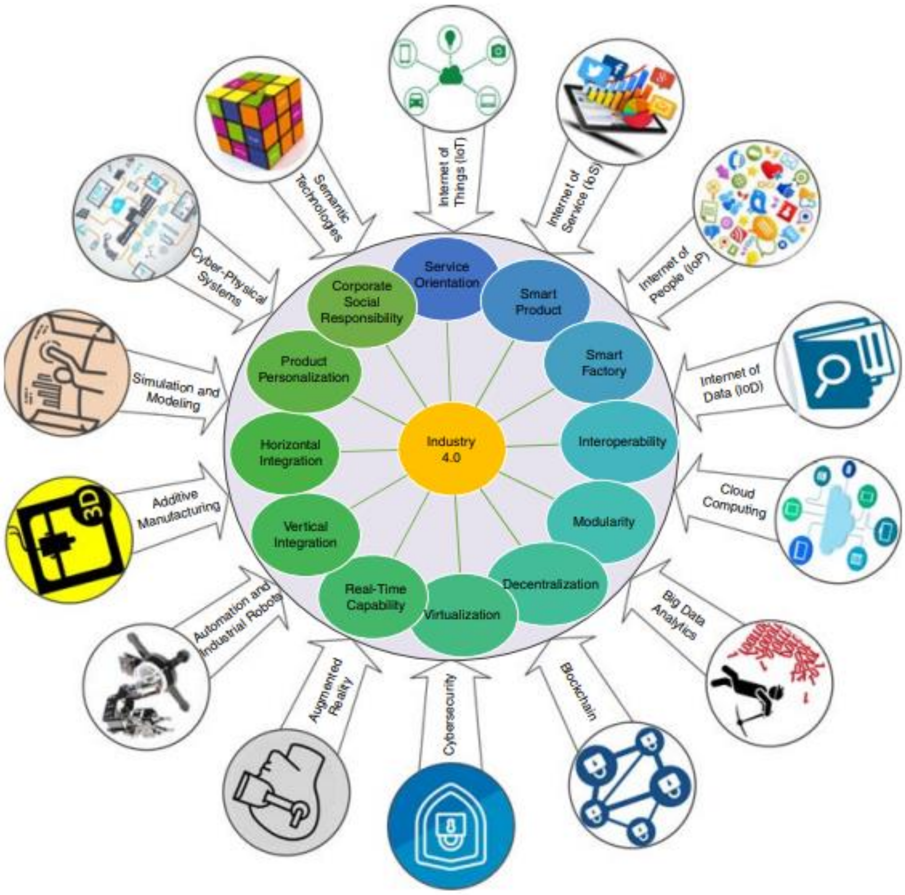

Figure 2.2: Parts of a Smart Factory Source: (Ghobakhloo, 2018, p. 914)

The demand for the innovation, good quality and lower priced goods has made it necessary for design integrated units or systems that require adopting a holistic view to ensure that the constituent elements can work well together to produce the desired effect as depicted in Figure 2.2 (Pham, Pham & Thomas, 2008). For a competitive factory, all elements, including communication channels, communication protocols, interfaces and other connections have to be correctly engineered in order to interact with other units and systems in its environment (Pham, Pham & Thomas, 2008). Developments in the manufacturing space demand that integration design be viewed as a total systems-engineering activity (Haynes & Frost, 1994; Pham, Pham & Thomas, 2008).

The competitive nature of the manufacturing sector demands waste elimination, minimisation of incompatibilities, fragmentation and inconsistencies (Dellermann et al., 2017; Pham et al., 2008). Smart manufacturing offers the symbiotic and synergetic relationship between different system components promoting higher system effectiveness coupled with robustness. Pham, et al. (2008) aver that smart factories that are highly integrated have improved control and coordination for a sustainable competitive edge that is not possible from individual systems.

The IoT has made it possible to transform products, services and whole industries through dynamic global network infrastructure (Manyika et al., 2015; Dellermann et al., 2017). Everyday smart products are getting connected, challenging the traditional logic of value creation and offering new innovative business models (Dellermann et al., 2017). Innovation is not without its own pitfalls. There is an accelerated interdependence on partners as firms join ecosystems that support smart manufacturing (Baines, 2004; Dellermann, et al., 2017).

The smart factory requires appropriate maturity levels on a number of fronts (Odważny, Szymańska & Cyplik, 2018). Processes should be repeatable according to set and acceptable standards and the data collected should be organised and aggregated to support automation as well as robotisation of production processes (Odwazny, et al. 2018). Access to qualified staff who will program and operate devices as well as availability of a capital budget to support the project is of great importance in making sure that a smart factory is deliverable (Pham et al., 2008; Odwazny, et al., 2018).

The information age has made it possible to collect large amounts of data from systems and processes. These data are however of little value unless the data are analysed and decisions drawn from them. This phenomenon gave rise to big data analytics which allows organisations to gain value from data through identifying patterns of what is likely to happen, when and be prepared with the relevant solution for optimal results (Ghobakhloo, 2018).

Data analytics has been around for a number of years however it has been found to be a great weapon in achieving a sustained competitive advantage (Ghobakhloo, 2018; Fasth-Berglund & Stahre 2013). The industrial application of big data enables manufacturers to streamline production processes, maximise asset efficiency as well as administer predictive and preventative maintenance (Ghobakhloo, 2018).

2.1.1 Augmented Reality

To support the smart factory, augmented reality is another advancement in computer software that allows for the visualisation of computer graphics as they look in the real working environment. Augmented reality can be used for fault finding, training as well as planning and real time monitoring (Doshi, Thomas, Smith & Bouras, 2016). Maintenance functions, employee training and quality management processes have been reported to be made easier in industry through the implementation of augmented reality. A digital twin of the smart factory is created online through the merging of physical sensors to the simulation model. Adjustments and optimisation to the process can be performed in isolation through the digital twin without disturbing the physical process (Luca et al., 2018; Ghobakhloo, 2018).

2.1.2 Blockchain Technology

A blockchain is essentially a distributed database of records, or public ledger of all transactions or digital events that have been executed and shared among participating parties, where each transaction in the public ledger is verified by the consensus of a majority of the participants in the system. Once entered, information can never be erased (Crosby, Pattanayak, Verma & Kalyanaraman, 2016).

Blockchain technology is critical to Industry 4.0 and a smart-factory set up. Blockchain allows unlimited smart devices to perform transparent, fast, secure, fully autonomous and frictionless transactions (Devezas & Sarygulov, 2016). Blockchain has been in widespread use in the financial sector in cryptocurrency, however there is a space for it in Industry 4.0 to operate as a ledger for trustworthy and autonomous relationships for factory components (Ghobakhloo, 2018).

Blockchain technology is vital for three main functions, namely entry validation, safeguarding of the entries and preserving of the historic record (Crosby et al., 2016). Blockchain technology is critical to creating a decentralised IOT in which a hub controls the interaction between devices. Blockchain technology can facilitate the implementation of the decentralised IOT platform through serving as the general ledger used for trusted record keeping of all information exchanged between decentralised IOT topology (Crosby, et al., 2016).

2.1.3 Collaborative Robots

Collaborative robots or cobots are designed to operate alongside humans in a shared workspace, without the need for conventional protection such as safety cages or light curtains (Bogue, 2016). A number of researchers has indicated that robots have been used in various industries for more than half a century (Christensen, Raynor & McDonald, 2015; Bloss, 2016; Bogue, 2016).

Robots started off as bulky and muscular one-armed giants operating in steel cages or other protective safety environments (Bloss, 2016). Robots were mainly used for bulky, labour-intensive work that employees were more than happy to let go, however their use required strict safety measurements to be put in place to protect employees (Long, Chevallereauo, Chablat & Girin, 2017).

According to Bloss (2016), safety and security limitations used to preclude humans from working side by side with robots; however the advent of collaborative robots has changed that status quo. Human and robot collaboration can greatly improve productivity, product quality and give rise to other benefits (Heinzmann & Zelinsky, 2003; Bloss, 2016; Bogue, 2016). The industry has rapidly accepted collaborative robotics technology and, now, the units are widely known as Cobots (Bloss, 2016). Cheaper manufacturing costs are often used as a source of competitive advantage and automation has been a major source of driving manufacturing costs down (Bloss, 2016; Bogue, 2016).

Today's manufacturing is highly customised with smaller batch sizes and a lot of changeovers require robots that are nimble and agile enough to take on the next batch (Baines, 2004). Cobots are the perfect fit to carry out tasks with and amongst human employees as the demand in manufacturing is growing and the lead times are getting shorter (Bloss, 2016; Burke et al., 2017; Daudt & Wilcox, 2018).

Collaboration between employees and robots can close the gap between the challenges of increase in demand for goods as well as the phenomenon of a young population that would rather work with electronics technology as opposed to labour-intensive work (Bloss, 2016). Cobots' programming is not as intense as that of traditional robots argues Bogue (2016), and their initial cost is lower, with fast easy setup and programming, portability from application to application and faster return on the investment (Christensen, et al,. 2015). Cobots can work side by side with humans on production lines as shown in Figure 2.3.

Figure 2.3: Cobot working with employee   Source: (Redazione, 2017)

Employee safety has been raised as a major point of concern. However international safety standards were developed to ensure the safety of the employees (Long et al., 2017). Cobots are designed to work with humans due to their lightweight structure, flexible links and compliant actuators resulting in reduced factory foot print (Bischoff et al., 2010; Long et al., 2017). Cobots can also work side by side employees physically, (Figure 2.2) assisting with difficult tasks thereby improving task ergonomics and improving on cycle times (Helms et al., 2002; Hägele et al., 2002; Cherubini et al., 2016).

2.1.4 Cyber Physical Systems

Cyber-Physical Systems (CPS) are defined as integrations of computation and physical processes (Lee, 2008). A CPS integrates computing, communication and storage capabilities with monitoring and / or control of entities in the physical world and must do so dependably, safely, securely, efficiently and in real-time (Zhang, Xie, Dong, Gang, & Zhou, 2013).

Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa. The need for a smart factory and smart manufacturing has brought about a different type of thinking in how the computer systems and physical systems interact. In order to support the smart factory concept, it is imperative that a Hybrid Systems Science that simultaneously supports computational and physical systems be developed, providing organisations with a unified framework for robust design flow with multi-scale dynamics and with integrated wired and wireless networking for managing the flows of mass, energy and information in a coherent way (Sha, Gopalakrishnan, Liu & Wang, 2008).

The Cyber Physical System has a role to play in the modern and smart manufacturing way where a ubiquitous infrastructure consisting of a variety of global and localized networks, users, sensors, devices, systems and applications may seamlessly interact with each other and even the physical world in unprecedented ways. Smart manufacturing will bring about competitive advantages through networked building control systems such as HVAC and lighting. If effectively employed, CPS could significantly improve energy efficiency and demand variability, reducing the dependence on fossil fuels and greenhouse gas emissions (Lee, 2008; Tu et al., 2018). The CPS shows promise to integrate these activities and resources by synchronising information between the cyber and physical worlds and sharing production information between different stakeholders at different locations across a distributed and collaborative supply chain (Wang et al., 2016).

2.1.5 Internet of Things

The International Telecommunication Union (ITU) cited by Wortman and Fluchter (p. 55; 2015) defines the Internet of Things (IoT) as ‘‘a global infrastructure for the Information Society, enabling advanced services by interconnecting (physical and virtual) things based on, existing and evolving, interoperable information and communication technologies’’. IOT has often been looked at from an emphasis of things which become connected on the Internet as well as on Internet-related aspects of the IoT, such as Internet protocols and network technology (Wortmann & Fluchter, 2015).

Major strides in hardware development have been made in the last decade or so thus making it possible to produce smarter devices that can be connected onto the Internet (Tu, Lim & Yang, 2018). The decline in size, cost and energy consumption and hardware dimensions that are closely linked to each other, now allows the manufacturing of extremely small and inexpensive low-end computers (Wang et al., 2016; Tu et al., 2018). Availability of tiny networked computers at lower cost gives manufacturing facilities an option to smart manufacturing as opposed to traditional, isolated systems.

The decentralised IoT is increasingly becoming a popular technology in both the consumer and the enterprise space. A number of devices in the smart manufacturing scenario need to be networked to enable the exchange of data between themselves autonomously (Lee, 2008). This requirement has made it necessary for decentralised IoT platforms.

Recent studies also show that integrating IoT technologies, such as RFID, into shop floor operations can greatly optimise and improve manufacturing and production operations (Zhou et al., 2015; Wang et al., 2016; Tu et al., 2018). Firms are encouraged to adopt new IT infrastructure that has the capability to track and manage large volumes of data in anticipation of the millions of embedded devices and industrial powered machines that can communicate and collaborate (Tu et al., 2018).

2.1.6 Industrial Robotics

The Robot Institute of America, (1979) defines a robot as a reprogrammable, multifunctional manipulator designed to move material, parts, tools or specialised devices through variable programmed motions for the performance of a variety of tasks. Efficient manufacturing gives a competitive edge in business (Bogue, 2016). The subject of robotics has fascinated scientists for many years and has showed that when the environment is well ordered, these machines can function well and have demonstrated their ability to carry out useful work (Virk, 1997).

Lean manufacturing and industrial robotics have always been associated. Hedelind and Jackson (2011) aver that robotics have long been accepted in industry as a way to improve quality, efficiency and performance in manufacturing industries. An opposing view is that industrial robotics and automation may create complexity in the system and sometimes bring questions whether robotics is always for manufacturing industries (Hedelind & Jackson, 2011).

Automation, including automated inspection and packaging, is becoming an increasingly important part of pharmaceutical manufacturing. The many benefits of automation include efficiency, saving workers from hazardous environments or repetitive tasks (Figure 2.4), reducing training overhead, eliminating human error, increasing repeatability and reproducibility and in cleanrooms, removing the potential for human contamination (Markarian, 2014).

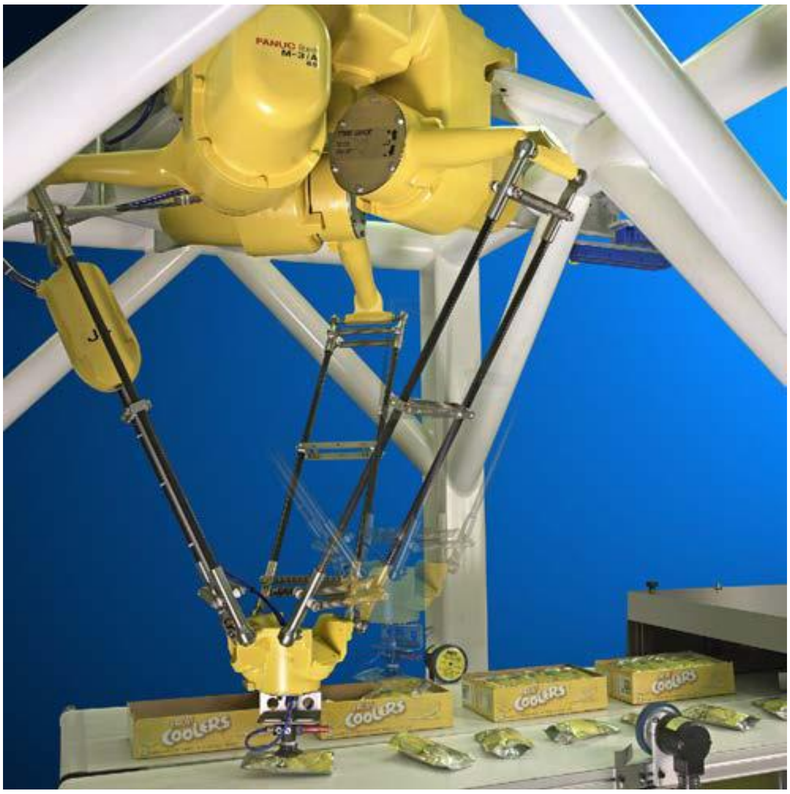

Figure 2.4: Industrial Robot Source: (Bloss, 2013, p. 529: Robots use machine vision and other smart sensors to aid innovative picking, packing and palletising).

2.3 TECHNOLOGY ACCEPTANCE THEORY LITERATURE

Information technology has been used to drive development in the present day industry. The introduction and use of information technology in work environments is not without resistance (Dajani, 2016; Schrier et al.,. 2010; Zhang, 2014). The acceptance, adoption and use of information technology has been extensively researched (Scannell et al., 2012; Ashraf et al., 2014; Dajani, 2016). Technology acceptance theories have been studied in order to gain an understanding of how technology is accepted and used within organisations or by individuals. It is important to understand individuals' inherent perceptual behaviours, which may appear different across cultures and/or across personal and demographic characteristics (Abbasi, Tarhini, Hassouna & Shah, 2015; Wang et al., 2016).

Several models and frameworks have been developed to explain the technology acceptance theories (Wang, et al., 2016). The Technology Acceptance Model (TAM), is the most commonly applied model in the diffusion and adoption models, followed by the Innovation Diffusion Theory (IDT) (Dwivedi, Williams, Lal & Schwarz, 2008).

Other models include the Theory of Reasoned Action (TRA), which is the origin of TAM, Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology-Organisation-Environment (TOE) framework (Hoti, 2015).

Sophonthummapharn (2009) states that there is a similarity in the different theories in that they predict and describe an individual’s behaviour toward technological innovation. It is neither possible nor sufficient to have one theory that applies to all innovation types due to the diversity (Baker, 2012). TAM has been influential in explaining the individual’s intentions of using technology. In this study, TAM will be used to explain the technology acceptance for smart factories.

Technology acceptance is dependent on a number of variables including but not limited to perceived usefulness, perceived ease of use, results demonstrability as well as usage behaviour (Dajani, 2016; Scannell et al., 2012). User type and type of usage of technology have a bearing on how technology will be accepted. Technology acceptance is a complex decision process and is best looked at and analysed based on the specific technology in question. Dajani (2016) posits that technology acceptance models depend on various theories in explaining the use of information technologies, such as the diffusion of innovation theory introduced by Rogers (2003), the theory of reasoned action by Fishbein and Ajzen (1977) and the theory of planned behaviour introduced by Ajzen (1985).

Ashraf et al. (2014) aver that self-efficacy represents a person’s belief regarding his or her capacity to carry out a specific task using a technology, whereas facilitating conditions refer to the degree to which a person believes that the necessary infrastructure exists to support the use of the system. Technology acceptance, especially in a manufacturing environment, can also be influenced by factors such as performance expectancy, social influence and facilitating conditions as well as effort expectancy. The bigger the effort employees are expected to put into the adoption of new technology the more likely they are not to support its adoption (Dajani, 2016).

2.3.1 Technology Acceptance Model (TAM)

Due to its importance, TAM has metamorphosed ceaselessly like an organic being since its introduction (Lee, Kozar & Larsen, 2003). Attention has been given to the model to determine what factors affect users’ beliefs and attitudes in accepting information systems and factors contributing to user resistance (Schrier, Erdem & Brewer, 2010). Research has been done and Aijen and Fishbein (1980) developed the Theory of Reasoned Action (TRA) to "provide an explanation of the determinants of computer acceptance that is general, capable of explaining user behaviour across a broad range of end-user computing technologies and user populations, while at the same time being both parsimonious and theoretically justified" (Davis et al., 1989, p. 985).

TAM theory has been extensively researched in an attempt to replicate it with other technologies and longitudinal situations in a bid to verify whether it is a parsimonious model (Lee, et al., 2003). Research has also been conducted to compare and verify whether TAM and TRA can be differentiated, TRA being the origin of TAM (Zhang et al., 2014). It has been widely researched to verify whether TAM is superior to TRA (Lee et al., 2003; Zhang et al., 2014). The chronological progress of the TAM theory is depicted in Figure 2.5.

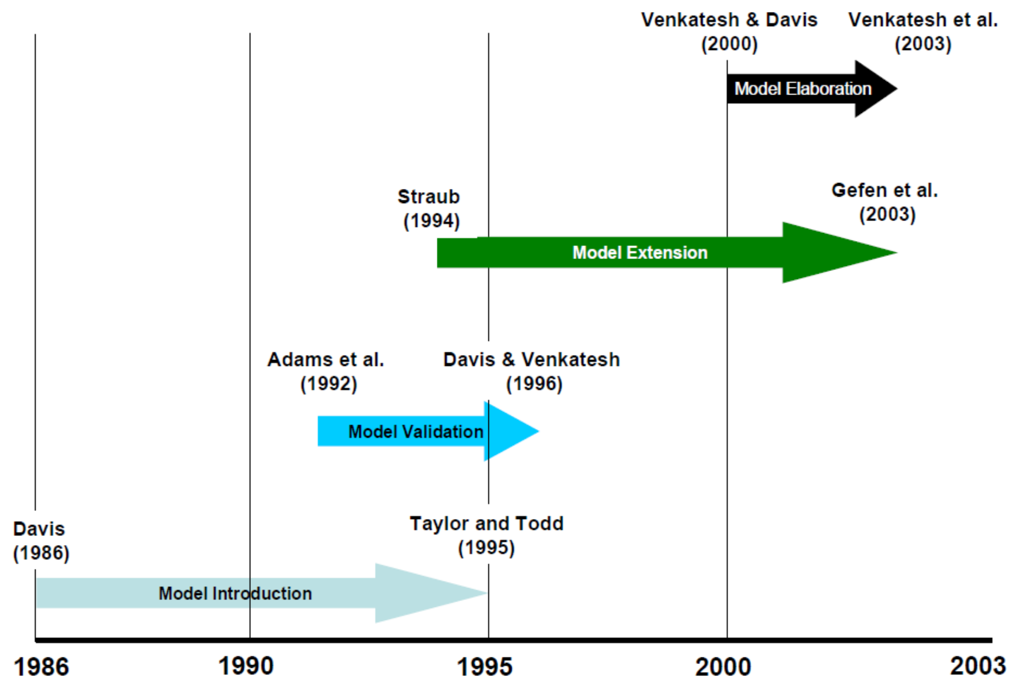

Figure 2.5: Chronological Progress of TAM Research Source: (Lee, Kozar & Larsen, 2003)

TAM is the most widely accepted model in the context of information systems acceptance (Zhang et al., 2014). The original TAM focuses on two theoretical constructs, namely perceived usefulness (PU) and perceived ease of use (PEOU), which are the fundamental determinants of system acceptance and use (Davis, 1989). PU is defined as the degree to which a person believes that using a particular system would enhance his or her job performance (Zhang et al., 2014; Schrier et al., 2010). Findings in research conducted on TAM found that users believe that a system high in PU is more likely to produce a positive use-performance relationship (Schrier et al., 2010). Task, technology and experiential characteristics lead to a common fit as depicted in figure 2.6 (Schrier et al., 2010).

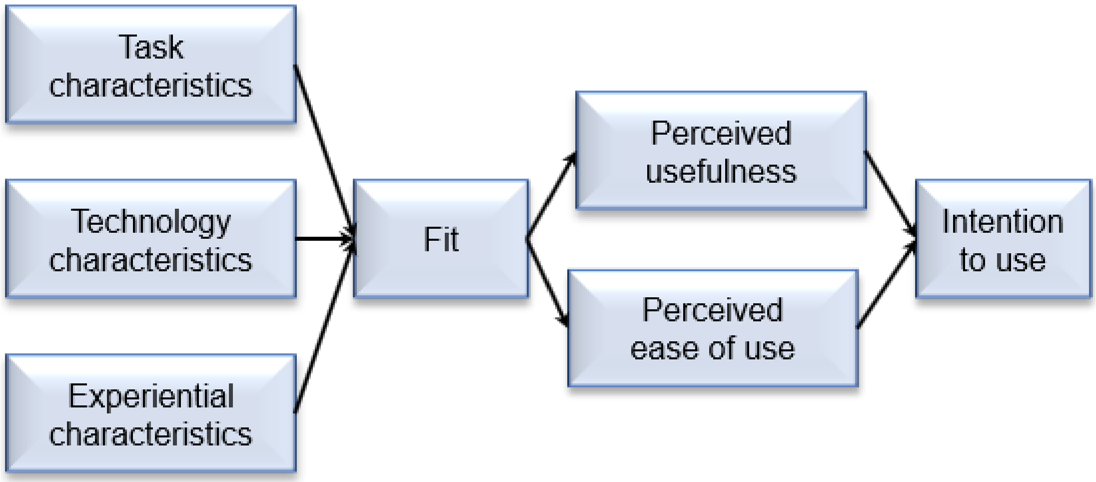

Figure 2.6: Hybrid TAM/TTF model Source: (Schrier et al., 2010).

PEOU on the other hand refers to the degree to which a person believes that using a particular system would be free of effort (Zhang et al., 2014; Schrier et al., 2010). Users are more inclined to accept an application perceived to be easier to use. TAM further theorises that PU and PEOU will mediate the effect of external variables, such as interface design and behavioural intentions (Venkatesh & Bala, 2008). Wang, Wan and Zhang (2016) aver that TAM has proven to be a robust theoretical framework as it has been extensively tested in different contexts.

It is important to separate technologies associated with computer controlled machines used in manufacturing and assembly lines for production of goods purposes into a broader subset referred to as shop floor manufacturing technologies (Scannell et al., 2012; Onga, Laia & Wang, 2004). In rolling out smart manufacturing technology, management should be aware that non-voluntary technology usage is often more impacted by subjective norms. Management should devise ways to counter possible unwillingness of employees to comply with new regulations governing use of the new technology (Schrier et al., 2010).

Shop floor manufacturing technology behaviour investigates two sets of variables namely external and internal. Scannell et al. (2012) avers that perceived benefits or usefulness of engaging with the technology as well as prior knowledge of engaging with technology has a major part to play in how individuals will accept and use technology.

2.4 TECHNOLOGY UTILISATION

Employees who are exposed to technology and are willing to use it are more likely to perform their functions more efficiently and effectively compared to those employees who are not open to use of the technology (Schrier, Erdem & Brewer, 2010). For technology to have a positive impact on performance, it must be the right fit for the required purpose. Schrier et al. (2010) aver that technology utilisation is a factor of fit for the user's needs, social norms and habits as well as availability. Employees tend to be aligned to want to use a technology if they find that it goes hand in hand with their perceived benefits.

2.4.1 Attitude towards the Smart Factory

Hassanein and Head (2007) define attitude as predisposition to respond in a particular way towards a particular object or class of objects in a consistently favourable or unfavourable manner. Attitudes can either be positive or negative towards a situation or object and this is referred to as bias (Elias et al., 2012). A person's attitude is a window of one's behaviour and can influence an individual's choice of action and responses to challenges (Motshegwe & Batane, 2015; Zhang, 2016). A biased view towards those attitude objects for which the assessment is positive and against those attitude objects which the assessment is negative (Elias et al., 2011).

Success in the implementation of the smart manufacturing concept lies in the management's understanding of employees' attitude towards technology (Elias et al., 2011). The employees will find value and add to productivity if their attitude towards technology is positive. Employees with a negative attitude towards technology will possibly find it as a threat and therefore not support it. On the other hand, employees who think that the technology use will increase productivity are more likely to either use or support its use (Elias et al., 2011).

Management needs to investigate the network mechanisms and culture in which the employees operate. Occupied roles and patterns of connections have an influence on the way employees accept or reject technology through the influence of their social circles (Rice & Aydin, 1991). Before employees can be expected to accept the new technology, it is management's prerogative to ensure that employees have a positive attitude towards technology (Elias et al., 2012).

According to Wang et al. (2016), use of information technology and the attitudes of the users are related. Employees who have a negative attitude towards technology, will most likely view technology in the workplace as a threat (Elias et al., 2012). Elias et al. (2012), argue that employees whose attitude towards technology is negative, will have their intention to reduce the use of such technology, thereby decreasing the odds that the technology will actually be used. It is management's prerogative to understand the implications of technology acceptance in order to strategise accordingly for the successful implementation of technology information systems (Elias et al., 2012; Wang et al., 2016).

2.4.2 Drawbacks of Technology Acceptance Theory

The meta-analysis rigorously substantiates the conclusion that has been widely reached through qualitative analyses: namely that TAM is a powerful and robust predictive model (King & He, 2006). In as much as the TAM has been widely accepted and applied, it is not without its positive antagonists. Lee, Hsieh and Hsu (2011) question whether this model can be applied to analyse every instance of technology adoption and implementation as each instance is unique. More often than not, students who are used as a convenience sample respondents in TAM studies, are not exactly like either of the other two groups suggesting that study results should not be generalised to other contexts and vice versa (King & He, 2006). Chuttur (2009) criticises the empirical value, narrow explanatory and predictive power, insignificance and lack of practical value.

King and He (2006) aver that in some instances, there are possible sources of bias (non-significant results are seldom published and there may be a lack of objective and consistent search criteria). In his article on the shortcomings of the TAM model, Bagozzi (2007) indicated that the model is presented in a too simplistic manner and eliminates important variables and processes. Furthermore, some of the key weaknesses were identified as follows:

- Two critical gaps were identified in the framework with the proposed linkages – using information technology - intentions to use information - actual use;
- The absence of sound theory and a method for identifying the determinants of perceived usefulness and perceived ease of use, as well as other bases for decision making;
- It neglects group, social and cultural aspects of decision-making;
- The reliance on naïve and over-simplified notions of affect or emotions; and
- The overdependence on a purely deterministic model without consideration of self-regulation processes (Bagozzi, 2007; Leo, 2017).

2.4.3 Summary of Technology Acceptance Theories

This sub-section introduced the academic theories related to technology acceptance. In this section, the technology acceptance model was presented as the most common theory used to explain why technology is accepted or rejected. Many theories exist, however this study uses TAM to understand how external factors influence attitudes towards technology. The theory highlighted how attitude, can positively or negatively influence the intention to use technology.

The following deliverables were achieved in this sub-section: an understanding of the technology acceptance theory; how external variables affect attitude and the influences on the intention to use the technology. The research objective of identifying the factors influencing the attitudes towards smart factories in the pharmaceutical sector and developed a conceptual model (RO_2) was partly achieved in this section.

The next sub-section discusses the factors influencing technology acceptance. The influencing factors, the national factors, as well as the organisational factors will be discussed.

2.4.4 Macro Factors In Technology Acceptance

Technology adoption goes beyond the boundaries of an organisation. It therefore needs to be looked at in a holistic approach that includes the role of socio-cultural macro-context (Bayerl et al., 2013). Research has shown that some societies are more open to adopt technology than others (Corfield & Paton, 2016). Each organisation has a specific need for technology for its applications. However, technology should offer standardised solutions to facilitate implementation and coordination across socio-cultural contexts (Bayerl et al., 2013; Corfield & Paton, 2016). An organisation should synchronise and align its needs to standards in its supply network. Therefore the type of technology to be adopted largely depends on the macro factors governing a firm's operating environment (Sha et al., 2004).

Practical implications of technology are not always enough to determine the technology to choose. According to Avgerou (2001), innovation inside an organisation is rarely a result of free choice and action. It is to a large extent determined by events, trends, pressures, opportunities, or restrictions in the international or national arena.

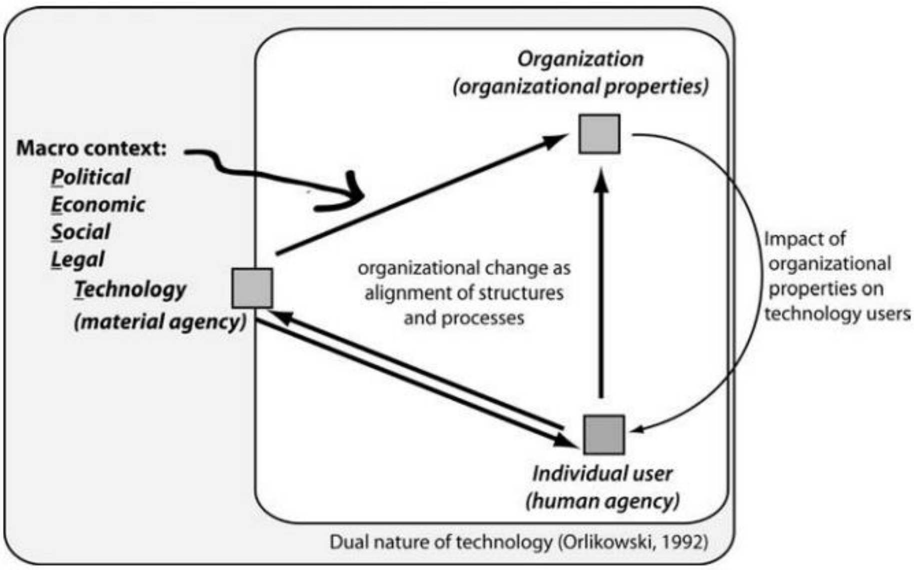

Figure 2.7: Macro Factors in Technology Adoption Source: (Bayerl, et al., 2013, p. 801)

Bayerl et al., (2013) state that the prevalent micro-perspective of the socio-material agency of technology for organisational change needs to be extended towards a macro-level perspective of the external organisational contexts (Figure 2.7). A full political, economic, social, technological, legal and environmental (PESTLE) analysis should be done as it influences technology adoption (Avegrou, 2001; Adjasi, 2009; Bayerl et al., 2013).

2.4.5 Organisational Factors in Technology Adoption

Technology use is central to any organisation today, yet the choice, adoption and employment of technology is still not as smooth as it should in most cases. Acceptance and adoption of technology is influenced by user perceptions, attitudes and beliefs towards technology (Erumban & de Jong, 2006). The value of an information system to a person, institution or country is realised only if users accept the system (Orr, 1999). Specific factor in an organisation such as capital availability, organisational strategy, level of education on employees as well as support in the supplier value chain affect the adoption of technology (Orr, 1999; Avegrou, 2001; Bayerl, 2013).

For successful smart factory adoption, resources and costs for smart factory adoption should be available within an organisation and this is usually a prohibitive factor due to initial costs (Erol, Schumacher & Sihn, 2016). The smart factory is a relatively new concept, hence a limited number of academic theories have been proposed to explain the factors which influence smart factories (Leo, 2017). Kang and Kim (2016), evaluated the factors affecting smart factories by using the balanced scorecard model. Erol et al. (2016) developed a maturity model for smart factories to assess an organisation's readiness and maturity. In this study, nine organisational dimensions were identified, namely Strategy, Leadership, Customers, Products, Operations, Culture, People, Governance and Technology. These studies have not used the TAM to identify factors which influence smart factories.

This research study only focusses on Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Parent Company and Security and International / National Standards. These variables were selected because of the time limitation to complete this study. Leo's

(2017) MBA research into smart factories in South Africa also identified these variables.

2.4.6 Factors Influencing Technology Acceptance

Academic theories relating to technology acceptance were discussed in the previous sub-section. The TAM will form the basis of the conceptual model for this study. The importance of an employee’s attitude towards technology in the workplace was highlighted in the preceding section. TAM theory was applied to explain how attitude influences the intention to use technology, positively or negatively. Lastly, the drawbacks of the technology acceptance model were discussed.

This sub-section will develop a conceptual model by examining the factors influencing technology acceptance in the workplace, in order to link the independent variables to the dependent variable in this study, which is technology acceptance in the workplace. To gain an understanding of the factors influencing technology acceptance, both macro- and micro-level factors will be examined and explained. The following sub-section will explain and describe the independent variables to be used in this study.

2.4.6.1 Training and Development

Skilled and well educated employees are the greatest driver of competitiveness in manufacturing (Kagermann, Wahlster & Helbig, 2013). Companies should focus on training and upskilling employees to be able to use innovation effectively. Lack of skills related to smart manufacturing is a major cause for concern in South Africa. It is important that companies invest in skills training to generate a wider base for smart manufacturing (Kyobe, 2011).

Technical skills required for some of the applications in the use of smart devices is very specialised in nature and the availability of these skills can be a deciding factor especially in a developing economy, such as South Africa. Targeted and deliberate training of employees might be necessary before the companies can adopt smart manufacturing. Training equips employees with the relevant knowledge and therefore takes away the ambiguity that can potentially be a barrier to adoption and acceptance of technology (Erumban & de Jong, 2006).

Employees often judge themselves through self-efficacy defined as a person’s belief regarding his or her capacity to carry out a specific task using a technology (Scannell, Calantone & Melnyk, 2012; Dajani, 2016). Training within an organisation should be given to boost the self-efficacy of employees. Necessary management support should be availed together with facilitating conditions that will make employees believe that there is sufficient management support to use the proposed technology (Bogue, 2016).

Employee training should be at the top of the list for any organisation before a smart factory implementation. Industry 4.0 has brought about a deliberate shift from a product-based economy to a knowledge-based economy (Onga, Laia, & Wang, 2004). There has been a demand for workers with greater knowledge who possess higher order reasoning and thinking capabilities. Hence organisations are required to educate and train their employees so that they are ready to work with smart technologies thus improving their acceptance levels of the new technology. Onga et al. (2004) aver that organisations need to train employees from anywhere within the organisation using asynchronous e-learning. Asynchronous learning saves on time and costs as well as reaps benefits associated with employee retention, improved compliance and meeting business needs (Onga et al., 2004).

Training employees in preparation for adopting smart manufacturing should not only focus on the technical aspects of the proposed technology. Employees should be made aware of the benefits emanating from adopting technology, as this will in turn drive their willingness and desire to embrace the technology (Schrier, Erdem & Brewer, 2010). The more employees get to understand the perceived benefits in terms of cost and cycle time reductions in adopting a technology, the more likely they are to readily accept a technology and this information should be imparted during training (Schrier et al., 2010; Talukder, 2012).

Factory workers are known for their affinity for practical and pragmatic solutions that will aid in lessening the burden of executing work. Training of employees should be done to expose the employees to the usefulness of technology and this will increase their acceptance of the technology (King & He, 2006).

Training and Development have been identified as important factors that influence a person's attitude towards a smart factory and it has been proposed that they have a relationship with the dependent variable, Attitude towards a Technology Acceptance as shown in Figure 2.8.

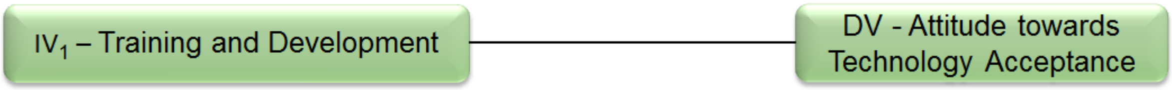

Figure 2.8: Relationship of Training and Development and Attitude towards Technology Acceptance

2.4.6.2 Individual Characteristics

Despite impressive advances in hardware and software capabilities, the troubling problem of under-utilised systems continues, resulting in lacklustre returns on organisational investments in information technology (Venkatesh & Davis, 2000; Talukder, 2012). Individual technology acceptance is based on a number of factors. Chief amongst them, attitude, subjective norm, self-efficacy, innovativeness and technological experience were identified as individual context factors (Talukder, 2012). Individuals who utilise technology that is available to them are able to perform tasks more efficiently and effectively than individuals who do not (Mathieson & Keil, 1998), assuming that the technology is well designed (Schrier et al., 2010).

Acceptance of a technology by an individual can be explained by the psychological theory of reasoned action (TRA) that seeks to explain behaviour. TAM primarily looked at the perceived ease of use (EU) and perceived usefulness (PU) and the dependent variable behavioural intention (BI), which TRA assumed to be closely linked to actual behaviour in the acceptance and use of a technology (King & He, 2006). Other factors include prior experience, image and enjoyment of innovation which have influence on an individual's adoption of technological innovation (Talukder, 2012).

Individual innovativeness is one of the characteristics that drives individuals' acceptance of new technologies. Innovativeness is defined as the propensity of an individual to adopt innovations relatively sooner as opposed to others. It is also defined as an attitude that has a propensity towards adopting new technologies

(Venkatesh & Davis, 2000). Individuals' level of education, experience and ability to use computer systems affects how much an individual is willing to adopt and use a technology (Venkatesh & Davis, 2000; King & He, 2006). Scannell et al. (2012) argued that prior technology experience and compatibility can successfully predict technology adoption as individuals will call on their prior computer knowledge.

Individual Characteristics have been identified as an important factor that influences a person's attitude towards a smart factory and it is proposed that it has a relationship with the dependent variable, Attitude towards a Technology Acceptance as shown in Figure 2.9.

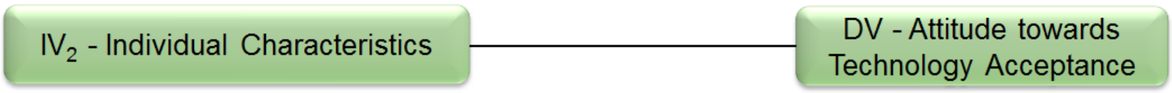

Figure 2.9: Relationship of Individual Characteristics and Attitude towards Technology Acceptance

2.4.6.3 Organisational Culture

Organisational culture is a major factor in technology acceptance and adoption. The prevalent culture in an organisation can either encourage or impede technology adoption (Corfield & Paton, 2016). Organisational culture suggests that similar culture, norms and values in a certain company differentiate it from another group from a different company (Corfield & Paton, 2016). Some organisations have a strong support culture and this works both ways for management or employees.

A company with a strong support culture will be able to implement the smart manufacturing technologies with relative ease as the employees will be willing to support management (Denison, Hooijberg, Lane & Lief, 2012). Technology adoption in any organisation requires some internal changes to support or implement the new technology. The company should be able to have a culture that supports the changes from a management and employees point of view. Research has shown that some cultures such as the German and Japanese readily accept technology and this has been a critical success factor in organisations operating within these cultures (Gu, Cao & Duan, 2012).

Executives play a major role in an organisation relating to culture, shaping the attitudes and decision processes as well as strategic outcomes. Added to these roles is the resource allocation and gatekeeping on the alternative investment routes (Sharp, Lyer & Brush, 2017). Resource allocation is a major factor in the success of any technology adoption undertaking. The amount of resources allocated to the process of technology adoption in smart manufacturing has been found to influence the level and pace of adoption (Elias et al., 2011). Depending on the level of technology in an organisation, upgrading technology to reach smart manufacturing levels can be costly.

The availability of financial resources either to acquire new systems or upgrade current systems to required levels can be daunting especially in developing countries (Kyobe, 2011). Support infrastructure may not be available, requiring the organisation to have a very high initial capital outlay which inhibits the adoption of technology. In order to understand the smart factory better, the relationship between resource allocation and costs should be investigated at as a factor affecting the adoption.

Management needs to be aware that not only are individual attitudes in adopting technology important, but the organisational policies, procedures and approaches also play a part (Talukder, 2012). Effective acceptance and adoption of a technology is dependent on supporting and facilitating conditions within the organisation on the use of innovative technologies. Organisational factors in the form of training, managerial support and incentives can motivate employees to positively react to adoption of technology (Talukder, 2012).

The culture within an organisation may also be viewed from the social systems that exist in an organisation. Talukder (2012) avers that the adoption of innovation can be driven by the existing social environment. If the organisational culture supports innovation and is extensively used by other employees, the social environment is likely to play an important role in adoption of innovation (Talukder, 2012). Social pressure in the workplace is rife and may lead to employees adopting the technology due to its widespread use rather than its usefulness. It is important for management to identify employees whose beliefs and opinions are perceived important by their peers and people who are in social networks (Talukder, 2012).

Organisational Culture has been identified as an important factor that influences a person's attitude towards a smart factory and it has been proposed that it has a relationship with the dependent variable, Technology acceptance in the workplace as shown in Figure 2.10.

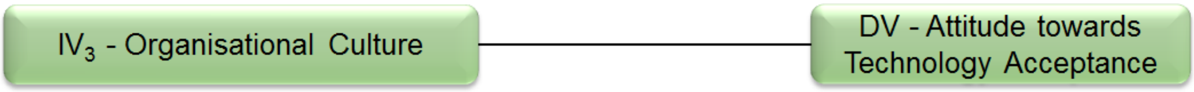

Figure 2.10: Relationship of Organisational Culture and Attitude towards Technology Acceptance

2.4.6.4 Job Security

Job security is a major factor in the adoption of smart factories. Employees always fear for the continued existence of their jobs and they are bound to have subjective perceptions of whether they will keep their jobs or lose them in the long term (Witte, 2005). There is a prevalent perception that human substitutability by machines has reached unprecedented proportions and employment is susceptible to computerisation (Frey & Osborne, 2013). The rise of the smart period and Industry 4.0 has seen large numbers of organisations going the automation route. Automation has been seen as a potential threat that will ultimately lead to technology-induced unemployment (Frey & Osborne, 2013).

Studies done in the USA and Europe in 2013 showed that some jobs will not be required in the near future, resulting in renewed concerns that automation and digitalisation might result in a jobless future (Arntz, Gregory & Zierahn, 2016). Employees are bound to be wary of the potential risks to their employment and therefore their livelihoods if technology is adopted. This will lead to their perception towards adopting smart manufacturing to be either negative or positive depending on how they view their future prospects in the organisation once technology has been adopted.

Smart factories go through some changes in operation resulting in the realignment of roles in supporting new processes (Deloitte University Press, 2017). Some roles will become redundant due to new process capabilities such as virtual / augmented reality. The implementation of a smart factory will bring about changes where people's old roles are affected, bringing about a sense of resistance and mistrust from employees.

Unfamiliar roles emerge from the adoption of a smart factory. The technological changes brought about by smart factories may mean that humans and cobots work side by side. This technological change in the workplace will mean that employees work differently from the way they normally do. Cobots have made this transition much faster as they are designed for speed of deployment, flexibility and safety (Collaborative Robot Buyer's Guide, 2018). Employees will need to be trained how to work around cobots in order to secure their jobs. However the menial and repetitive tasks will be done by cobots (Bloss, 2013). Cobots work with precision (Collaborative Robot Buyer's Guide, 2018) and they offer the consistent quality required in the pharmaceutical manufacturing industry.

A change management process that is agile and adaptive is required to maintain a motivated workforce who will achieve a greater impact and be ready to be innovative in cross-functional roles (Deloitte University Press, 2017). Management should cross-train employees for new roles that are in line with smart technology support. Job security is a major factor on the employees' part hence management should make all efforts to insure that employees' minds are put at ease so that they can fully support implementation of the smart factory.

Job Security has been identified as important factor that influences a person's attitude towards a smart factory and it has been proposed that it has a relationship with the dependent variable, Attitude towards a Smart Technology Acceptance (Figure 2.11).

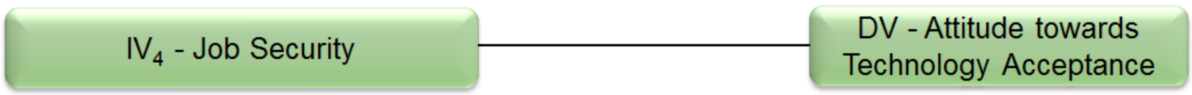

Figure 2.11: Relationship of Job Security and Attitude towards Technology Acceptance

2.4.6.5 Resources and Costs

Migration from an automated factory to a smart factory is no easy feat in terms of financial and time resources. An organisation needs to invest a substantial amount of money to realise the smart factory dream (Arntz, Gregory & Zierahn 2016; Bogue, 2016). The type of employee required for the successful running of a smart factory moves from a normal operator to a highly trained and technical employee resulting in shifts in labour costs (Daudt & Willcox, 2018).

Technical talent is a scarce resource that costs a large amount of money. An organisation needs to have the financial muscle to bring the scarce human talent together to run a smart factory. More often than not highly technical resources are not always found in the same area and it takes a lot of money to bring them into one area (Daudt & Willcox, 2018).

Technologies that deliver a smart factory come from different parts of the world and they need to be brought to one area through complex transportation networks (Baines, 2004). Transportation and energy costs are high in setting up a smart factory and this tends to discourage firms unless they are prepared to carry the investment cost (Dellermann, Fliaster & Kolloch, 2017). The smart factory scenario imposes substantial challenges due to its futuristic nature yet it is realistic and achievable (Erol, Schumacher & Sihn, 2016). According to Erol et al. (2016) challenges arise in the implementation of smart factories due to the immense financial resources required to acquire new technology.

Resources and costs have been identified as important factors that influence a person’s attitude towards a smart factory and it has been proposed that they have a relationship with the dependent variable, Factors affecting technology acceptance in the workplace (Figure 2.12).

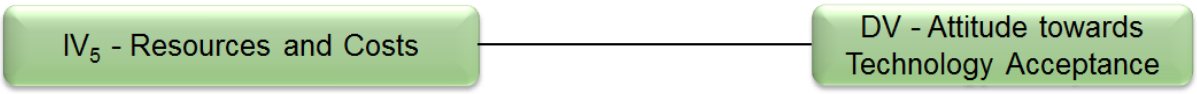

Figure 2.12: Relationship of Resources and Costs and Attitude towards Technology Acceptance

2.4.6.6 Trust

The African proverb states that when there are no enemies within, the enemies without cannot hurt you. This proverb hints at trust and collaboration, as well as the quality of relationships within a team (De Bruyn, 2017). Trust can be described as a well-recognised mechanism for assessing the potential risk associated with cooperating with autonomous agents Griffiths (2006). Trust can be based on either experience or recommendation and is demonstrated by confidence in the goodwill of others, which is produced through interpersonal interactions dealing with matters of uncertainty or risk (Ring & Van der Ven, 1994).

Prieto (2009) argues that acceptance, approval, confidence or respect can be practical ways of showing trust. In business, any commercial entity would like its customers to believe in its products without a shade of doubt (Prieto, 2009; De Bruyn, 2017). According to Mayer, Davis and Schoorman (1995), the influence of trust in technology has been widely researched in the e-commerce space. In other studies, trust has been seen as an important element in strengthening organisational commitment and can increase productivity (Lee & See, 2004).

The era of cobots has brought about some misgivings from some employees due to lack of trust (Bloss, 2016). Cobots require the human-machine interaction and this requires certain levels of trust in terms of employee safety and acceptance (Bogue, 2016). Employees are more inclined to accept and adopt a technology they trust and will not readily accept technologies they do not trust (Daudt & Willcox, 2018). When it comes to trust, culture and background have a strong influence on how technology is quickly and easily accepted (Baba, Falkenburg, & David, 1996).

Employees' perception of safety with human-robots is another factor closely integrated to trust (Kagermann, et al., 2013). A study by Calitz, Poisat and Cullen (2017) established that communication is an essential element, which will have the most significant impact on human-robot trust.

Trust has been identified as an important factor that influences a person's attitude towards a smart factory and is proposed that it has a relationship with the dependent variable, Factors affecting technology acceptance in the workplace as shown in Figure 2.13.

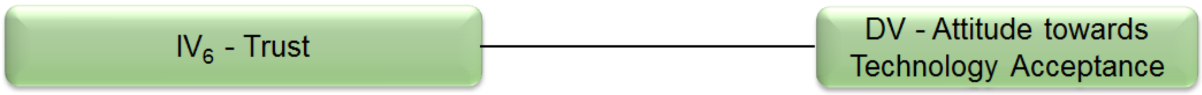

Figure 2.13: Relationship of Resources and Costs and Attitude towards Technology Acceptance

2.4.6.7 Security and International / National Standards

A smart factory is created through the integration of a number complex physical components as well as IT standards and protocols. By design, a smart factory brings a number of technologies together and these technologies are governed by international and sometimes national standards (Fulton & Hon, 2010). Standards aim to promote trade by the removal of barriers caused by differences in national practices. Standards are there to protect consumer interests through adequate and consistent quality of goods and services (Fulton & Hon, 2010).

National and international standards promote economy in human effort, materials and energy in the production and exchange of goods as well as promote quality of life, safety and health and the protection of the environment. When standards are international the communication and cooperation in economic, intellectual, technological and scientific endeavours between interested parties become easier (Oddy, 1996).

Data security is by far the most challenging barrier to cloud computing adoption (Gorelik, 2013). Questions around data security are always asked upfront before smart factory implementation (Gorelik, 2013; Long et al., 2017). From an organisational point of view, data are one the most precious corporate asset and companies want to know that their data are safe (Gorelik, 2013; Bogue, 2016; Crosby et al., 2016). The smart factory concept is more likely to use cloud computing for data storage due to the big data analytics that are synonymous with smart manufacturing. Pertinent questions get asked about data storage and data encryption during transfer in the public cloud and disaster recovery (Gorelik, 2013).

Before engaging a cloud-computing company, investigations on the service provider should be done to make sure that it has more than one data centre and in diverse geographical locations, complies with international data storage and access standards as well as with security breach investigative capabilities (Fulton & Hon, 2010; Gorelik, 2013; Bogue, 2016; Crosby et al., 2016; Long et al., 2017).

Security and International / National Standards have been identified as important factors that influence a person's attitude towards a smart factory and it has been proposed that they have a relationship with the dependent variable, Attitude towards a Technology acceptance as shown in Figure 2.14.

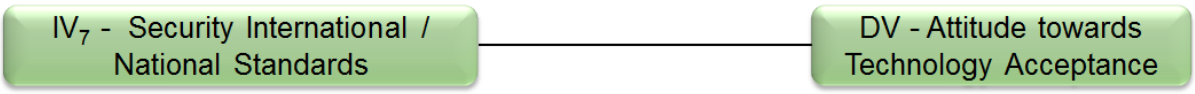

Figure 2.14: Relationship of Resources and Costs and Attitude towards Technology Acceptance

2.4.6.8 Parent Company

The business landscape has changed vastly from the 1970s towards the 1990s as a number of American, European and to an extent the Asian conglomerates have expanded into the less developed world for manufacturing. Some of the expected benefits of offshore manufacturing are low labour costs, access to raw materials and access to markets (Hill & Hult, 2017).

In some instances, the subsidiary companies have become central to the overall performance of the parent company depending on the strategic direction the company has taken (Danping Lin, Lee, Lau, Yang & Lin, 2017). It is the parent company's responsibility to make sure that quality and manufacturing standards are managed and are at the same level in all manufacturing sites, regardless of location (Denisia & Gheorghina, 2008).

Adoption of smart factory technology can be viewed as more of a corporate governance function as opposed to local management of the company due to other factors like costs involved, communication with other sister factories and supply chain (Burke et al., 2017; Hill & Hult, 2017). In their study on the relationship between the spill over of benefits to local companies from the multinational companies, Belderbos, Van Roy and Duvivier, (2012) concluded that affiliates of foreign multi-national enterprises have higher productivity levels, which can be attributed to the transfer of superior technologies. The relationship between spill-over from the multinational companies to domestic organisations is empirically difficult to test, as prior completed research indicates inconclusive results as to whether it has a positive or negative effect on the local organisation (Leo, 2017).

The outcome is not always positive when it comes to spill-overs from the parent company to the subsidiary as a number of factors are at play including, but not limited to technology and human capital that are willing and able to manipulate the relevant technology (Hill & Hult, 2017). Multinational firms are usually large in nature with a number of tiers in management, resulting in bureaucracy that delays decision making processes in taking up and implementing new projects (Leo, 2017).

The Parent Company has been identified as an important factor that influences a person's attitude towards a smart factory and it is proposed that it has a relationship with the dependent variable, Attitude towards technology acceptance in the workplace as shown in Figure 2.15.

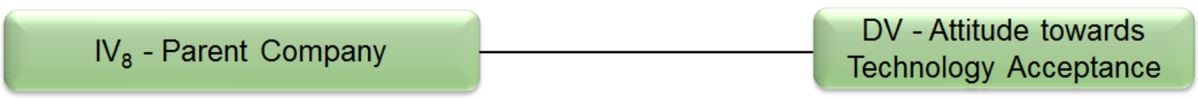

Figure 2.15: Relationship of Resources and Costs and Attitude towards Technology Acceptance

2.4.7 Factors influencing smart factories summary

A literature review of factors influencing technology acceptance in the workplace were discussed. The smart factory concept was explained together with different technologies that make up a smart factory. Factors which influence technology acceptance in the workplace according to the academic literature were discussed. The factors identified for this study are *Training and Development, Individual Characteristics, Organisational Culture, Job Security, Resources and Costs, Trust, National and International Standards* and *Parent Company*.

The following deliverables were achieved: a comprehensive understanding of the factors which influence technology acceptance across countries; the factors which influenced technology acceptance within the organisational context. These partly achieved the research objective of identifying the factors influencing the attitudes towards smart factories in the pharmaceutical sector and developing a conceptual model (RO_2). In the next section, based on the literature reviewed in this chapter, the conceptualised model for the Attitude towards a Technology acceptance will be formulated.

2.5 PROPOSED CONCEPTUAL MODEL OF THE ATTITUDE TOWARDS A SMART FACTORY

Based on the literature review, the conceptualised model for the Attitude towards a Smart Factory has been formulated in this chapter. The model is depicted in Figure 2.8 and consists of the independent variables, *Training and Development, Individual Characteristics, Organisational Culture, Job Security, Resources and Costs, Trust, National and International Standards* and *Parent Company*. These variables are applicable to all employees and management in an organisation.

The independent variables and the dependant variable are highlighted in Figure 2.7. The dependent variable is *Attitude towards a Smart Factory*.

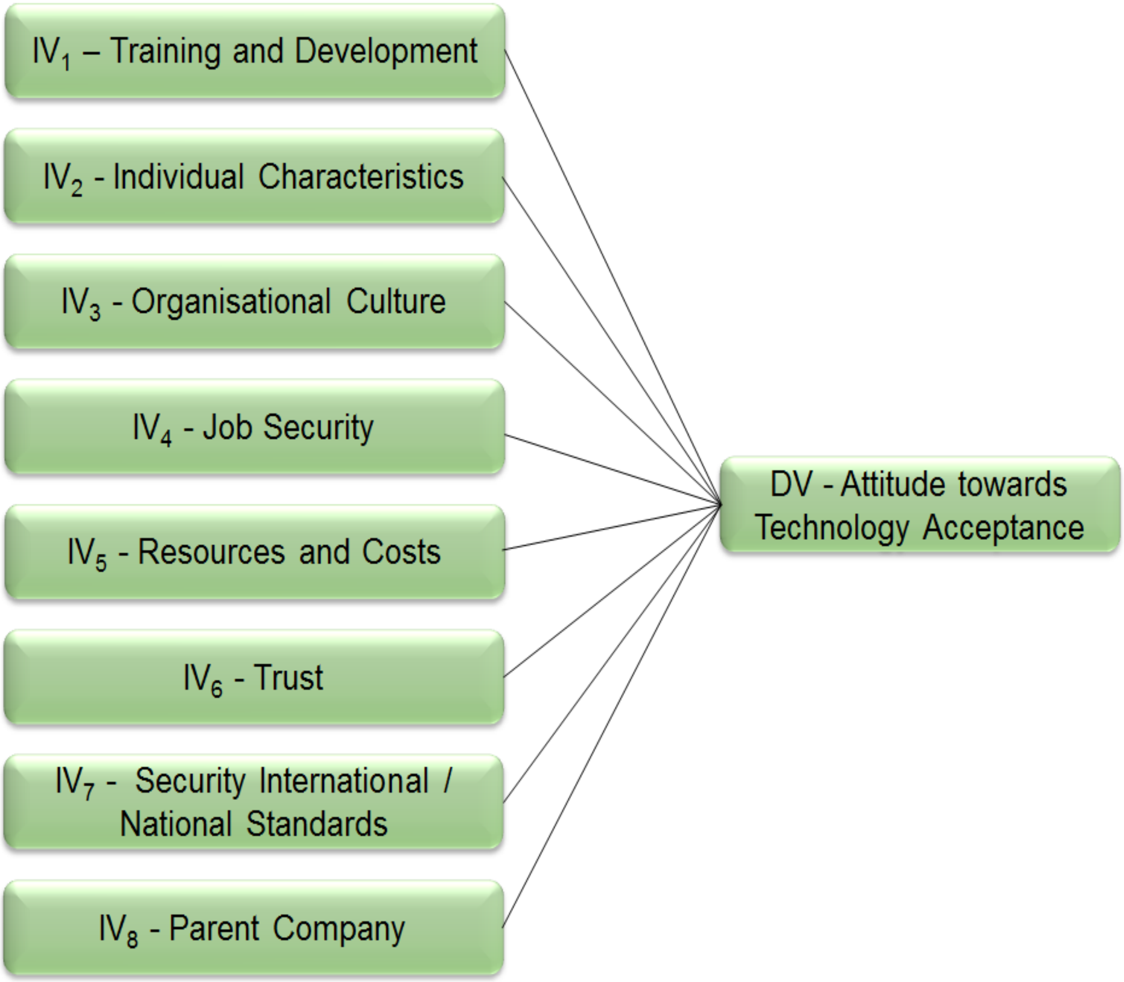

Figure 2.16: Attitude towards a Smart Factory Implementation Conceptual Model

2.6 CHAPTER 2 SUMMARY

This chapter addressed the research question RQ1 which states; "*What are the characteristics of smart factories in the manufacturing industry?*" and RQ2 which states; "*What factors need to be included in the proposed model to measure the perceptions of employees and management on the factors influencing the attitudes towards smart factories within the pharmaceutical sector*". The literature review was done to achieve the research objectives in order to identify the characteristics of smart factories in the manufacturing industry (RO1) and identify the factors influencing the attitudes towards smart factories within the pharmaceutical sector (RO2) and develop a conceptual model (RO3) as depicted in Figure 2.8.

In the first section, the smart manufacturing concept of Industry 4.0 and smart factories were discussed. The smart factory was positioned as the future in manufacturing through the use of various smart technologies like Blockchain, CPS and augmented reality. The literature reviewed also presented that organisational competence in manufacturing can be improved through adoption of the smart factory concept.

Adoption of technology literature was reviewed and TAM was found to be the most common theory used to explain the acceptance or rejection of a technology. Several theories in technology acceptance in the workplace were stated and TAM explained on how it influences attitudes towards intention to use technology positively or negatively.

Factors which influence technology acceptance in the workplace were discussed according to the academic literature reviewed. Due to different factors reviewed, it was presented that technology should be adopted according to the individual organisation. In the final section of this chapter, the proposed conceptual model was shown with the factors influencing the *Attitude towards a Smart Factory* as: *Training and Development, Individual Characteristics, Job Security, Resources and Costs, Trust, Security and International / National Standards Parent Company.*

Chapter 3 will address the research question RQ_3 which states; "*What research design and methodology can be followed to better understand and reproduce this research study in future?*". The research objective of justifying and explaining the research design and methodology that will be used for this study with sufficient information for future reproduction (RO_3) will be presented.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

3.1 INTRODUCTION

The previous chapter addressed significant concepts relating to this research, such as smart factories. Their antecedents and measurements were discussed. Chapter 2 addressed the research question RQ_1 which states; "*What are the characteristics of smart factories in the manufacturing industry?*" and RQ_2 which states; "*What factors need to be included in the proposed model to measure the perceptions of employees and management on the factors influencing the attitudes towards smart factories within the automotive sector*?" The research objectives of performing a literature review in order to identify the characteristics of smart factories in the manufacturing industry (RO_1) and identify the factors influencing the attitudes towards smart factories within the pharmaceutical sector and develop a conceptual model (RO_2) were achieved.

This chapter explains the research design and methodology used for this study in sufficient detail to achieve the research objective (RO_3). Table 3.1 shows the research question and objective pertaining to this chapter. Figure 3.1 depicts an overview of the chapter followed by Section 3.1 describing the definition of research. Section 3.2 discusses the research philosophy and design, existing research paradigms and the paradigm chosen for this study. The various research methodologies are discussed with focus on the methodology associated with positivism. Section 3.3 describes the form and purpose of the literature review. Section 3.4 formulates the hypotheses for this study, based on the proposed conceptual model.

Section 3.5 discusses the survey design, which includes the questionnaire description, questionnaire scale, questionnaire constructs and measuring instruments. Section 3.6 includes a discussion on the population, sample and sampling technique. It includes strengths and weaknesses of the data collection method, questionnaire distribution and data analyses. Section 3.7 discusses the reliability and validity requirements for the questionnaire design and Section 3.8 the ethical requirements for the study. Chapter 3 concludes with a summary of the research design and methodology.

Figure 3.1: A schematic overview of Chapter 3

Table 3.1 presents the research questions and objectives related to Chapter 3.

Table 3.1: Research Question and Research Objective of Chapter 3

RESEARCH QUESTION	RESEARCH OBJECTIVE
RQ_3: What research methodology could be used for this research study and be replicated in the future?	RO_3: Explain the components of the research methodology for this study.

3.1.1 Definition of Research

Research is defined as enunciating a problem, formulating a hypothesis, gathering and analysing the data to reach a viable conclusion for the purposes of establishing a solution to a problem or to formulate and prove a theory (Kothari, 2004, p. 2). Research can be defined as the scientific and systematic search for pertinent information on a specific topic (Johnston, 2014). Leedy and Ormrod (2010) aver that research is analysing, collecting and interpreting information by a methodical and structured process to gain new insights and/or to enhance the body of information on the phenomenon in question. Collis and Hussey (2013) have determined that current definitions of research have the following components in common:

- A procedure of inquiry and examination;
- Are organised and systematic; and
- Increases knowledge.

The definition proposed by Kothari (2004) will be used for this study. The definition of research indicates that research design and methodology consist of specific processes. The purpose of these processes are summarised as follows:

- Reviewing and synthesising current knowledge/literature;
- Investigating an existing problem or situation;
- Providing a solution to a problem;
- Examining and studying more general issues;
- Constructing, producing or hypothesising a new system or procedure;
- Explaining new phenomena;
- Creating a new body of information; and
- Combining any of the above (Collis & Hussey, 2013).

Saunders, Lewis and Thornhill (2009) proposed a metaphor that is called the Research Onion, which illustrates research as the peeling of progressive layers that the researcher must make during the research process. The model, as seen in Figure 3.2, starts from the outside moving inward through each layer of the onion. The researcher starts the research process by choosing a research philosophy from the outer-most layer.

The subsequent layers are selected one by one, moving toward the centre of the onion and at each layer the researcher must make selections relating to the research approach, the research strategy, the research choices, time horizons and techniques and procedures to be followed in the study (Saunders et al., 2009).

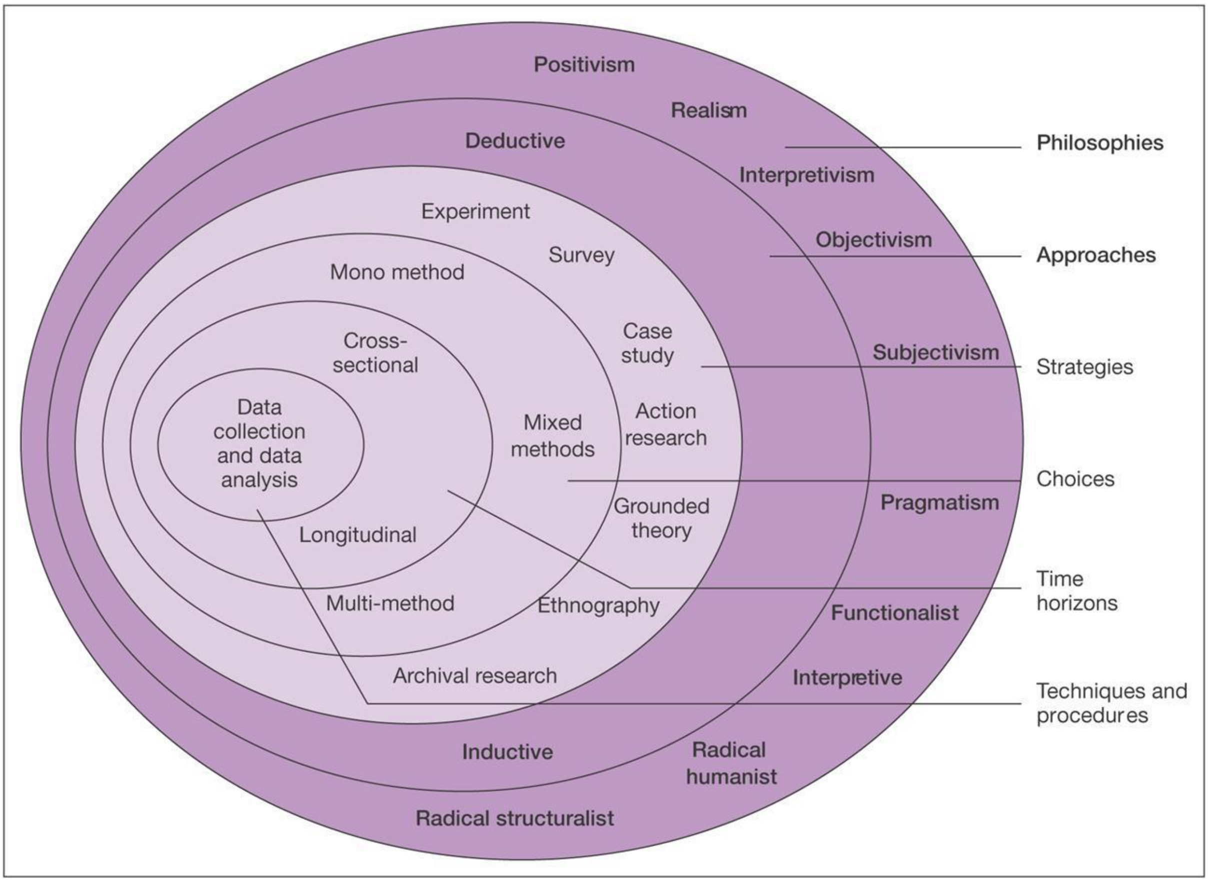

Figure 3.2: Research Onion (Saunders et al., 2009)

3.2 RESEARCH PHILOSOPHY, DESIGN AND PARADIGM

In the following sub-sections the research philosophy, research design and paradigm for this study will be discussed.

The research paradigm is the way in which data about a research project should be gathered, analysed and used. According to Saunders et al. (2009) choosing the philosophical framework is the initial step in the research process, which comprises the first and outer-most layer of the Research Onion. Collis and Hussey (2014) stated that a positivistic research was the only research paradigm used throughout the past centuries. Natural sciences were the main focus of research until the 19th century. In this paradigm, positive information is the foundation of knowledge and is rooted in realism. The aim of the research is to clarify cause and affect relations concerning variables.

A positivistic approach measures social phenomena and follows a logical approach to ensure that an objective methodology is supported. Therefore, positivistic study is associated with quantitative analysis as variables are measurable, objective, scientific and experimental in nature (Collis & Hussey, 2014). Quantitative analysis methods are associated with positivistic research, as variables are believed to be measurable (Collis & Hussey, 2014).

The second paradigm, interpretivism, is focussed on social sciences as opposed to the natural sciences in the positivistic studies. Interpretivist research is rooted in idealism. Unlike positivism, which is built on objective beliefs, the central belief of social scientists is that reality is highly subjective as it is formed by perceptions of the individual's view of reality. The social phenomena that are being studied are affected by the researcher and therefore cannot be objective. According to Collis and Hussey (2014) phenomena that are being studied by positivists cannot be analysed by statistical methods but can only endeavour to define, interpret or come to terms with the phenomena being studied.

Scientific research has a purpose of aiding the process of transforming theories believed into theories known. Positivism and interpretivism have been identified as the two major research philosophies in the Western tradition of science. The research to be used is dependent on the aim of the study, which leads to the choice between qualitative and quantitative approaches. In both social and natural studies, the goal of research is to explain the cause and effect relationships between variables.

Data gathered in a positivistic study can either be quantitative or qualitative. Therefore, the terms quantitative and qualitative will be used to define the data rather than paradigms. Qualitative and quantitative research have a distinct difference (Blumberg et al., 2008) The aim of the study can either be exploratory, conformational or quantifiable and the planned use of the findings can be policy formulation or process understanding (Kumar, 2011).

3.2.1 Qualitative Research

In order to communicate meaning in social relationships, the only tools available are words and symbols. The words and symbols used are relative to the context in which they are used as well as to the values, assumptions and beliefs of the author and reader. The message within the words or symbols can only be fully understood if all the variables are clearly understood. Understanding of Qualitative Data can only be done in context (Collis & Hussey, 2003).

Qualitative Research is therefore primarily exploratory research that provides insights into the problem or helps to develop ideas or hypotheses for potential quantitative research. Qualitative research is especially effective in obtaining culturally specific information about the values, opinions, behaviours and social contexts of particular populations (Collis & Hussey, 2014; Saunders et al., 2009).

Underlying motivations, reasons and opinions are used to obtain greater understanding of the subject matter under research. Qualitative Research is subjective therefore numerical values cannot be assigned to these conclusions. Social relationships are analysed by using Qualitative research methods.

Common factors in all qualitative research are identified below:

- Qualitative research studies the phenomena and all its complexities;
- Qualitative research is done in the natural settings of the occurrence of the phenomena;
- Qualitative research does not attempt to quantify the variation of the situation, phenomenon or problem;
- Qualitative data of an observed phenomenon are used to identify the characteristics; and
- Qualitative data are gathered and measured through nominal or ordinal, scaled variables (Kumar, 2011; Leedy & Ormrod, 2010).

3.2.2 Quantitative Research

Quantitative research is an organised system using experimental observations and assumptions about behaviour in order to establish admissible logic and a causal rationale that can be used to predict behavioural patterns based on empirical research (Garbarino & Holland, 2009). The purpose of the research is to substantiate or refute a recommended hypothesis by using statistical analysis of gathered numeric data (Leedy & Ormrod, 2010; Mitchell & Jolley, 2010; Maree et al., 2016). While Qualitative Research studies the full complexity of a phenomenon, Quantitative research aims to address questions about relationships between variables that are measured numerically with the focus on a specific aspect of the phenomenon (Collis & Hussey, 2014).

Numeric data are gathered systematically and objectively from a selected population in order to extrapolate the findings to the greater population. Quantitative research therefore attempts to establish statistical relationships between variables by determining the amount of variation contained in the quantitative data gathered and measured on quantitative variables. The purpose of the research is to prove or negate a proposed hypothesis by using statistical analysis of gathered numeric data (Leedy & Ormrod, 2010; Mitchell & Jolley, 2010).

Common factors in all quantitative research were identified as:

- Quantitative analysis is used to determine the amount of the variation (Kumar, 2011);
- Causal relationships are predicted through quantitative research;
- Quantitative research aims to predict causal relationships;
- The quantitative research process describes the characteristics of a population;
- Quantitative data are gathered and measured by using primarily quantitative variables; and
- Quantitative analysis is used to determine the amount of the variation (Kumar, 2011).

The necessity for statistics as a fundamental component of measureable research is a common misconception. The researcher can only endorse or refute conclusions based on his/her understanding of the analysed data using quantifiable analysis (Kumar, 2011). Correlation analysis is one of the statistical methods frequently used by researchers to confirm or negate the relationship between two variables. Correlation can be defined as relationships among variables or the measure of linear association between two variables (Fox & Bayat, 2010).

Correlation analysis determines the extent of the change, when one variable relates to change in another. A correlation occurs if one variable increases, the other variable would either increase (positive correlation) or decrease (negative correlation). This correlation behaves in a predictable fashion (Leedy & Ormrod, 2010; Fox & Bayat, 2010; Collis & Hussey, 2014). This study will be in the quantitative study paradigm.

The correlation coefficient measures the strength of such correlation (Fox & Bayat, 2010). This correlation coefficient (r) can range from -1 (a perfect negative correlation) to +1 (a perfect positive correlation). A relationship between variables, if a correlation exists, is when one variable increases, another variable either increases (positive correlation) or decreases (negative correlation). The various strengths of correlation can be seen in Table 3.2.

Table 3.2: Strengths of Correlation (Collis & Hussey, 2014)

Correlation Coefficient	Interpretation
+1.00	Perfect positive linear association
+0.90 to +0.99	Very high positive correlation
+0.70 to +0.89	High positive correlation;
+0.40 to +0.69	Medium positive correlation
+0.01 to +0.39	Low positive correlation
0	No linear association
-0.01 to -0.39	Low negative correlation
-0.40 to -0.69	Medium negative correlation
-0.70 to -0.89	High negative correlation
-0.90 to -0.99	Very high negative correlation
-1.00	Perfect negative linear association

The variables that are studied are each classified as either the dependent or independent variable. The value of the dependent variable is influenced by one or more independent variables. Another view of the relationship between these variables is that the independent variable can be seen as the cause and the dependent variable can be seen as the effect (Collis & Hussey, 2014).

As this study will collect quantitative data, statistical data analysis methods are used to present the data. The data that are captured will be analysed against the secondary data that was collected in Chapter 2 thereby testing the conceptual model illustrated in Figure 2.8. In addition, both descriptive data analysis and inferential data analysis techniques are used to analyse the data. The descriptive statistics that will be conducted include frequency distributions of demographic information and the measurement items. The interpretation of the Cohen's d intervals is as shown in Table 3.3.

Table 3.3: Interpretation intervals for Cohen's d

Cohen's d	Interpretation
<0.20	Not significant
0.20 - 0.49	Small
0.50 - 0.79	Medium
0.80+	Large

Multivariate data analysis will be conducted, which will help the researcher to create knowledge and better decision making as it allows for multiple measurements to be analysed simultaneously (Hair, Black, Babin & Anderson, 2010). The multivariate methods that will be used is Exploratory Factor Analysis (EFA). EFA is used to explore the relationships among variables to identify patterns, to reduce the number of variables and to detect structure in the relationship between variables (Hair et al., 2010; Schreiber, Stage, King, Nora & Barlow, 2006).

The hypothesised model will be tested to determine to what degree the observed data fit the expected or hypothesised structure. Any changes that will be made to the conceptual model after analysing the data will be discussed in Chapter Four.

Before designing a research project, the researcher identifies the research paradigm pertinent to the project. The research paradigm informs the design on what methods the researcher uses for gathering and analysing research information (Collis & Hussey, 2014).

3.2.3 Research philosophy of this study

This research study is anchored in the positivistic philosophy. The researcher will use quantitative methods to find the causal relationships between the dependent variable of *Technology Acceptance in the Workplace*, the independent variables, *Skills and Training, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and International / National Standards* and *Parent Company* is the primary objective of this research paper. This will be achieved by using quantitative analysis, including correlation analysis.

The positivistic paradigm allows a large sample to be examined and conclusions on the population to be inferred from statistical analyses. The researcher does not influence the results with a personal worldview. The potential respondents are employees of Aspen Pharmacare in Port Elizabeth, South Africa. The quantitative methods allows a large quantity of data to be analysed quickly (Vance et al., 2014).

The research study will make use of quantitative research as its benefits outweigh the advantages of qualitative research. The comparative ease coupled with reduced time and money regarding the questionnaire distribution and data collection from respondents are beneficial. A variety of statistical tools and software programmes are available in order for researchers to analyse the data.

In this study, the on-line survey tool QuestionPro was used. The statistical analysis was conducted with the assistance of the NMU Statistical consultant, Dr Danie Venter using Statistica and Amos.

Additionally, the sample size is perfectly suited as large samples can be used to gather information with the quantitative approach. Hence, the use of this approach will be followed because of its capability to evaluate and measure a relatively large sample size.

3.2.4 Research Design

The positivistic paradigm dictates that a literature review anchors the research in relevant theory (Collis & Hussey, 2013). The boundaries of the research are set and a conceptual framework derived from the literature. Primary and/or secondary data are collected in a manner determined by the paradigm. In the quantitative paradigm, primary data are collected from original sources like questionnaires, experiments and interviews with individuals and/or focus groups (Collis & Hussey, 2013; Collis & Hussey, 2003; Creswell, 2003).

The source of the data is a sample or a subset that represents the population considered. The members of the sample set will answer a structured questionnaire anonymously (Collis & Hussey, 2013). The questionnaire must be designed so that respondents are not guided into specific answers (Creswell, 2003).

3.2.5 Demographic Profile of Respondents

The respondents in the study are employees of a pharmaceutical manufacturing company based in Port Elizabeth in South Africa. The demographic data to be collected will include Gender, Age, Years of Service, Job Level, Education Level and Department. The male and female respondents will have their responses analysed against each of the variables and the results interpreted. The age groups will be subdivided into 18 – 25 years, 26 – 35 years, 36 – 45 years and 56 – 65 years. These groups will be analysed against each other against the variables with the view to identify any difference in perception.

The years of service by the employees and management is subdivided into 4 different groups from less than 2 years to over 10 years of service. Demographic data on job levels will be collected and this data will be used to group employees into unionised level (Grade 1 – 6), skilled (7 – 9), professional (10 – 11). Management level starts at Grade 12 – 14 while Grades 15 and 16 form senior management. Respondents' data on education level will be collected through the questionnaire.

Respondents will select from below matric, national diploma, undergraduate and post graduate sections. This data will be analysed with a view to identify differences in perception. The questionnaire ends the demographic section with the department section. Data on respondents' departments will be collected and analysed.

3.3 LITERATURE REVIEW

Collis and Hussey (2013) define literature as an accessible body of knowledge that has been built over time on a specific subject matter. They add to the definition by stating that this body of knowledge consists of all sources of secondary data applicable to a field of interest. The secondary data sources may consist of conference papers, academic journals, professional journals, reports, books, statistics, broadcast media, industry data, archives, internal documents and theses (Collis & Hussey, 2013).

The literature review is the systematic development of a body of knowledge that provides insight into a specific subject area (Collis & Hussey, 2003). A critical review of the literature will enable the researcher to identify shortcomings and hence the body of knowledge can be expanded (Creswell, 2003). Rowley and Slack (2004) state that a literature review intends to identify and collate secondary data into a useful body of knowledge within a subject field. This has been accomplished in Chapter 2.

The literature review process commenced with obtaining a list of top journals in the fields of business and management. Keywords were identified from the formulation of the research topic and the description of the research problem. Google Scholar and the Nelson Mandela University library, using Ebscohost, Emerald and ScienceDirect supplied the means of surveying online literature and refining the research parameters/keywords. Other sources such as textbooks and company publications were used.

A previous master's dissertation (Leo, 2017) was also used to guide the research on smart factory implementation in South Africa. Words or phrases known as keywords were used to summarise the research topic. These keywords are used in search strings to find potentially relevant sources (Leedy &

Ormrod, 2010). The relevant sources were referenced in the literature. The researcher started by reviewing the most recent literature and then moved to earlier publications. The references and authors in the applicable publications led to the discovery of the authors of prior relevant studies (Collis & Hussey, 2014).

3.4 RESEARCH HYPOTHESIS

The conceptual model was developed in Chapter 2 and shown in Figure 2.8. This section describes the proposed hypotheses for this treatise as illustrated in Figure 3.3. To assess the formulated hypotheses, the null hypotheses will be accepted or rejected via statistical analysis. The theoretical framework was used to establish relationships between the dependent variable, *Attitude towards Technology Acceptance in the Workplace,* and the independent variables *Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and International / National Standards* and *Parent Company.* The statistical analyses will test the hypotheses developed in this research study either to accept or reject the proposed relationships indicated in the hypothesised model shown in Figure 3.3.

The following hypotheses have been formulated in order to test the relationship between the Dependent and Independent Variables:

H_1 = *Training and Development are positively related to Attitude towards Technology Acceptance in the Workplace;*

H_2 = *Individual Characteristics are positively related to Attitude towards Technology Acceptance in the Workplace;*

H_3 = *Organisational Culture is positively related to Attitude towards Technology Acceptance in the Workplace;*

H_4 = *Job Security is positively related to Attitude towards Technology Acceptance in the Workplace;*

H_5 = *Resources and Costs are positively related to Attitude towards Technology Acceptance in the Workplace;*

H_6 = *Trust is positively related to Attitude towards Technology Acceptance in the Workplace;*

H_7 = *Security and International / National Standards are positively related to Attitude towards Technology Acceptance in the Workplace;* and

H_8 = *Parent Company is positively related to Attitude towards Technology Acceptance in the Workplace.*

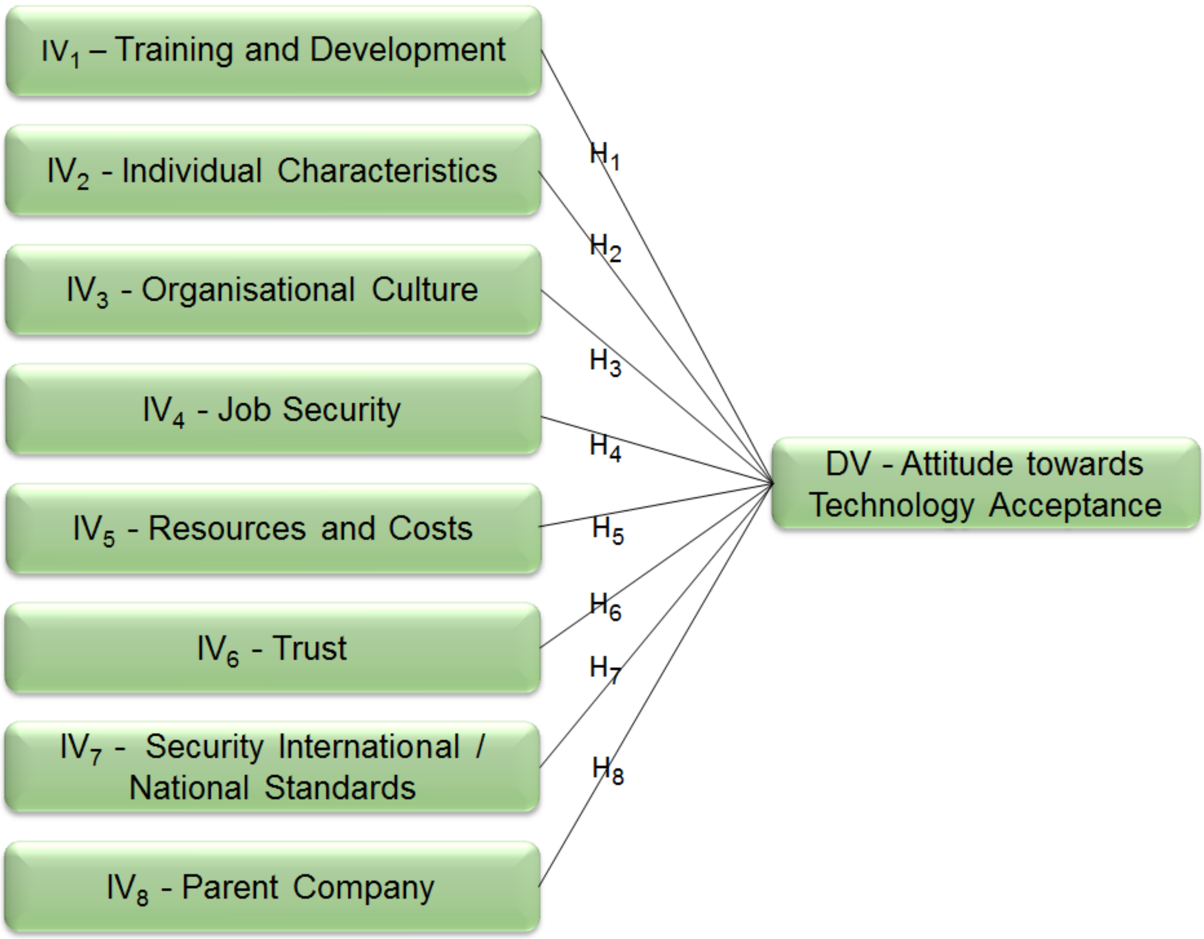

Figure 3.3: Hypothesised Conceptual Model for the Attitude towards Technology Acceptance

Each of the above hypotheses form an instrument in the questionnaire design. Data on *Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and*

International / National Standards and *Parent Company* will be collected using the questionnaire. The following section discusses the instrument and the questions forming the instrument.

3.5 SURVEY DESIGN

In the following sub-sections the design of the questionnaire will be discussed.

3.5.1 Survey Research Defined

The survey technique is the most prevalent method of collecting information from respondents. The information collected would include demographic information and any other information that can be collected by a well-researched and structured questionnaire (Collis & Hussey, 2013). The questionnaire will be sent to respondents and the responses analysed by using a suitable statistical package.

The response rate would determine what level of statistics is applicable. A small sample will result in the use of descriptive statistics only. No data can be inferred for the population if the sample is too small (Wegner, 2012). Survey questionnaires offer an advantage in that the respondents could be anywhere and only cost and technology could possibly limit access to the questionnaire (Collis & Hussey, 2013).

The following sub-section discusses the questionnaire design used for this research study.

3.5.2 Questionnaire Design

A questionnaire is the most extensively used technique of collecting data from respondents concerning their attitudes, beliefs, values, habits, ideas, opinions, feelings, perceptions, plans and demographics (Collis & Hussey, 2014). A questionnaire design must consider the time, the expense and the effort that is invested in data collection (Collis & Hussey, 2013; Creswell, 2003). The questions should be targeted to the intended group of respondents. The questions should be limited to collect data that are only relevant to the study and they should be easy to understand. The questions should be engaging and appropriate.

A questionnaire must be correctly structured, provide clear guidelines on how to complete the questionnaire, contain closed, objective, relevant, clear and concise questions and must be of a measured length, in order to satisfy the accuracy required by proper research (Kelley, Clark, Brown & Sitzia, 2003). Researchers have asserted that measurement is the foundation of many social research frameworks and it is necessary to quantify the observations.

Researchers posited that numerals are assigned to an occurrence that indicates differences in the quality or degrees of agreement (Wegner, 2012). The purpose is to gain insight about a population by surveying a sample of that population. This research approach is known as a descriptive survey (Leedy & Ormrod, 2010; Maree, et al., 2016). Table 3.3 depicts the questionnaire used in the study.

Table 3.4: Questionnaire for the Research

Please place a tick for each selection, one tick per question. Please complete all questions.							
1. Demographics							
1.1	**Gender**	**Male**	**Female**				
1.2	**Age**	**18 - 25 Years**	**26 - 35 Years**	**36 - 45 Years**	**46 - 55 Years**	**56 - 65 Years**	
1.3	**Years of Service**	**Less Than 2 Years**	**2 - 4 Years**	**5 - 9 Years**	**10 Years+**		
1.4	**Job Level**	**Grade 1 - 6**	**Grade 7 - 9**	**Grade 10 - 11**	**Grade 12 - 14**	**Grade 15 - 16**	
1.5	**Education level**	**Below Matric**	**National Diploma**	**Undergraduate Degree**	**Post Graduate Degree**		
1.6	**Department**	**Production**	**IT & Engineering**	**Quality Assurance**	**Validation**	**Warehousing**	**Support Services**
In the following sections, please indicate by circling the appropriate number, the extent to which you agree with the following statements.							
Please give a response for each statement.							

No.	**Training and Development**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
2.1	Training is important when new technologies are implemented.	1	2	3	4	5
2.2	In my organisation, adequate training is provided when new technologies are introduced.	1	2	3	4	5
2.3	Training enhances my interest in new technologies.	1	2	3	4	5
2.4	New skills are required when technologies are implemented.	1	2	3	4	5
2.5	In my organisation, there is continuous investment in the improvement of my skills.	1	2	3	4	5
2.6	My organisation supports my learning and capability development.	1	2	3	4	5
No	**Individual Characteristics**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
3.1	I trust my abilities to perform my organisational duties.	1	2	3	4	5
3.2	I easily adapt when new technologies are implemented.	1	2	3	4	5
3.3	Innovation / new technologies enhances my job performance.	1	2	3	4	5
3.4	I perceive new technologies as being easy to understand and use.	1	2	3	4	5
3.5	I take initiative in implementing new ideas or technologies.	1	2	3	4	5
3.6	I feel empowered to implement new ideas or innovation.	1	2	3	4	5
3.7	I view adaptability as important for new technologies.	1	2	3	4	5
No	**Trust**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
4.1	In my organisation, new technologies are reliable.	1	2	3	4	5
4.2	Good communication aids trust with new technologies.	1	2	3	4	5
4.3	My innovative ideas are taken seriously.	1	2	3	4	5
4.4	I get the support required to implement innovative ideas.	1	2	3	4	5
4.5	I rely on and trust automation.	1	2	3	4	5
4.6	I view my personal safety as an important factor when technologies are implemented.	1	2	3	4	5
4.7	I accept new technologies more readily from people I trust.	1	2	3	4	5
No	**Organisational Culture**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
5.1	The culture within my organisation actively encourages innovation and technology adoption.	1	2	3	4	5

5.2	The culture within my organisation is open and supports new innovative ideas.	1	2	3	4	5
5.3	An entrepreneurial-style culture is nurtured within my organisation	1	2	3	4	5
5.4	I am involved in the decision making process when innovation or new technologies are implemented.	1	2	3	4	5
5.5	Organisational culture supports innovation or new technologies adoption.	1	2	3	4	5
5.6	The new MES leadership culture will positively influence innovative / new technologies adoption.	1	2	3	4	5

No	Resources and Costs	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
6.1	Basic infrastructure exists to enable advanced technologies adoption.	1	2	3	4	5
6.2	My organisation has the required IT resources to adopt innovation and new technologies.	1	2	3	4	5
6.3	In my organisation, the IT department drives innovation.	1	2	3	4	5
6.4	Cost for innovation/new technologies is justified.	1	2	3	4	5
6.5	My organisation has the financial resources to adopt innovation or new technologies.	1	2	3	4	5
6.6	The benefits of innovation is greater than the cost of implementing new technologies.	1	2	3	4	5
No	**Job Security**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
7.1	I feel my job is secure, regardless of new technologies being implemented.	1	2	3	4	5
7.2	Job security is impacted negatively when new technologies are implemented.	1	2	3	4	5
7.3	My job security is more important than using new technologies.	1	2	3	4	5
7.4	Implementation of new technologies leads to job losses.	1	2	3	4	5
No	**Technology Acceptance**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
8.1	The implementation of innovation / technology will lower the cost within the organisation.	1	2	3	4	5
8.2	The implementation of innovation / technology will improve the productivity within the organisation.	1	2	3	4	5
8.3	The implementation of innovation / technology will improve the quality of products within the organisation.	1	2	3	4	5

8.4	The use of information will improve the organisation capabilities.	1	2	3	4	5
8.5	Innovation / new technologies will allow the organisation to gain and maintain a competitive advantage.	1	2	3	4	5
8.6	Training on the use of new technologies enhances my career opportunities.	1	2	3	4	5
8.7	Automation improves my job performance.	1	2	3	4	5
8.8	Innovation / new technologies increase complexity in my work environment.	1	2	3	4	5

No	Technology Acceptance	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
8.9	Poor communication negatively influences new technology adoption.	1	2	3	4	5
8.10	Innovation / new technologies negatively impact career opportunities and development.	1	2	3	4	5
8.11	My job performance is affected negatively when innovation / technologies are implemented.	1	2	3	4	5
8.12	General support of colleagues is important for new technologies adoption.	1	2	3	4	5
8.13	New technologies increase the risk of cyber threats.	1	2	3	4	5
No	**Security International / National Standards**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
9.1	My organisation’s information is secure when using new technologies (e.g. cloud computing)	1	2	3	4	5
9.2	The current laws and regulations are sufficient to protect the use of cloud computing.	1	2	3	4	5
9.3	International standards hinder the implementation of innovation and new technologies.	1	2	3	4	5
9.4	In general, new technologies (e,g. cloud computing) are more secure than traditional methods / technologies.	1	2	3	4	5
9.5	Government policies and initiatives encourage companies to adopt advanced technologies (e.g. Internet of Things)	1	2	3	4	5
No	**Parent Company**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
10.1	The parent company supports the adoption of new technologies in local subsidiary.	1	2	3	4	5
10.2	The parent company has implemented superior technologies.	1	2	3	4	5

10.3	Advanced technologies implemented within the parent company benefit the local subsidiaries.	1	2	3	4	5
10.4	The parent company supports new ideas in the subsidiaries.	1	2	3	4	5
10.5	The parent company understands local conditions when implementing new technologies.	1	2	3	4	5

Thank you for completing the questionnaire.

3.5.3 Questionnaire Scale

The scales on which the questionnaire statements are based are nominal for Section 1, Demographics, and ordinal for the remaining sections. In this survey, the Likert rating scale was comprehensively used as it provides an ordinal measure of a respondent’s attitude. This technique tests the degree to which respondents agree or disagree with a given statement and is a convenient method when attempting to measure a construct (Leedy & Ormrod, 2010; Kumar, 2011; Maree, et al., 2016).

The constructs in Section 2 to 10 used a five point Likert scale for each question. Measurement tools, such as questionnaires, collect data and they provide outcomes known as scales. Likert scale questionnaires measure respondent attitudes by asking for responses to a grouping of statements (Hartley, 2013). Responses are asked in a continuum in degrees of agreement from strongly disagree (1) to Strongly agree (5). Researchers, however, pointed out that not all scales measure identically and, therefore, may impact the validity of deduced conclusions (Janes, 1999; Wegner, 2012).

Typically, Likert scale questionnaires use at least a 5-point scale with the neutral point indicating neither disagreement nor agreement. Researchers have pointed out the argument regarding the effect on validity and reliability of a lack of a neutral point option (Hartley, 2013; Kalmijn, Arends & Veenhoven, 2011). Five-point scale Likert models have greater validity and reliability than four-point scales but insist that more research is needed to fully answer the question (Hartley, 2013).

Researchers and others argued that Likert scale questionnaires with a neutral point are more likely to have respondents selecting that point in their responses. Researchers stated that questionnaires with a neutral point response option enable respondents to falsely report indifference rather than make response of either agreement or disagreement (Hartley, 2013; Hills & Argyle, 2002). The current study questionnaire used a five-point Likert scale. Response #1 represented (strongly disagree), #2 represented (disagree), #3 represented (neutral), #4 (agree) and #5 (strongly agree) with the statement.

Elias (2015) suggested that a questionnaire have the following format as indicated in Table 3.6.

Table 3.5: Questionnaire layout (Elias, 2015)

Section	Rationale
Introduction	Introduces the research topic, the university and members of the research team including the supervisor. The introduction also made a statement on confidentiality and gave instructions on how to answer the questionnaire.
Question grouping	Questions order is logical and questions grouped together to reduce confusion. Section A normally contains questions related to demographics. The rest of the sections contain questions related specifically to the research.
Question length/complexity	Questions to be short in nature to be easy to grasp and quick to answer.
Conclusion	Acknowledgement and a note of appreciation to participants.
Duration	The whole questionnaire should be between 10 to 15 minutes to keep respondent interest.

3.5.4 Writing well-constructed questions

Chapter 2 identified the factors affecting technology acceptance in smart factories. The literature review identified some of the questions to be included in the questionnaire. A previous study in smart factories in the automotive industry used the same questions that will be used in this study (Leo, 2017).

The complete questionnaire is shown in Annexure C. The target survey population and the distribution process will be described below in Section 3.6.

3.6 DATA COLLECTION METHOD

The following sub-sections will discuss the population investigated in this study and the questionnaire distribution and data collection methods.

3.6.1 Population

Population in research is defined by Quinlan (2011) and Yount (2006), as all the units, items, components or persons pertinent to the study. The population of a research is also known as its universe (Quinlan, 2011). The population of this study comprises a total of about 1800 individuals employed as general staff and managers in all functional areas within the organisation. Where possible, a researcher can collect and analyse data from the entire population where it is possible through a census.

A census is not always possible due to practical restrictions on time, money and/or access to the required information (Neuman, 2006). Sampling techniques, therefore, provide numerous methods to reduce the amount of data needed in research (Saunders, et al., 2007). Sampling and sampling techniques will be discussed in the next topic.

3.6.2 Sample and Sampling Method

Sampling is a deliberate, strategic undertaking, whereby the most practical methods of gathering relevant data from within a sampling frame are used. This is the designated area from which data are collected (Maree, et al., 2016). Banning, Camstra and Knottnerus, (2012) aver that sampling is the process of choosing and studying parts of a group, with the purpose of generalising the results back to the entire group, which is the population. Sampling is defined as a deliberate, strategic undertaking, whereby the most practical methods of gathering relevant data from within a sampling frame are used. This is the designated area from which data are collected (Maree, et al., 2016).

The intention of a sampling technique is to attain accuracy and achieve precision in an impartial manner by allowing the sample to represent the population as closely as possible. Probability (objective) and nonprobability (subjective) sampling are the classification of sampling types (Landreneau, 2012). In probability sampling, the number of participants from whom the sample will be drawn is known in advance and each participant from the population has a nonzero likelihood of being chosen (Evans, 2010).

Random sampling, stratified sampling and systematic sampling are part of the probability sampling techniques (Saunders, et al., 2007). Alternatively, members are selected from the population by using a non-random approach within a non-probability sampling (Evans, 2010). Judgement sampling, snowball sampling, quota sampling and convenience sampling are included in non-probability sampling methods (Saunders, et al., 2007).

Convenience sampling was used for this study. Convenience sampling refers to selecting a sample that is most accessible and keen to contribute in the research and is able to deliver the necessary data (Hair, Money, Page, & Samouel, 2007). The advantages of reducing time and the cost of collecting information are realised in this type of sampling (Hair, Money, Page, & Samouel, 2007).

3.6.3 Questionnaire Distribution

The questionnaire was distributed in two ways. An online link was sent to employees and management who are office based and have access to email. Printed copies of the questionnaires were distributed to production shop floor employees who do not have access to company provided emails. A cover letter explained the purpose of the research gave the details of the supervisor and explained the confidentiality of the respondents. It included a URL link to the survey on the NMU QuestionPro system. The database has the ability to block duplicate entries.

3.6.4 Strengths and Weaknesses of the Data Collection Method Used

The literature presents online surveys as being convenient for the researcher and respondent, as they are flexible and easy to maintain and analyse (Evans &

Mathur, 2005; Guzi & de Pedraza García, 2015). On the other hand, online surveys exclude people who do not have access to the Internet. Furthermore they include only those who are prepared to respond to the survey (Evans & Mathur, 2005; Guzi & de Pedraza García, 2015).

In the last decade, the incidence of junk email has increased as well as the concern over issues of security and confidentiality. In spite of these concerns, Guzi & de Pedraza García (2015) found that the results of online surveys are comparable to the results obtained from probabilistic sampling surveys. The researcher therefore decided to use both the online and physical data collection methods.

3.7 RELIABILITY AND VALIDITY

The trustworthiness of research findings is affected by two factors, namely reliability and validity (Collis & Hussey, 2014). According to Leedy and Ormrod (2010), the reliability and validity of the measuring instrument influences the probability of attaining knowledge from the study, achieving statistical significance and the degree to which meaningful conclusions can be made from the data analysis.

3.7.1 Reliability

Reliability refers to the precision and accuracy of the measurement and the absence of variation if the study was repeated (Collis & Hussey, 2014; Saunders et al., 2009). Reliability refers to the degree to which an instrument can generate consistent results, this means that it is free from measuring errors (Kumar, 2012; Maree, et al., 2016; Collis & Hussey, 2014).

The measurement is said to be reliable if the repeated measurements of an unchanged entity return the identical result each time (Leedy & Ormrod, 2010). Validity on the other hand, denotes the degree to which the measurement tests what the researcher wants to test and the findings reflect the case under investigation (Collis & Hussey, 2014; Saunders et al., 2009).

There are two techniques used when measuring reliability namely test and retest reliability. Test reliability is when applying measures of internal consistency; retest reliability is repeating an event to determine if the same or similar results are recorded (Ihantola & Kihn, 2011). Cronbach Alpha is a statistical technique used to measure internal consistency reliability where questions within a questionnaire are tested statistically to determine how reliably they measure predetermined variables (Tavakol & Dennick, 2011). A high coefficient value indicates a high internal consistency while a low value indicates the opposite.

The researcher should question whether the findings and conclusions will stand up to scrutiny, the findings are consistent and whether, if replicated, the study would yield the same results (Collis & Hussey, 2014). In positivistic studies, reliability is considered significant, however, in interpretivist studies; it is of little significance (Collis & Hussey, 2014). Researchers have defined the following guidelines presented in Table 3.5.

Table 3.6: Cronbach Alpha Coefficient

Reliability Coefficient Interpretation	
Cronbach Alpha < 0.50	Unacceptable
Cronbach Alpha 0.50 – 0.69	Acceptable
Cronbach Alpha 0.70 - 0.79	Good
Cronbach Alpha ≥ 0.80	Excellent

A Cronbach Alpha score of between 0.50 and 0.69 has been deemed acceptable for new and experimental research (Collis & Hussey, 2014; Nunnally, 1978).

3.7.2 Validity

The trustworthiness of research findings is affected by two factors, namely reliability and validity (Collis & Hussey, 2014). According to Leedy and Ormrod (2010), the reliability and validity of the measuring instrument influences the probability of attaining knowledge from the study, achieving statistical significance and the degree to which meaningful conclusions can be made from the data analysis. In order to contribute to the existing body of knowledge, validity is an essential consideration as research conclusions must accurately reflect the variables measured in a manner that lends itself to applications outside of the research environment (Maree et al., 2016).

There are different kinds of validity namely, conclusion validity, which confirms relationships between variables, internal validity, which confirms the causal directions of relationships amongst variables, construct validity, which confirms that the scales employed actually measured the variables in question and external validity, which confirms the ability to generalise the findings of the study to a population (Onwuegbuzie & McLean, 2003).

Validity therefore is concerned with whether the correct concept has been measured in the study. Content validity was used in this research to ensure that the instrument measures the complete content of the construct under investigation, by presenting the instrument to a panel of subject-matter experts and implementing comments (Maree et al., 2016).

3.7.3 Exploratory Factor Analysis

Exploratory factor analysis is used to ensure the construct validity of the instrument and to identify items which should be removed. Eigenvalues were used to measure the distortion induced by the transformation and the eigenvectors and they inform the researcher how the distortion is oriented (Maree et al., 2016). The Scree plot shows the eigenvalues on the y-axis and the number of factors on the x-axis. The number of factors that should be generated by the analysis are indicated by the point where the slope of the curve is clearly levelling off.

The factor analysis is run to reduce the number of variables describing a complex concept to a few interpretable variables called factors (Rahn, 2018). Item and factor analysis are the two statistical methods used in the process of standardising an instrument. Item analysis is used to identify the items which are not suitable for use in the instrument. On the other hand, factor analysis is used to determine which items belong together in the sense that they are answered similarly and therefore measure the same dimension or factor (Maree et al., 2016). This study will use EFA for instrument validity.

3.7.4 Generalisability

The extent to which findings from a study, past deductions or suggestions from a treatise on a sample of a population can be generalised to those outside of the study from which the results were selected is referred to as generalisability (Carter & Hurtado, 2007). The requirements of both validity and reliability need to be met in order to generalise accurately and match the contextual nuances of the original sample to the generalised population (Carter & Hurtado, 2007).

The conclusions, inferences and predictions in this treatise are drawn from the 90 respondents from the employees and management at a pharmaceutical factory in South Africa. The researcher will be able to generalise to the entire population, as the requirements of validity and reliability, as determined by the above measures, will be satisfied.

3.7.5 Descriptive Statistics

Descriptive statistics were used in order to describe and summarise the data. Three types of measures of central tendency will be used to describe the data namely the mean, median and mode.

3.7.6 Inferential Statistics

This study tests the relationships between the independent variables *Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and International / National Standards* and *Parent Company* and the dependent variable *Attitude towards a Smart Factory* by applying and analysing the results of the ANOVA test.

3.7.7 Analysis of Variance

Analysis of Variance (ANOVA) is a statistical method used to compare the equality of means of samples across multiple populations. An ANOVA compares three or more population means and uses the F-statistic to test the differences between these means. The purpose of an ANOVA is to determine whether there is a statistical relationship between the factor and the response variable (Wegner, 2016).

The purpose of the ANOVA is to determine whether there is a statistical relationship between the factor and response variable, i.e whether the two measures are statistically independent or not. As with other hypothesis tests, the initial step is the formulation of a null hypothesis (H_0: there is no significant difference between the population means) and an alternative hypothesis (H_1: at least one of the population means differs from the others). Based on the outcome of the ANOVA, if the sample means are not significantly different, then it can be concluded that the factor has no influence on the outcome of the response variable and that the measures are statistically independent of each other. Alternatively, if at least one factor sample mean can be shown to be different to the other factor sample mean, then a statistical relationship has been found between the factor and the response variable (Wegner, 2016).

3.8 ETHICAL REQUIREMENTS

Research ethics form a pivotal part to any research project. It is concerned with the way in which research is collected and how the findings are conveyed (Collis & Hussey, 2014). It is a generally accepted practice to obtain ethical clearance for research that involves human or animal subjects (Collis & Hussey, 2014). The main purpose of obtaining ethical clearance is to ensure the research process embarked upon adheres to certain adequate standards (Cooper & Schindler, 2011).

These standards, amongst other things specifically relate to the issue of the rights and welfare of research subjects around issues such as informed consent, confidentiality of data and limitation of possible risks to people involved in research (Collis & Hussey, 2014). There is a list of ethical principles that researchers should adhere to (Bell & Bryman, 2007; Collis & Hussey, 2014):

- Avoid potential harm to participants throughout the research process;
- Respect the participant's dignity and avoid making the participant feel uncomfortable or anxious;
- Ensure that the researcher has knowledgeable consent from the participant;
- Protect the privacy of participants or avoid invading their privacy;
- Ensure confidentiality of the collected data;
- Protect the anonymity of participants;
- Avoid deception or misleading behaviour throughout the research process;

- Declare any affiliations, conflict of interests and sponsorship of the research;
- Communicate information in a transparent and honest manner;
- Ensure that the research does not exploit the participant, but that the research is mutually beneficial; and
- Avoid misrepresentation, misleading, misunderstanding or falsely reporting the findings of the research.

Nelson Mandela University has criteria stipulated which necessitates the requirement of full ethical clearance. This treatise did not meet the criteria needed for full ethical clearance, thus Ethical Clearance Form E provided by the NMU Business School was sufficient. The signed Form E is attached in Annexure B: Ethical Clearance Form E.

3.9 SUMMARY

The main aim of Chapter 3 was to describe the research design and methodology that will be used in conducting this study. Therefore, this chapter addressed *RQ_3: What research methodology could be used for this research study and be replicated in the future?* Which corresponds to *RO_3: Explain the components of the research methodology for this study.* To accomplish this, literature was reviewed to explore the main two research philosophies: interpretivism and positivism and the deductive and inductive approaches to research were discussed.

Furthermore, this chapter reviewed the differences between qualitative and quantitative research methodologies and outlined the different data collection methods associated with each methodology. The positivistic philosophy, deductive approach, mixed method research methodology, survey data collection method and cross-sectional time horizon were chosen for this study as illustrated in Figure 3.2.

This chapter further identified the unit of analysis as managers and employees at a pharmaceutical manufacturing company in Port Elizabeth, South Africa and discussed the sampling design method. The data collection methods of secondary data (conducted in Chapter 2) and primary data, which will be collected through the questionnaire, were discussed as well as the questionnaire development and operationalisation of questions through literature review in Chapter 2. The data analysis methods, the validity and reliability were discussed to ensure that the data collected are valid and reliable. This chapter concluded with the ethical requirements needed to conduct this study. The next chapter will analyse the collected data and the findings will be presented and discussed.

CHAPTER 4

RESULTS

4.1 INTRODUCTION

Research methodology and approach were discussed in Chapter 3. Chapter 3 addressed research question (RQ_3): *What research design and methodology can be followed to better understand and reproduce this research study in future?* The research objective $RO_{3:}$ What research design and methodology can be followed to better understand and reproduce this research study in future? Various statistical data analysis techniques that will be used in this study were introduced and explained in Chapter 3.

Chapter 4 will address $RO_{5:}$ *Evaluate the conceptual model for the attitudes towards smart factories in the pharmaceutical manufacturing sector*; and $RO_{6:}$ Interpret empirical results of the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing company and provide managerial conclusions.

This chapter further discusses the various aspects of the questionnaire, first demographics and then analyses and discusses the various measurement items. Exploratory Factor Analysis (EFA) is conducted so that the number of factors can be reduced and Cronbach's Alpha analysis can be done. Descriptive and inferential statistics are presented and the relationships between the dependent variable (DV): Attitude towards smart factory implementation and selected demographic information and various independent variable (IV's) and demographic information are explored. The chapter ends with a new model derived from the EFA. The Chapter outline is illustrated in Figure 4.1.

Figure 4.1: A schematic overview of Chapter 4

4.2 DATA ANALYSIS AND INTERPRETATION METHODS

The previous chapter described the survey used and collection process of the primary data. In this section, the methods used to analyse the data that were collected will be described. Univariate and multivariate data analysis are the two methods that will be used to analyse the data.

4.2.1 Univariate Analysis

Individual variables will be analysed using descriptive statistics without investigating their relationship with other variables. There are numerous statistical measures available to examine this type of data analysis. The data type determines the options of valid statistical measures to use. Categorical data such as Gender, Age, Years of Service, Job Level, Education Level and Department established in Section 1 of the survey will be analysed by the use of categorical frequency tables (count and percentage), bar and pie charts and the modal category (Collis & Hussey, 2014; Wegner, 2016). In this study the statistical methods used include categorical frequency tables, bar and pie charts.

4.2.1.1 Frequency Distribution

A frequency distribution is a mathematical function showing the number of instances in which a variable takes each of its possible values (Wegner, 2016). The frequency table summarises the distribution of values in a sample where each entry in the table contains the frequency or count of the occurrences of values within a particular group or interval.

4.2.1.2 Multivariate Analysis

Relationships between two or more variables will be analysed and interpreted by inferential statistics. One sample T-tests, EFA, Cronbach Alpha, inferential ranking of the factors and correlation analysis between the factors will be analysed. Multivariate analysis is essentially the statistical process of concurrently analysing multiple, independent variables with one or more dependent variables by using various multivariate analyses, normally correlational (Wegner, 2016).

Numerical data as established in Question group 2 to 10 of the survey allows more complex statistical analysis such as numeric frequency distribution, cumulative frequency distribution, histograms and frequency polygons, central tendency measures (mean, median and mode) and measures of association (Wegner, 2016). Statistical methods used in this study include numeric frequency distribution, central tendency measures and measures of association to simplify the process of analysing and interpreting the data.

4.2.1.3 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) tries to uncover the nature of the constructs influencing a set of responses by exploring the datasets and testing predictions (DeCoster, 1998; Yong & Pearce, 2013). EFA allows the researcher to group common variables into a descriptive category (Yong & Pearce, 2013). DeCoster (1998) states that there the two primary objectives of EFA, to determine the number of factors influencing variables and the strength of the relationship between each factor and each observed measure. The eigenvalues and scree plot are used to determine how many factors to retain (Yong & Pearce, 2013).

4.3 UNIVARIATE ANALYSIS AND DESCRIPTIVE STATISTICS

This subsection presents the descriptive statistics and provides univariate analysis, which is analysing individual variables without examining their relationship to other variables. The questionnaire was divided into ten sections. Section 1 captured demographic information such as Gender, Age, Years of Service, Job Level, Education Level and Department. The segment contains six questions.

Section 2 to 10 were designed to capture the respondent's perception of Skills and Training, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Attitude towards Technology, Security and International and National Standards and Parent Company in relation to the OEM. It measured a total of ten variables, each containing between 4 to 8 questions.

4.4 DEMOGRAPHIC PROFILE OF THE RESPONDENTS

A total of 118 employees and managers started the questionnaire or partially completed the questionnaire and a total of 106 respondents fully completed the questionnaire, 89% response rate. All the respondents were based at the Port Elizabeth pharmaceutical manufacturing factory, South Africa.

4.4.1 Gender

There were n=106 respondents who completed the survey, 57% (n=60) being male and 43% (n=46) female as shown in Figure 4.2.

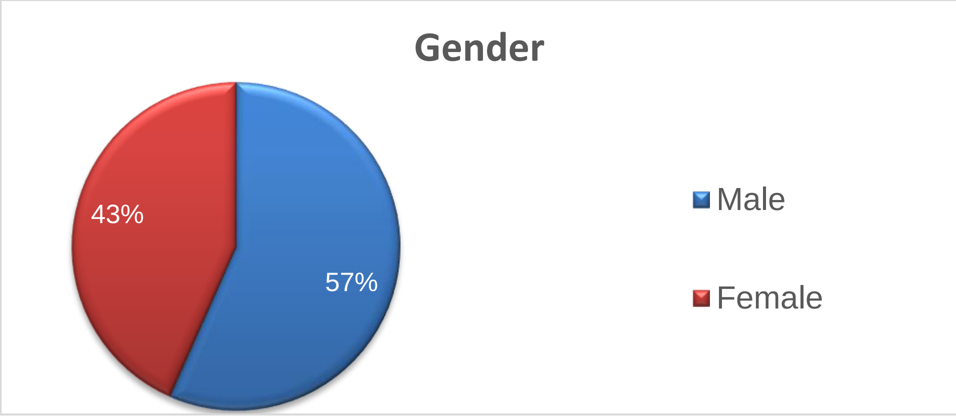

Figure 4.2: Gender of Respondents

4.4.2 Age

Of the respondents, 37% (n=39) are 35 years and younger, whilst the 46 years and older account for 23% (n=24). The 36 years to 45 years old range accounted for the highest number of respondents making 40% (n=42). Figure 4.3 shows the age distribution frequency table. This finding is in line with the result shown in Figure 4.4 that the majority of employees have been with the company for more than 5 years.

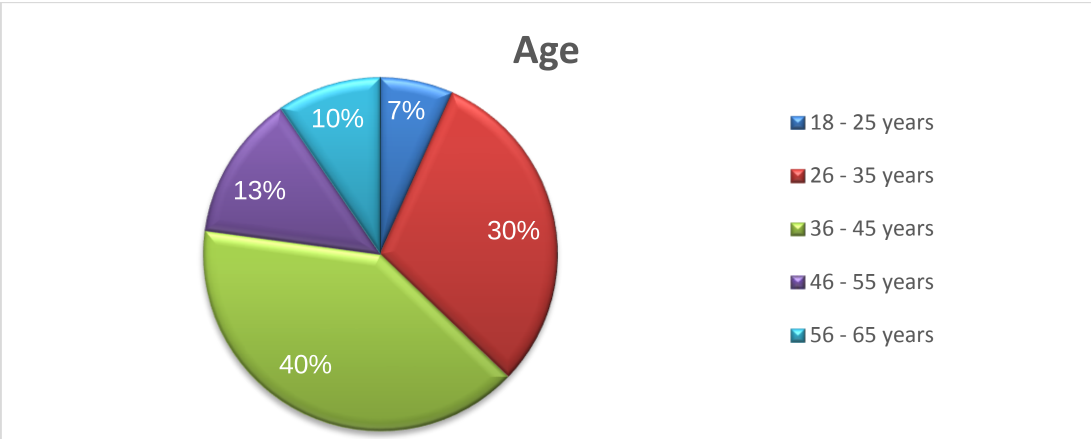

Figure 4.3: Age Frequency Distribution

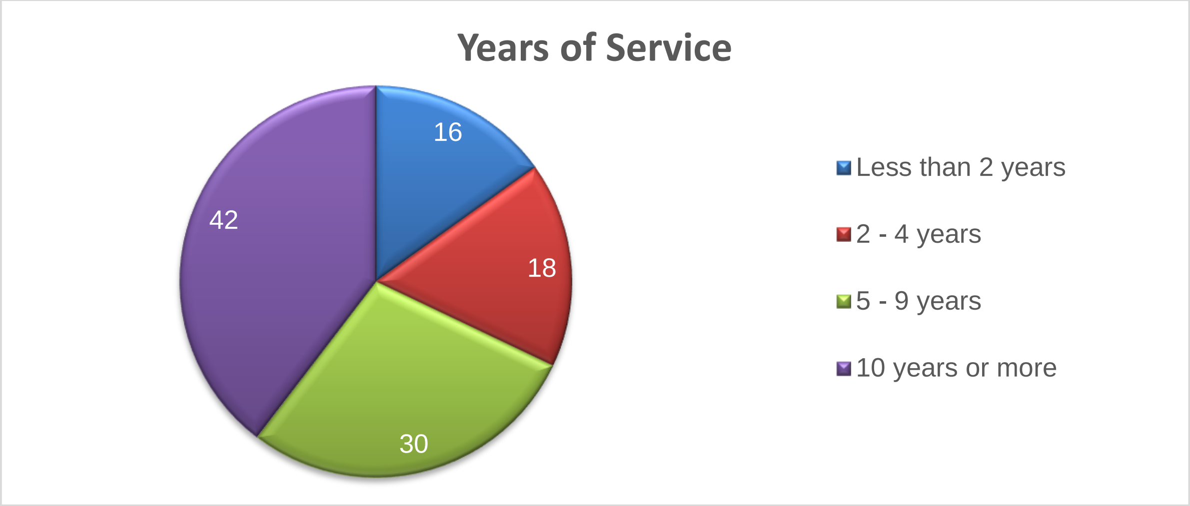

Figure 4.4: Frequency Distribution – Years Of Service

Figure 4.4 indicates that 68% (n=72) employees have 5 years and above of service within the organisation. Of the 72 employees, 42 had 10 or more years of service suggesting low staff turnover at the organisation. Only 15% (n=16) of the employees have less than 2 years within the organisation.

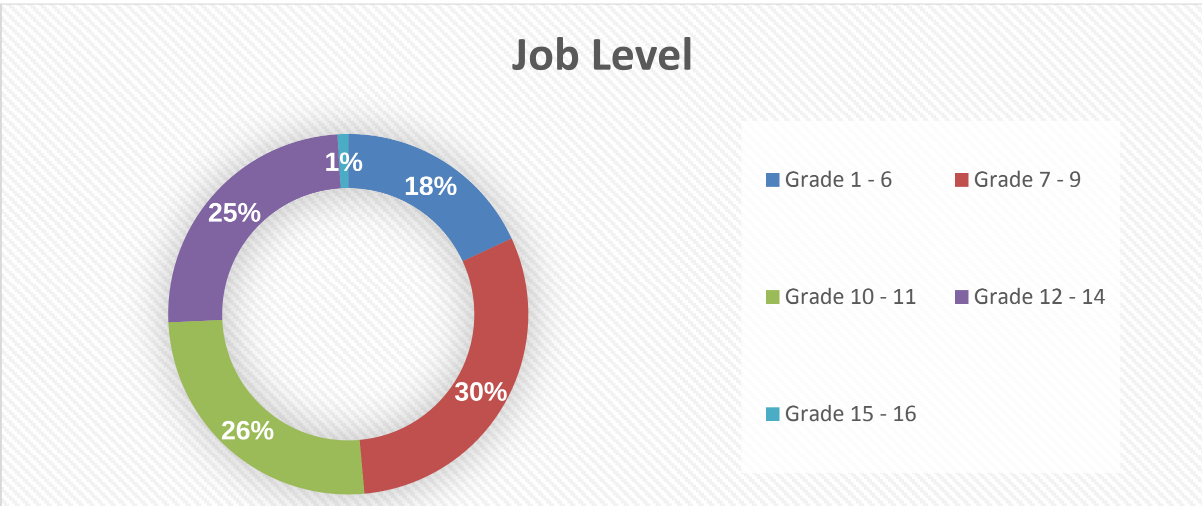

Figure 4.5: Frequency Distribution – Job Level

Figure 4.5 shows the job levels of the respondents. A total of 19 employees were in the bargaining unit job level of grades 1 – 6. The majority of the employees were in the skilled job level range of grades 7 – 11 accounting for 56% (n=59) of the total number of respondents. This can be attributed to the vast number of skilled professionals required in a large pharmaceutical manufacturing factory for support services. A total of 25% (n=26) of the respondents were in the management. There are so many departments in a pharmaceutical manufacturing factory and each requires managers. This explaining the number of the respondents in management.

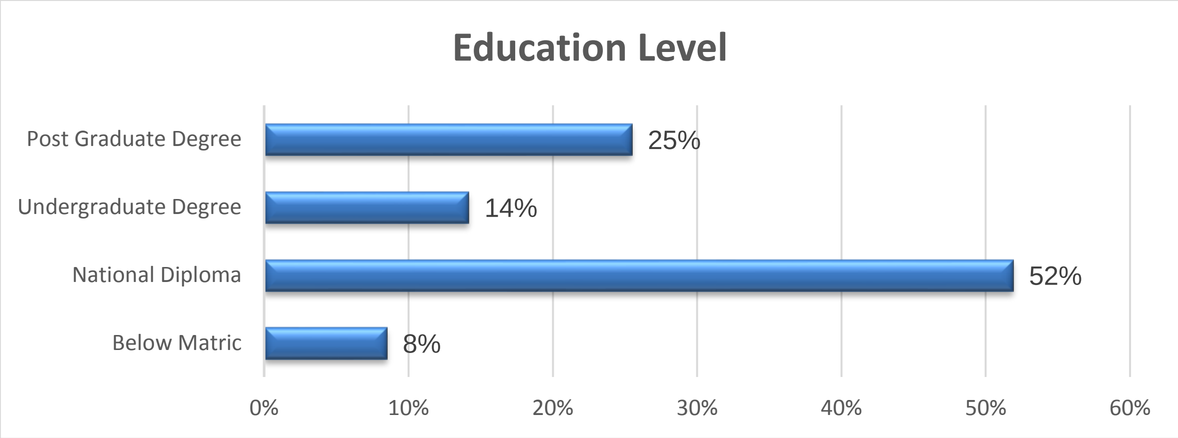

Figure 4.6: Frequency Distribution – Education Level

Figure 4.6 shows employees without a university degree representing 60% (n=64) of the respondents. This is due to the entry requirements for employees in the bargaining council range as well as in artisan type engineering and support services work. Twenty five percent (n=26) of the respondents had a post graduate degree and this is due to the job requirements for the quality assurance, management and other services within the organisation.

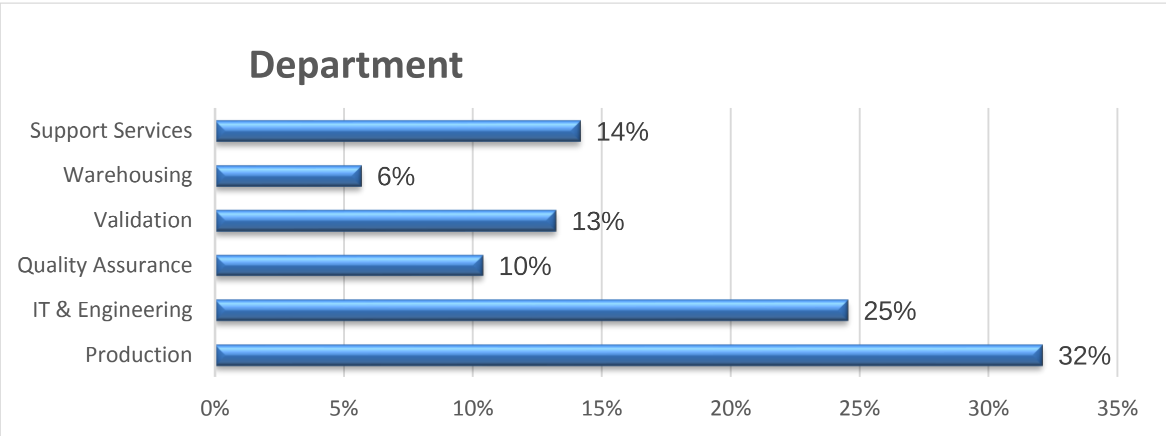

Figure 4.7: Frequency Distribution - Department

Figure 4.7 shows the number of respondents by department. Production accounted for 32% (n=34) respondents whilst the quality-associated departments of support services, quality assurance and validation accounted for 37% (n=40) of the respondents. This can be attributed to the highly regulated pharmaceutical industry that requires use of different levels of quality assurance for regulatory compliance.

4.5 FREQUENCY DISTRIBUTION FOR MEASUREMENT ITEMS

Factor items on the questionnaire were answered by 106 respondents. A total of 93% (n=99) of the respondents agreed that training was important when a new technology is to be adopted. There was a 100% (n=106) response from the employees trust in their ability to execute their duties which shows employee confidence in their capabilities. Of the respondents, 86% (n=91) answered that they take the initiative in the implementation of new ideas. Of the 106 respondents, 78% (n=82) of the employees believed that new technology in the organisation is reliable while 77% (n=81) rely on and trust automation. Personal safety was viewed as an important factor when technologies are implemented by 98% (n=104).

Of the respondents, 82% (n=87) agreed that basic infrastructure existed in the organisation for the adoption of a new technology. The question *“Job security is impacted negatively when new technologies are implemented”* was reversed and 53% (n=53) responded positively whilst 27% (n=29) was undecided. Of the respondents, 60% (n=64) were undecided on whether government policies and initiatives encourage adoption of advanced technologies. Of the respondents, 76% (n=79) however agreed that the parent company supports technology adoption in the local subsidiary. The full frequency table is in Annexure E.

4.6 EXPLORATORY FACTOR ANALYSIS

Exploratory Factor Analysis (EFA) is a technique that seeks to uncover the nature of the constructs influencing a set of responses. EFA is a multivariate statistical approach that checks how the constructs influence a set of responses by exploring the datasets and testing predictions. The researcher can group common variables into descriptive categories through the use of EFA (DeCoster, 1998; Yong & Pearce, 2013). The two primary objectives of EFA are to determine the number of factors influencing variables and the strength of the relationship between each factor and each observed measure (DeCoster, 1998). The eigenvalues and scree plot are used to determine how many factors to retain (Yong & Pearce, 2013).

4.6.1 Training and Development

EFA Table 4.1 shows 2 factors as indicated by the Eigenvalues and 3 factors indicated by the Scree Plot (Figure 4.8). The minimum loading deemed significant was 0.537 accounting for a percentage of Total Variance of 59.3%.

Table 4.1: EFA Eigenvalues – Training and Development (n = 104)

Factor	Eigenvalue	% Total Variance
1	2.138	35.6
2	1.423	23.7
3	0.951	15.9
4	0.704	11.7
5	0.598	10.0
6	0.186	3.1

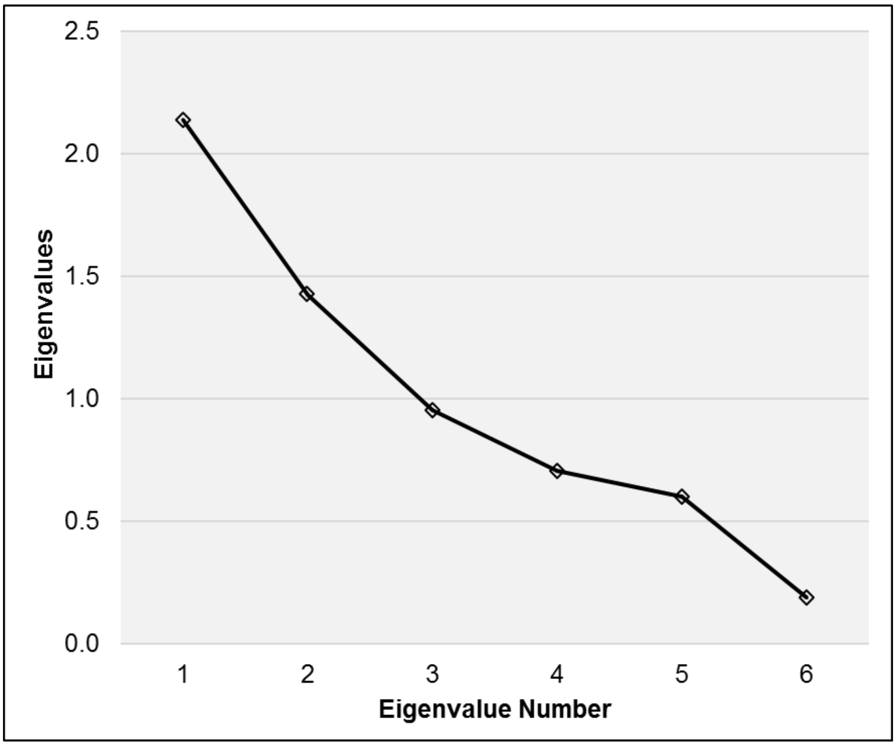

Figure 4.8: Scree Plot – Training and Development

The items were further analysed resulting in two factors namely *Organisational Support* and *Training*. Organisational Support had items Q2.2, Q2.5 and Q2.6 while Training had the remaining statements.

Table 4.2: Exploratory Factor Analysis (EFA) Loadings (2 Factor Model) - F.1(n = 104)

Item	Factor 1	Factor 2
Q2.5 In my organisation there is continuous investment in the improvement of my skills.	**.912**	.017
Q2.6 My organisation supports my learning and capability development.	**.909**	.008
Q2.2 In my organisation adequate training is provided when new technologies are introduced.	**.685**	-.106
Q2.1 Training is important when new technologies are implemented.	-.030	**.816**
Q2.3 Training enhances my interest in new technologies.	.049	**.661**
Q2.4 New skills are required when technologies are implemented.	-.033	**.561**
Expl.Var	2.132	1.428
% of Total	.355	.238
Minimum loading deemed significant = .537; Percentage of Total Variance Explained = 59.3%		

Table 4.2 indicates a minimum loading was deemed significant at 0.537 and the percentage of total variance explained was 59.3%. Additionally, the two factors each with 3 items in Table 4.2 were named: Factor 1 – Organisational Support and Factor 2 – Training.

4.6.2 Individual Characteristic

EFA Table 4.3 indicates 2 factors Eigen value and Scree plot in Figure 4.9 indicate 1 factor.

Table 4.3: EFA Eigen Values – Individual Characteristics (n = 106)

Factor	Eigenvalue	% Total Variance
1	2.891	41.3
2	1.186	16.9
3	0.987	14.1
4	0.782	11.2
5	0.567	8.1
6	0.397	5.7
7	0.189	2.7

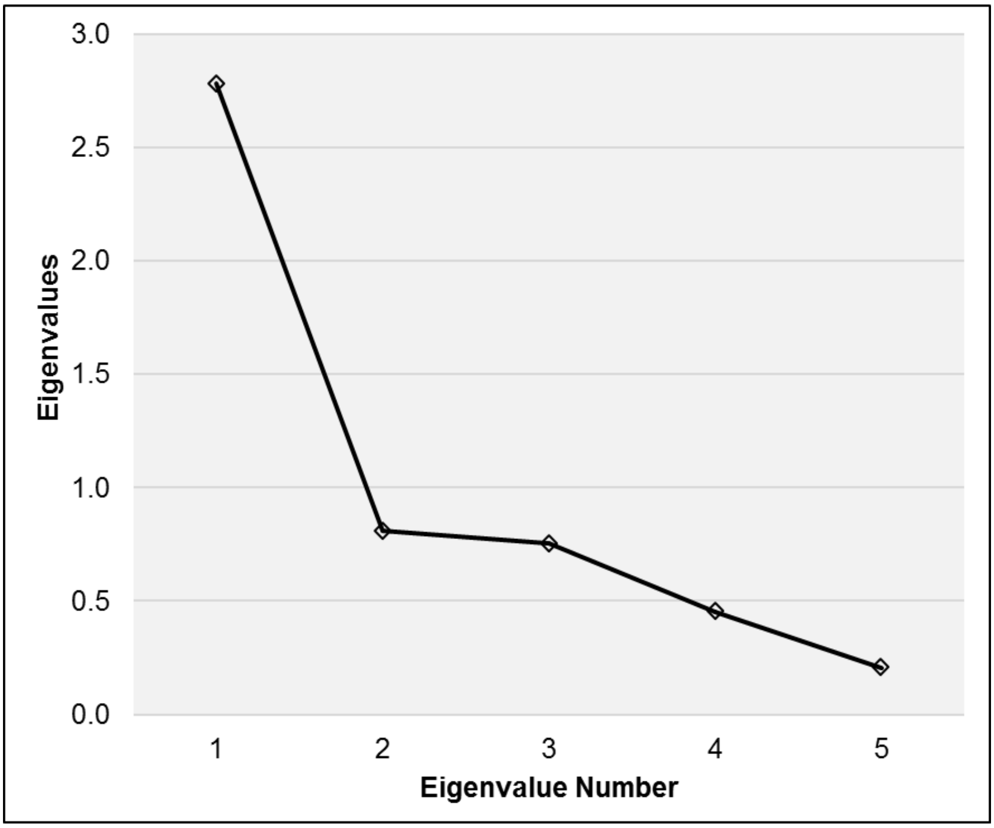

Figure 4.9: Scree Plot – Individual Characteristics

The minimum loading deemed significant was 0.610 and 2 items Q3.1 and Q3.3 loaded 0.609 and 0.237 and were omitted for further analysis. Item Q3.7 was omitted. Item Q3.1 was omitted and the EFA indicated two factors as indicated by the Eigenvalues and one factor indicated by the Scree Plot.

Table 4.4: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.2 (n = 106)

Item	Factor 1
Q3.2 I easily adapt when new technologies are implemented.	.867
Q3.5 I take initiative in implementing new ideas or technologies.	.811
Q3.4 I perceive new technologies as being easy to understand and use.	.801
Q3.6 I feel empowered to implement new ideas or innovation.	.618
Q3.3 Innovation / new technologies enhance my job performance.	.590
Minimum loading deemed significant = .533; Percentage of Total Variance Explained = 55.6%	

Table 4.4 indicates one factor with 5 items with a minimum loading deemed significant at 0.533 and the percentage of total variance explained was 55.6%.

4.6.3 Trust

EFA Table 4.5 indicates 3 factors the Eigen values and one factor indicated by the Scree Plot.

Table 4.5: EFA – Peer Support

Factor	Eigenvalue	% Total Variance
1	2.062	29.5
2	1.380	19.7
3	1.087	15.5
4	0.849	12.1
5	0.751	10.7
6	0.518	7.4
7	0.353	5.0

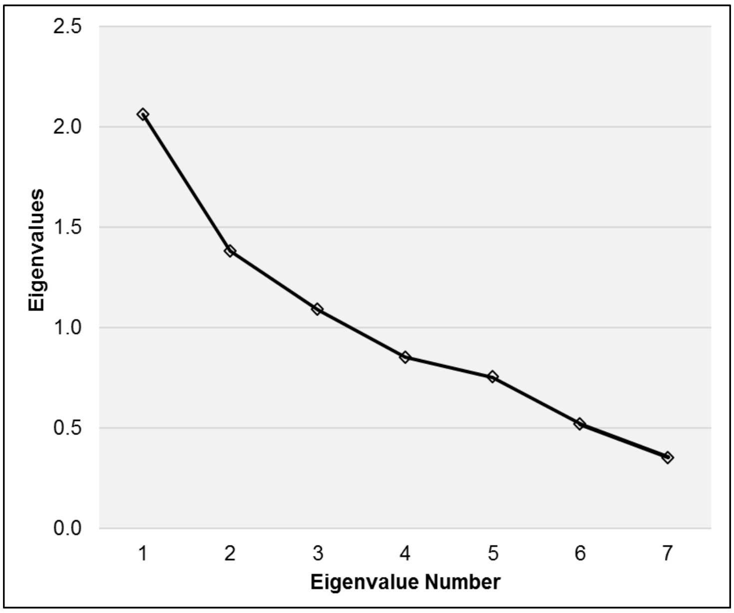

Figure 4.10: Scree Plot – Peer Support

EFA was conducted on a one factor model and item Q4.6 was omitted for further analysis. The EFA then showed three factors by the Eigenvalues and one factor by the Scree plot. Items Q4.2 and Q4.5 were omitted and the EFA then showed two factors by the Eigenvalues and one factor by the Scree Plot. A one factor and a two factor EFA were conducted, however the two factor solution was problematic. Q4.1

cross loaded and Q4.7 in a single item factor analysis was omitted. The two factors were identified as Peer Support and Trust. Peer Support minimum loading deemed significant was 0.533 and the percentage of Total Variance explained was 62.4% as shown in Table 4.6 and Figure 4.11.

Table 4.6: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.3.1 (n = 106)

Item	Factor 1
Q4.4 I get the support required to implement innovative ideas.	**.867**
Q4.3 My innovative ideas are taken seriously.	**.812**
Q4.1 In my organisation, new technologies are reliable.	**.678**
Minimum loading deemed significant = .533; Percentage of Total Variance Explained = 62.4%	

Factor on Trust was further tested with the 4 items not in the table above. Table 4.6 shows the Eigenvalue and Scree Plot (Figure 4.11) as 2 factors.

Table 4.7: EFA – Trust

Factor	Eigenvalue	% Total Variance
1	1.417	35.4
2	1.126	28.2
3	0.804	20.1
4	0.653	16.3

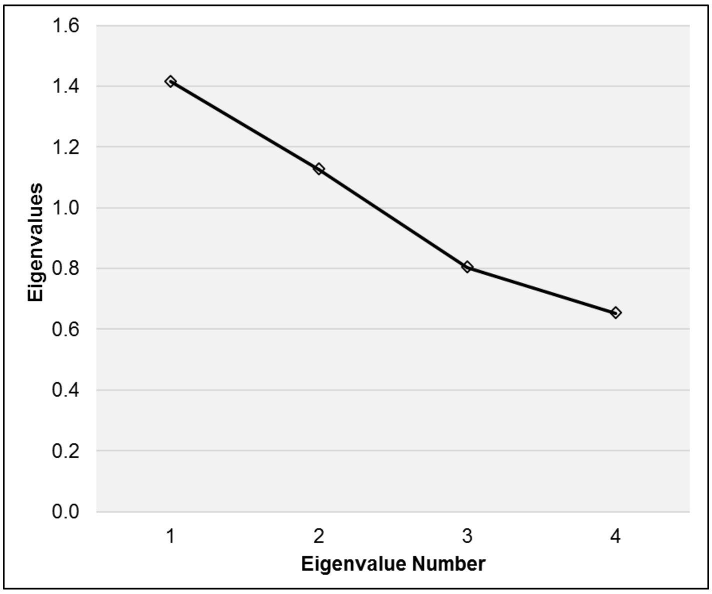

Figure 4.11: Scree Plot – Trust

The 2 factor EFA indicate that item Q4.2 needed to be omitted. Three items remained in the 1 factor model. Table 4.7 indicates a one factor model with a final minimum loading deemed significant at 0.533 accounting for a percentage of Total Variance explained of 47.2%. This factor should be treated with caution as it accounts for 47.2% of variance.

Table 4.8: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.3.2 (n = 106)

Item	Factor 1
Q4.7 I accept new technologies more readily from people I trust.	**.776**
Q4.6 I view my personal safety as an important factor when technologies are implemented.	**.708**
Q4.5 I rely on and trust automation.	**.559**
Minimum loading deemed significant = .533; Percentage of Total Variance Explained = 47.2%	

4.6.4 Organisational Culture

EFA Table 4.9 indicates 6 items and 2 factors by the Eigenvalues and the Scree Plot, Figure 4.12 indicate 1 factor.

Table 4.9: Exploratory Factor Analysis (EFA) Eigenvalues - F.4 (n = 106)

Factor	Eigenvalue	% Total Variance
1	3.111	51.9
2	1.056	17.6
3	0.737	12.3
4	0.505	8.4
5	0.382	6.4
6	0.209	3.5

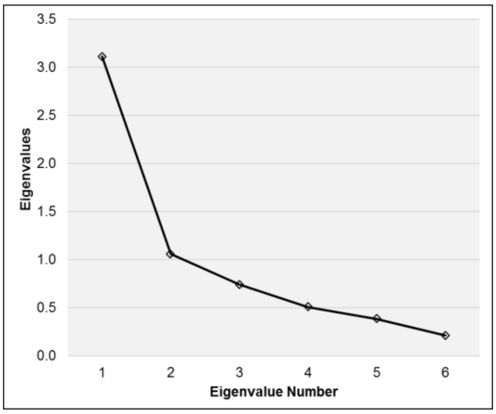

Figure 4.11: Scree Plot – Organisational Culture

The minimum loading deemed significant was 0.533 and item Q5.6 and was omitted for further analysis. After omission of the item the EFA Eigen Value indicated 1 factor and scree plot indicated 1 factor. Table 4.9 indicates final minimum loading deemed significant of 0.533 accounting for a percentage of Total Variance of 60.5%. Five items remained in the 1 factor model.

Table 4.10: EFA – Organisational Culture

Item	Factor 1
Q5.2 The culture within my organisation is open and supports new innovative ideas.	**.878**
Q5.1 The culture within my organisation actively encourages innovation and technology adoption.	**.836**
Q5.3 An entrepreneurial-style culture is nurtured within my organisation.	**.819**
Q5.5 Organisational culture supports innovation or new technologies adoption.	**.771**
Q5.4 I am involved in the decision making process when innovation or new technologies are implemented.	**.537**
Minimum loading deemed significant = .533; Percentage of Total Variance Explained = 60.5%	

4.6.5 Resources and Costs

Three factors are indicated in Table 4.11 by the Eigenvalues and one factor by the Scree plot Figure 4.12.

Table 4.11: EFA – 3 factors Eigen value and Scree plot in Figure 4.13 indicate 1 factor.

Factor	Eigenvalue	% Total Variance
1	2.361	39.3
2	1.122	18.7
3	1.002	16.7
4	0.735	12.2
5	0.427	7.1
6	0.354	5.9

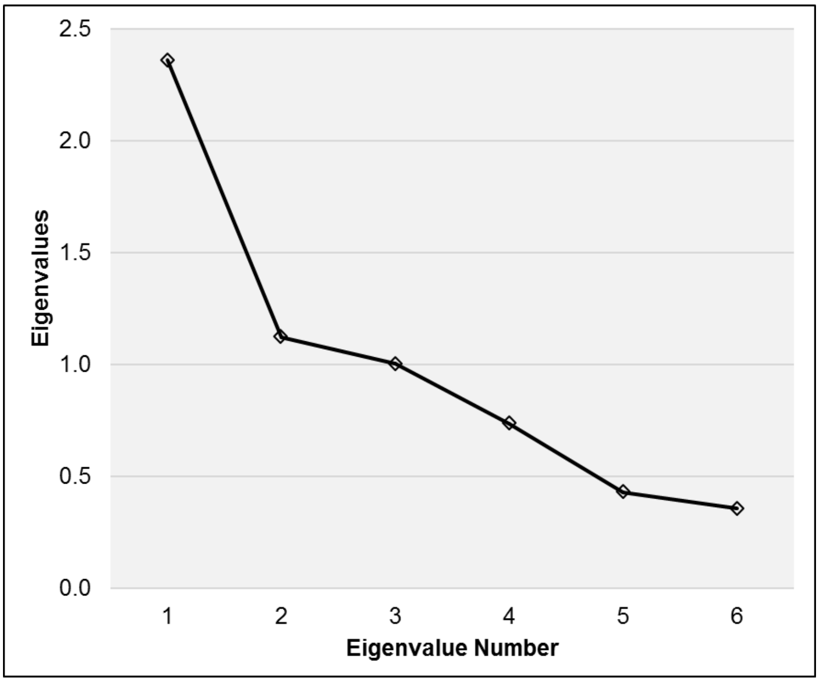

Figure 4.12: Scree Plot – Resources and Costs

The minimum loading deemed significant was 0.535 and items Q6.6 and Q6.5 loaded 0.461 and 0.332 respectively and were omitted for further analysis. After omission of items the EFA Eigenvalue indicated 1 factor and scree plot indicated 1 factor. Table 4.12 indicates final minimum loading deemed significant of 0.535 accounting for a Percentage of Total Variance Explained of 54.6%. Four items remained in the 1 factor model.

Table 4.12: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.5 (n = 105)

Item	Factor 1
Q6.2 My organisation has the required IT resources to adopt innovation and new technologies.	.798
Q6.3 In my organisation, the IT department drives innovation.	.760
Q6.1 Basic infrastructure exists to enable advanced technologies adoption.	.732
Q6.4 Cost for innovation/new a technology is justified.	.658
Minimum loading deemed significant = .535; Percentage of Total Variance Explained = 54.6%	

4.6.6 Job Security

One factor indicated by both the Eigenvalues and the Scree Plot in Table 4.13 and Figure 4.13.

Table 4.13: EFA Job Security

Factor	Eigenvalue	% Total Variance
1	1.853	46.3
2	0.988	24.7
3	0.726	18.2
4	0.433	10.8

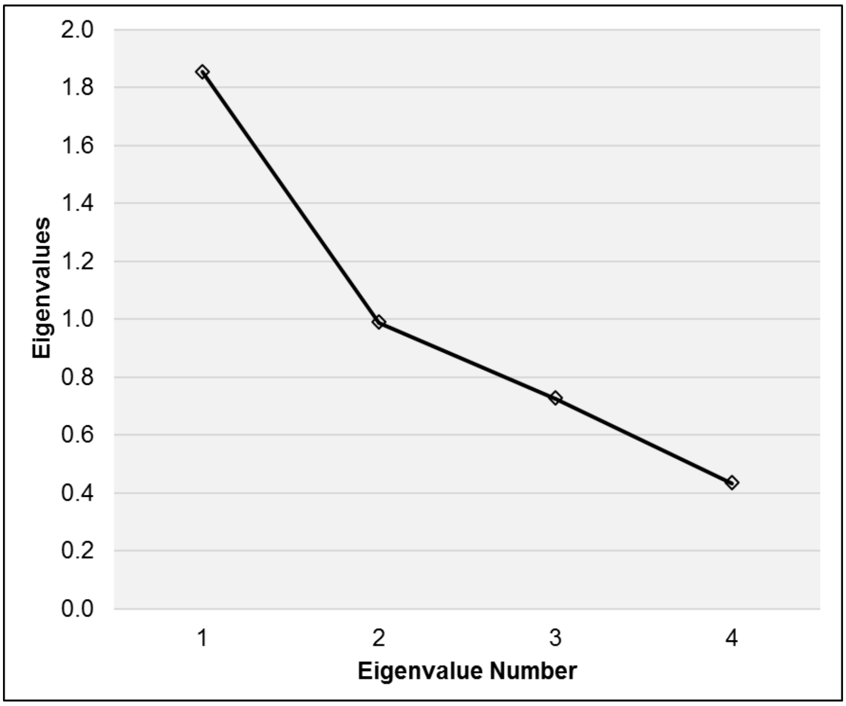

Figure 4.13: Scree Plot – Job Security

The minimum loading deemed significant was 0.537 and item Q7.3 loaded 0.339 and was omitted for further analysis. After omission of the item the EFA Eigen Value indicated 1 factor and scree plot indicated 1 factor. Table 4.14 indicates final minimum loading deemed significant of 0.535 accounting for a percentage of Total Variance of 59.8%. Four items remained in the 1 factor model.

Table 4.14: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.6 (n = 105)

Item	Factor 1
Q7.4 Implementation of new technologies leads to job losses.*	.849
Q7.2 Job security is impacted negatively when new technologies are implemented.*	.783
Q7.1 I feel my job is secure regardless of new technologies being implemented.	.679
Minimum loading deemed significant = .535; Percentage of Total Variance Explained = 59.8%	

4.6.7 Attitude towards Innovation / Technology

EFA Table 4.15 indicates 5 factors Eigen value and Scree Plot in Figure 4.14 indicate 2 factors.

Table 4.15: EFA – Attitude towards Innovation / Technology

Factor	Eigenvalue	% Total Variance
1	3.598	27.7
2	1.841	14.2
3	1.362	10.5
4	1.27	9.8
5	1.028	7.9
6	0.757	5.8
7	0.681	5.2
8	0.594	4.6
9	0.55	4.2
10	0.44	3.4
11	0.332	2.6
12	0.312	2.4
13	0.235	1.8

The minimum loading deemed significant was 0.540 and item Q8.6 loaded 0.106, 0.162 and 0.108 in the 3 factor model analysis and was omitted for further analysis. After omission of items both the EFA Eigenvalues and the Scree Plot indicated 4 factors.

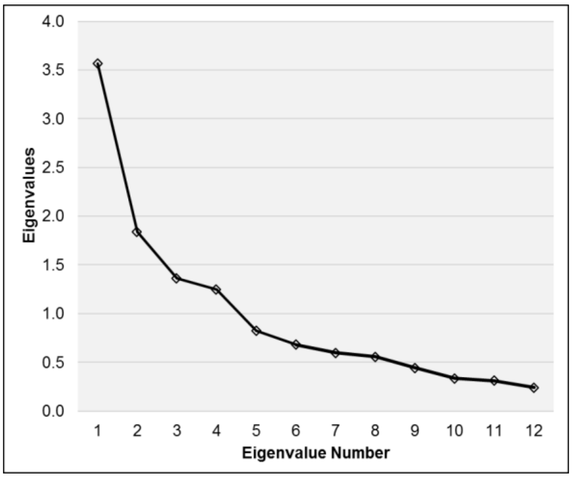

Figure 4.14: Scree Plot – Attitude towards Innovation / Technology

Four factor solution is statistically problematic and has cross loadings and items with opposite signs. Further analysis yielded 3 factors on both Eigen Value and Scree Plot. Table 4.8 indicates final minimum loading deemed significant of 0.535 accounting for a Percentage of Total Variance Explained of 56.4%. Information and Communication Factor removed due to cross loading. 3 new factors namely – Factor 1 - *Innovation and Technology Implementation*, Factor 2 - *Technology Agreeable* and Factor 3 - *Automation and Support.*

Table 4.16: Exploratory Factor Analysis (EFA) Loadings (3 Factor Model) - F.7 (n = 103)

Item	Factor 1	Factor 2	Factor 3
Q8.3 The implementation of innovation / technology will improve the quality of products within the organisation.	**.776**	.049	.190
Q8.2 The implementation of innovation / technology will improve the productivity within the organisation.	**.698**	.013	.375
Q8.8 Innovation / new technologies increase complexity in my work environment.*	**.661**	-.105	-.262
Q8.1 The implementation of innovation / technology will lower the cost within the organisation.	**.601**	.138	.116
Q8.4 The use of information will improve the organisation capabilities.	.130	**.820**	.075
Q8.9 Poor communication negatively influences new technology adoption.	-.198	**.785**	.129
Q8.5 Innovation / new technologies will allow the organisation to gain and maintain a competitive advantage.	.505	**.645**	.218
Q8.11 My job performance is affected negatively when innovation / technologies are implemented.*	.200	.298	**.723**
Q8.12 General support of colleagues is important for new technologies adoption.	-.069	.074	**.675**

Q8.10 Innovation / new technologies negatively impact career opportunities and development.*	.263	.202	**.562**
Q8.13 New technologies increase the risk of cyber threats.*	.173	-.475	**.548**
Q8.7 Automation improves my job performance.	.285	.213	.526
Expl.Var	2.425	2.142	2.200
% of Total	.202	.179	.183
Minimum loading deemed significant = .540; Percentage of Total Variance Explained = 56.4%			

4.6.8 Security and International Standards

Both EFA Table 4.17 indicates 2 factors Eigenvalues and Scree Plot in Figure 4.15 indicate 2 factors.

Table 4.17: EFA – Security and International Standards

Factor	Eigenvalue	% Total Variance
1	1.949	39.0
2	1.257	25.1
3	0.803	16.1
4	0.606	12.1
5	0.385	7.7

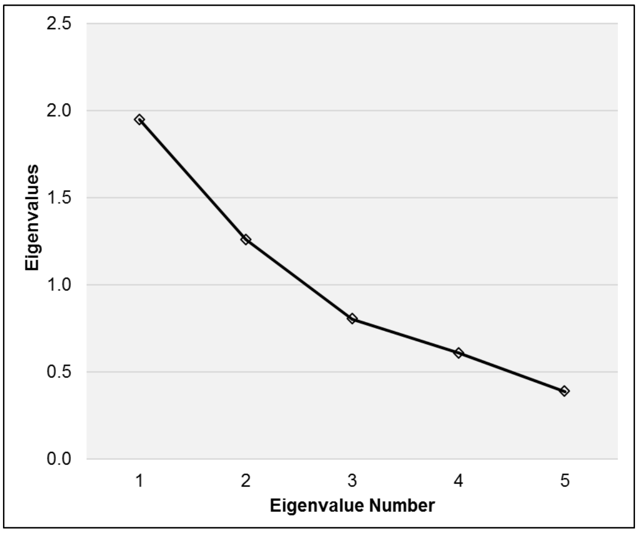

Figure 4.15: Scree Plot – Security and International Standards

The minimum loading deemed significant was 0.535. No further analysis was conducted as both Eigen Value and Scree Plot indicated 2 factors. Table 4.18 indicates final minimum loading deemed significant of 0.535 accounting for a Percentage of Total Variance Explained of 64.1%. the one factor identified was Security and the other factor Government Laws and Regulations. Five items remained in the 1 factor model.

Table 4.18: Exploratory Factor Analysis (EFA) Loadings (2 Factor Model) - F.8 (n = 105)

Item	Factor 1	Factor 2
Q9.1 My organisations information is secure when using new technologies.	**.852**	.110
Q9.4 In general new technologies are more secure than traditional methods / technologies.	**.772**	-.230
Q9.3 International standards hinder the implementation of innovation and new technologies.*	**.626**	.028
Q9.2 The current laws and regulations are sufficient to protect the use of cloud computing.	-.139	**-.879**
Q9.5 Government policies and initiatives encourage companies to adopt advanced technologies.	.381	**-.700**
Expl.Var	1.878	1.328
% of Total	.376	.266
Minimum loading deemed significant = .535; Percentage of Total Variance Explained = 64.1%		

4.6.9 Parent Company

One factor indicated by both the Eigen Values and the Scree Plot in Table 4.19 and Figure 4.16.

Table 4.19: EFA – Parent Company

Factor	Eigenvalue	% Total Variance
1	2.636	52.7
2	0.940	18.8
3	0.646	12.9
4	0.470	9.4
5	0.307	6.1

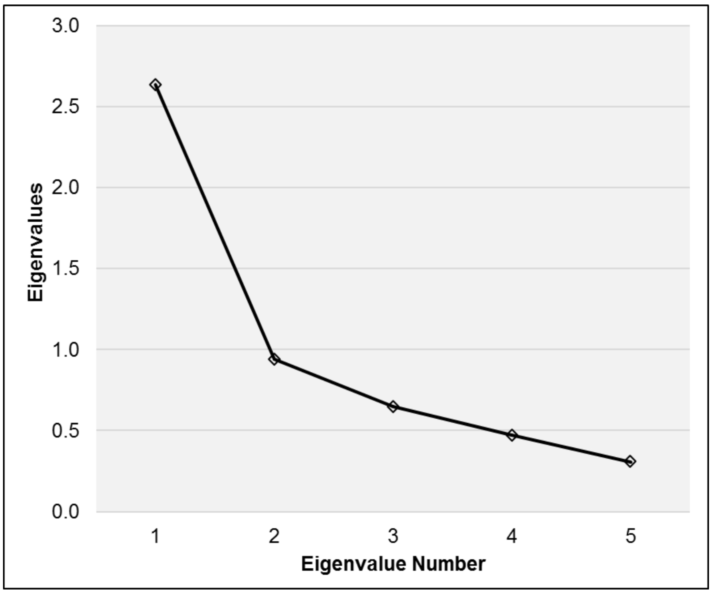

Figure 4.16: Scree Plot – Parent Company

Table 4.20 indicates final minimum loading deemed significant of 0.537 accounting for a percentage of Total Variance of 52.7%. Five items remained in the 1 factor model.

Table 4.20: Exploratory Factor Analysis (EFA) Loadings (1 Factor Model) - F.9 (n = 104)

Item	Factor 1
Q10.3 Advanced technologies implemented within the parent company benefit the local subsidiaries.	**.872**
Q10.4 The parent company supports new ideas in the subsidiaries.	**.828**
Q10.1 The parent company supports the adoption of new technologies in local subsidiary.	**.755**
Q10.2 The parent company has implemented superior technologies.	**.557**
Q10.5 The parent company understands local conditions when implementing new technologies.	**.557**
Minimum loading deemed significant = .537; Percentage of Total Variance Explained = 52.7%	

4.7 RELIABILITY

Reliability was discussed in detail in Chapter 3. The reliability of the data that were captured and the results of inferential statistics used to test secondary research objectives RO_4 and RO_5 will be presented and discussed in this section.

The statistical technique named the Cronbach Alpha which was previously discussed in Section 3.7.1, will be used as a reliability measure for internal consistency in this quantitative research. This approach is most commonly used when there are multiple Likert questions in a questionnaire that form a scale and the reliability of the scale needs to be determined if the scale is reliable (Tavakol & Dennick, 2011). The Cronbach's alpha coefficient is used to measure internal inconsistency. This coefficient of reliability ranges from 0 to 1 in providing the overall assessment of a measure's reliability. A low coefficient value indicates a low internal consistency while a high value indicates the opposite. Table 3.4 in Section 3.7.1 defines the guidelines for reliability coefficient. Table 4.11 indicates the calculated Cronbach Alpha for each of the variables.

Three variables had Cronbach Alpha values below 0.5 and these values are below the acceptable internal reliability. These are the only variables with unacceptable reliability and the results must be interpreted with caution. A Cronbach Alpha value of between 0.50 and 0.69 has been considered acceptable for new and experimental research (Collis & Hussey, 2014; Nunnally, 1978).

The internal reliability for all other measuring instruments is sufficient, ranging from 0.63 to 0.81. These values are higher than the minimum requirement of 0.50. The 3 factors namely *Training, Information and Communication and Government Laws and Regulations* were below the minimum acceptable internal reliability Cronbach Alpha of 0.5. These 3 factors have alpha values below 0.50 which cannot be improved by omitting or reversing items. Results for these factors should be treated with caution.

Table 4.21: Cronbach's alpha coefficients for the factors (n = 106)

Factor	Cronbach Alpha co-efficient
Organisational Support	0.79
Training	0.43
Individual Characteristics	0.75
Peer Support	0.70
Trust	0.43
Organisational Culture	0.81
Resources and Costs	0.72
Job Security	0.66
Innovation and Technology Implementation	0.65
Technology Agreeable	0.71
Automation and Support	0.64
Security	0.63
Government Laws and Legislation	0.46
Parent Company	0.73

4.8 DESCRIPTIVE STATISTICS

The validity (discussed in Chapter 3) and reliability (illustrated in section 4.5) of the summated scores derived from the various factors have been established. In this section, descriptive statistics for these scores are presented. Table 4.22 show the central tendency and dispersion of the factors. A total of 106 respondents returned the questionnaire.

Table 4.22: Central Tendency and Dispersion: Factors (n = 106)

Factors	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Organisational Support	3.54	0.78	1.33	3.33	3.67	4.00	5.00
Training	4.49	0.52	2.00	4.33	4.67	4.67	5.00
Individual Characteristics	4.12	0.44	2.67	4.00	4.17	4.29	5.00
Peer Support	3.52	0.60	1.33	3.33	3.67	4.00	4.67
Trust	4.16	0.43	2.67	4.00	4.33	4.33	5.00
Organisational Culture	3.45	0.66	1.00	3.05	3.60	4.00	5.00
Resources and Costs	3.75	0.56	1.75	3.50	3.88	4.00	5.00
Job Security	3.39	0.74	1.33	2.67	3.67	4.00	5.00
Innovation and Technology Implementation	3.73	0.50	2.75	3.50	3.75	4.00	4.75
Technology Agreeable	4.53	0.48	3.33	4.00	4.67	5.00	5.00
Automation and Support	3.66	0.47	2.20	3.45	3.60	3.95	4.80
Security	3.56	0.62	2.00	3.33	3.67	4.00	4.33
Government Laws and Legislation	3.18	0.50	2.00	3.00	3.00	3.50	4.50
Parent Company	3.63	0.42	2.20	3.40	3.80	3.80	4.80

Table 4.22 shows the central tendency and dispersion of the factors. Eighty-one percent (n=86) of the respondents were very positive about Training. Ninety three (n=104) were positive to very positive on their Individual Characteristics and on Trust of new technology. Eighty percent (n=85) of the respondents scored positively to the Resources and Costs variable. Innovation and Technology Implementation had 79% (n=84) of the respondents responded positively to very positively. Ninety seven percent (n=103) of the respondents were positive to very positive about the factor Technology Averse. Seventy four percent (n=78) responded positively to Automation and Support. Sixty seven percent (n=71) responded positively to Parent Company. Table 4.23 shows the frequency distribution of the factors.

Table 4.23: Frequency Distributions: Factors (n = 106)

Factors	Very Negative 1.00 to 1.79		Negative 1.80 to 2.59		Neutral 2.60 to 3.40		Positive 3.41 to 4.20		Very Positive 4.21 to 5.00	
Organisational Support	3	3%	11	10%	26	25%	52	49%	14	13%
Training	0	0%	1	1%	6	6%	13	12%	86	81%
Individual Characteristics	0	0%	0	0%	7	7%	72	68%	27	25%
Peer Support	1	1%	6	6%	40	38%	54	51%	5	5%
Trust	0	0%	0	0%	8	8%	40	38%	58	55%
Organisational Culture	1	1%	11	10%	38	36%	51	48%	5	5%
Resources and Costs	1	1%	3	3%	17	16%	67	63%	18	17%
Job Security	2	2%	13	12%	37	35%	45	42%	9	8%
Innovation and Technology Implementation	0	0%	0	0%	22	21%	68	64%	16	15%
Technology Agreeable	0	0%	0	0%	3	3%	27	25%	76	72%
Automation and Support	0	0%	3	3%	24	23%	69	65%	10	9%
Security	0	0%	6	6%	42	40%	32	30%	26	25%
Government Laws and Legislation	0	0%	14	13%	55	52%	36	34%	1	1%
Parent Company	0	0%	2	2%	33	31%	70	66%	1	1%

4.9 ONE-SAMPLE T-TESTS FOR THE FACTORS

One-sample t-tests were conducted to determine if the mean scores of the population of employees in the pharmaceutical company for the various factors can be described as negative, neutral or positive. The limits for the T test are shown in Table 3.4. The results of these tests are reported in Table 4.24.

Table 4.24: One-sample t-Tests: Factors (n = 106; H1:m ≠3.40; d.f. = 105)

Variable	Mean	S.D.	t	p	Cohen's d
Organisational Support	3.54	0.78	1.90	.061	n/a
Training	4.49	0.52	21.67	<.0005	2.11 – Large
Individual Characteristics	4.12	0.44	16.86	<.0005	1.64 – Large
Peer Support	3.52	0.60	1.97	.051	n/a
Trust	4.16	0.43	18.18	<.0005	1.75 - Large
Organisational Culture	3.45	0.66	0.71	.479	n/a
Resources and Costs	3.75	0.56	6.34	<.0005	0.62 – Medium
Job Security	3.39	0.74	-0.10	.924	n/a
Innovation and Technology Implementation	3.73	0.50	6.78	<.0005	0.66 – Medium
Technology Agreeable	4.53	0.48	24.13	<.0005	2.34- Large
Automation and Support	3.66	0.47	5.75	<.0005	0.55- Medium
Security	3.56	0.62	2.68	.009	0.26- Small
Government Laws and Legislation	3.18	0.50	-4.46	<.0005	0.44 – Small
Parent Company	3.63	0.42	5.65	<.0005	0.55 – Medium

Table 4.24 depicts that the variables with positive mean scores and small practical significance are IV12: Security (μ = 3.56; d = 0.26), IV13: Government Laws and Legislation (μ = 3.18; d = 0.44), and IV7: Resources and Costs (μ = 3.75; d = 0.62), IV9: Innovation and Technology Implementation (μ = 3.73; d = 0.66), IV11: Automation and Support (μ = 3.66; d = 0.55) and IV14: Parent Company (μ = 3.63; d = 0.55), yielded a positive mean score with moderate practical significance. IV2: Training (μ = 4.49; d = 2.11), IV7: Individual Characteristics (μ = 4.12; d = 1.64), IV5: Trust (μ = 4.16; d = 1.75), and Technology Agreeable (μ = 4.53; d = 2.34) generated a positive mean score with large practical significance.

Although IV1: Organisational Support (µ = 3.54; d = 0.06), IV4: Peer Support (µ = 3.52; d = 0.06), IV6: Organisational Culture and Job Security had a positive mean score, however the factors had no statistical significance (p = 0.004) and were deemed practically insignificant as the Cohen's d score was below 0.20. This finding show that the employees did not value the Organisational Culture, Peer Support and Job Security as a significant factor in technology acceptance, therefore the organisation should focus on factors like Trust, Training and Individual Characteristics.

4.10 INFERENTIAL RANKING OF FACTORS

Variables are ranked, using matched-pair t-tests (statistical significance) and Cohen's d (practical significance), such that:

a) The mean of the first variable in Significant Group i differs statistically and practically from the mean of the first variable in Significant Group (i + 1);
b) The mean of all variables in Significant Group i do not differ significantly from the mean of the first variable in that group.

Table 4.25: Inferential Ranking of Mean Factors (n = 106)

Variables	Rank	Significance Group	Mean	SD
Technology Agreeable	1	1	4.53	0.48
Training	1	1	4.49	0.52
Trust	3	2	4.16	0.43
Individual Characteristics	3	2	4.12	0.44
Resources and Costs	5	3	3.75	0.56
Innovation and Technology Implementation	5	3	3.73	0.50
Automation and Support	5	3	3.66	0.47
Parent Company	8	4	3.63	0.42
Security	8	4	3.56	0.62
Organisational Support	8	4	3.54	0.78
Peer Support	8	4	3.52	0.60
Organisational Culture	12	5	3.45	0.66
Job Security	12	5	3.39	0.74
Government Laws and Regulations	14	6	3.18	0.50

Table 4.25 shows the order in which the factors were ranked. The most important factors were found to be the employees Technology Agreeable ranked number (1) with a mean of 4.53 and a Standard Deviation of 0.48, Training (2) both in the Significance Group 1, Trust (3) and Individual Characteristics (4) both in Significance Group 2. The research showed that Resources and Costs, Innovation and Technology Implementation as well as Automation and Support were the other important factors in Significance Group 3.

Parent Company, Security, Organisational Support and Peer Support were ranked in Significance Group 4. Organisational Culture and Job Security were ranked in Significance Group 5. The least ranked variable was Government Laws and Regulations ranked (14) and Significance Group 6 with a mean of 3.18 and a Standard Deviation of 0.50. These findings showed that the factors Technology Agreeable, Training, Trust and Individual Characteristics were viewed by respondents as having the biggest impact and employees felt that these were the critical factors for success in technology acceptance. From these findings, these are the factors that the organisation should focus on to ensure technology acceptance.

4.11 CORRELATIONS BETWEEN THE FACTORS

In this section the correlation between the factors will be evaluated. Pearson's correlation is one of the statistical methods commonly used by researchers to confirm or negate statistical association between two variables. It can be defined so relationships among variables or measures of linear association between two variables (Wegner, 2012; Collis & Hussey, 2014). The change in one variable relates to a change in another and the extent of this change is what correlation analysis determines. This correlation coefficient (r) can range from -1 (a perfect negative correlation) to +1 (a perfect positive correlation).

Correlations are statistically significant at 0.05 level for $n = 106$ if $|r| >= .191$ and practically significant if $|r| >= .300$, thus significant (both statistically and practically) if $|r| >= .300$ (Gravetter & Wallnau, 2009). Table 4.17 show the different correlations of the independent variables.

Table 4.26: Pearson Product Moment Correlations - Factors (n = 106)

	Organisational Support	Training	Individual Characteristics	Peer Support	Trust	Organisational Culture	Resources and Costs
Organisational Support	-	-.046	***.305***	***.664***	.059	***.630***	***.467***
Training	-.046	-	.203	.067	-.018	-.011	-.006
Individual Characteristics	***.305***	.203	-	***.350***	***.315***	.297	.040
Peer Support	***.664***	.067	***.350***	-	.137	***.688***	***.589***
Trust	.059	-.018	***.315***	.137	-	.094	.178
Organisational Culture	***.630***	-.011	.297	***.688***	.094	-	***.499***
Resources and Costs	***.467***	-.006	.040	***.589***	.178	***.499***	-
Job Security	.264	.052	***.370***	***.372***	-.049	***.371***	.256
Innovation and Technology Implementation	.193	-.265	.190	***.320***	.125	.184	.263
Technology Agreeable	.021	.163	***.359***	.210	.157	.108	-.063
Automation and Support	.169	-.045	***.381***	.127	.198	.017	.078
Security	.008	.162	.257	.294	.068	.264	.173
Government Laws and Regulations	.055	.187	.163	.067	.141	.160	.275
Parent Company	***.421***	-.073	-.035	***.383***	.062	***.372***	***.608***

	Job Security	Innovation and Technology Implementation	Technology Agreeable	Automation and Support	Security	Government Laws and Regulations	Parent Company
Organisational Support	.264	.193	.021	.169	.008	.055	***.421***
Training	.052	-.265	.163	-.045	.162	.187	-.073
Individual Characteristics	***.370***	.190	***.359***	***.381***	.257	.163	-.035
Peer Support	***.372***	***.320***	.210	.127	.294	.067	***.383***
Trust	-.049	.125	.157	.198	.068	.141	.062
Organisational Culture	***.371***	.184	.108	.017	.264	.160	***.372***
Resources and Costs	.256	.263	-.063	.078	.173	.275	***.608***
Job Security	-	***.381***	.158	***.365***	***.396***	.169	.294
Innovation and Technology Implementation	***.381***	-	.210	***.356***	.025	-.102	-.055
Technology Agreeable	.158	.210	-	.272	***.406***	-.145	-.158
Automation and Support	***.365***	***.356***	.272	-	.148	.201	.160
Security	***.396***	.025	***.406***	.148	-	.179	.202
Government Laws and Regulations	.169	-.102	-.145	.201	.179	-	.293
Parent Company	.294	-.055	-.158	.160	.202	.293	-

Organisational Support was significantly correlated to Peer Support (|r| >= .664) indicating that both organisational support structures and peer support are important for the acceptance of technology to take place in the workplace. Peer Support was found to be significantly correlated to Organisational Culture (|r| >= .688). This can be attributed to the fact that organisations that have a supportive culture will enhance peer-to-peer support. Individual Characteristics and Trust were significantly correlated to (|r| >= .315) indicating that those who understand the technology are more likely to accept and trust its implementation.

Job Security and Automation and Support were significantly correlated (|r| >= .365) indicating that those who did not feel that their jobs were secure were in support of implementation of automation in pharmaceutical manufacturing. Factor Technology Averse and Security were found to be significantly correlated (|r| >= .406) showing that those who understand technology are aware of the security around use of technology. Parent Company was significantly correlated to Resources and Costs (|r| >= .608) indicating that for successful technology implementation, the parent company should support and make available required financial resources. Independent variable Government Laws and Regulations was statistically correlated to other independent variables, however it was not practically correlated to any other variable as it scored a highest of (|r| >= .293) to Parent Company which fell short of the requirement (|r| >= .300). This finding shows that the respondents did not think that the government regulations had much influence on their accepting technology.

4.12 HYPOTHESES TESTING

Hypotheses Formulation and Testing

The researcher constructed a conceptual framework based on the reviewed literature. The theoretical framework was used to establish relationships between the dependent variable, *Attitude towards a Technology Acceptance*, and the independent variables *Skills and Training*, *Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and International / National Standards* and *Parent Company.*

The various hypotheses were then formulated to test the relationship between the dependent variable and the independent variable. Table 4.27 illustrates these hypotheses, the relevant Pearson Correlation, the correlation strength and the accepted or rejected state of the hypothesis.

Table 4.27: Hypotheses Testing

Hypothesis	Hypothesis Description	Pearson Correlations	Correlation Strength	Hypothesis Accepted or Rejected
H_1	Skills and Training are significantly related to Attitude towards Technology Acceptance	0.193	Low Positive	Rejected
H_2	Individual Characteristics are significantly related to Attitude towards Technology Acceptance	0.381	Low Positive	Accepted
H_3	Trust is significantly related to Attitude towards Technology Acceptance	0.320	Low Positive	Accepted
H_4	Organisational Culture is significantly related to Attitude towards Technology Acceptance	0.184	Low Positive	Rejected
H_5	Resources and Costs are significantly related to Attitude towards Technology Acceptance	0.263	Low Positive	Rejected
H_6	Job Security is significantly related to Attitude towards Technology Acceptance	0.381	Low Positive	Accepted
H_7	Security and International / National Standards are significantly related to Attitude towards Technology Acceptance	0.406	Low Positive	Accepted
H_8	Parent Company is significantly related to Attitude towards Technology Acceptance	0.160	Low Positive	Rejected

The conceptual model with the proposed relationships as shown in Figure 3.3 was tested by using Pearson Correlations. Four of the eight hypotheses developed in this research study were accepted by means of statistical analysis through empirical evaluation. The model therefore needs to be adjusted by removing only H_1: Skills and Training, H_4: Organisational Culture, H_5: Resources and Costs and H_8: Parent Company as an independent variable of Attitude towards a Technology Acceptance.

The study showed that there was no relationship between the dependent variable DV: Attitude towards a Technology Acceptance and 4 out of the 8 independent variables as shown in Table 4.27.

4.12.1 Relationships between Demographic variables and the Factors (ANOVAs)

The fifth research objective will be discussed in this section to establish the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing organisation.

- RO_5: Establish the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing organisation.

In this study, the ANOVA test compared three population means, namely Gender, Age, Years of Service, Job Level and Education Level. The population means were compared against all independent variables, namely *Organisational Support, Training, Individual Characteristics, Peer Support, Trust, Organisational Culture, Resources and Costs, Job Security, Innovation and Technology Implementation, Technology Agreeable, Automation and Support, Security, Government Laws and Regulations* and *Parent Company.*

The null hypothesis was rejected and the alternative hypothesis accepted, as the results indicate that at least one of the population means differs from the other. Based on the statistical analysis, Job Level is the only variable which consistently differed from the others and therefore, Job Level can be used to analyse the perceptions between the groups.

Respondents in Grades 1 – 9 (n=51) were termed employees whilst employees in Grades 12 – 16 (n=26) are the Management.

4.12.2 Data Analysis of Variable Mean Values

The objective of this section is to establish if the employees and management have significantly different values to any of the measured variables. In cases where a significant difference was noted, it would signify that the perceptions are different between the groups in the way they perceive the different variables. The organisation would have to focus on the group rated lower on variables in order to improve. The organisation will have to focus on the lower-rated group and assign more effort, resources and costs in order to bring the two groups to par.

The significant difference between the two-groups was tested by performing a Cohen's d calculation. If there is both statistical and practical significance, there is said to be a significant difference between the two groups. The differences found are highlighted in Table 4.28 below. Management perceived Trust, Technology Agreeableness and Training as important factors. Employees perceived individual characteristics as important. Employees view individual characteristics as important as they mainly worry about individual performances as opposed to managers who are accountable for team results.

Table 4.28: Mean Values and Significant Difference of Factors

Variable	Job Level	Mean	S.D	Difference	F - Value	P (d.f =)	Cohen's d
Organisational Support	Management Employees	3.60 3.28	0.77 0.91	0.32	1.90	.061	n/a
Training	Management Employees	4.50 4.43	0.53 0.63	0.07	21.67	**<.0005**	**2.11 - Large**
Individual Characteristics	Management Employees	4.13 4.13	0.36 0.51	0.00	16.86	**<.0005**	**1.64 - Large**
Peer Support	Management Employees	3.41 3.50	0.69 0.58	-0.09	1.97	.051	n/a
Trust	Management Employees	4.24 4.17	0.43 0.47	0.07	18.18	**<.0005**	**1.75 - Large**
Organisational Culture	Management Employees	3.28 3.45	0.75 0.60	-0.18	0.71	.479	n/a
Resources and	Management	3.60	0.6	-0.19	6.34	**<.0005**	**0.62 -**

Variable	Job Level	Mean	S.D	Difference	F - Value	P (d.f =)	Cohen's d
Costs	Employees	3.79	0.52				**Medium**
Job Security	Management Employees	3.56 3.34	0.65 0.76	0.22	-0.10	.924	n/a
Innovation and Technology	Management Employees	3.80 3.72	0.50 0.51	0.08	6.78	**<.0005**	**0.66- Medium**
Technology Agreeable	Management Employees	4.49 4.50	0.48 0.49	-0.01	24.13	**<.0005**	**2.34 - Large**
Automation and Support	Management Employees	3.68 3.73	0.40 0.47	-0.04	5.75	**<.0005**	**0.55 - Medium**
Security	Management Employees	3.70 3.44	0.61 0.63	0.27	2.68	**.009**	**0.26 - Small**
Government Laws and Regulation	Management Employees	3.21 3.19	0.55 0.47	0.03	-4.46	**<.0005**	**0.44 - Small**
Parent Company	Management Employees	3.60 3.65	0.46 0.38	-0.05	5.65	**<.0005**	**0.55 - Medium**

4.12.3 Selected Demographic Variables: ANOVA tests

In the following two demographic variables, namely *Gender* and *Age* were further statistically evaluated using ANOVA tests. The descriptive statistics in Table 4.29 indicated that no trend was established between the means of the respondents on IV1: Organisational Support nor on IV2: Training as shown in Table 4.30.

Table 4.29: ANOVA – Organisational Support

Effect	F-value	D.F.	p	Cohen's d
Gender	0,05	1; 95	,823	n/a
Age	1,60	2; 95	,207	n/a
Years of Service	0,85	2; 95	,432	n/a
Job Level	1,03	2; 95	,360	n/a
Education Level	0,81	1; 95	,370	n/a

Table 4.30: ANOVA – IV2: Training

Effect	F-value	D.F.	p	Cohen's d
Gender	0,53	1; 95	,470	n/a
Age	0,43	2; 95	,651	n/a
Years of Service	0,49	2; 95	,613	n/a
Job Level	0,34	2; 95	,713	n/a
Education Level	0,52	1; 95	,474	n/a

The ANOVA tests conducted (Table 4-30) on IV2: Training indicate that no difference (p=0.001) was found between the respondents based on gender to Attitude towards Technology Acceptance.

Table 4.31: ANOVA - Individual Characteristics

Effect	F-value	D.F.	p	Cohen's d
Gender	12.27	1; 95	0.001	0.57
Age	1.49	2; 95	0.230	n/a
Years of Service	2.26	2; 95	0.109	n/a
Job Level	0.43	2; 95	0.649	n/a
Education Level	0.26	1; 95	0.612	n/a

The ANOVA tests conducted (Table 4-31) indicated a moderately significant difference (p=0.57) was found between the respondents based on Gender and Individual Characteristics to Attitude towards Technology Acceptance. Further analysis was conducted and the results were as Table 4.33.

Table 4.32: Post –Hoc Individual Characteristics

Effect	Level 1	Level 2	M_1	M_2	t-Test p	Cohen's d
Gender	Male	Female	4,23	3,98	,001	0,57

Further analysis showed that there is a statistical difference between men and women in relation to training. This could be attributed to the reason that most men have ambitions to climb the job-level ladder as opposed to women in the pharmaceutical manufacturing sector. The finding can be further attributed to men wanting to use the training as leverage for future selection into higher positions (p= 0.001; Cohen's d =0.57). IV4: Peer Support, IV5: Trust, IV6: Organisational Culture, IV7: Resources and Costs, IV8: Technology Averse, IV11: Automation and Support, IV12: Security, IV13: Government Laws and Regulations and IV14: Parent Company had no statistical and practical significance in the differences between the male and female respondents.

Table 4:33: ANOVA: IV8 - Security

Effect	F-value	D.F.	p	Cohen's d
Gender	10,94	1; 95	,001	0,66
Age	2,53	2; 95	,085	n/a
Years of Service	0,73	2; 95	,484	n/a
Job Level	0,33	2; 95	,717	n/a
Education Level	3,43	1; 95	,067	n/a

However the ANOVA tests conducted (Table 4-33) indicate a difference (p=0.001) between the respondents' gender and security. This finding could be attributed to the fact that most men value their job security more than women as men are traditionally the breadwinners in the South African society which the respondents are part of. Most women in South African society, on the other hand, take up jobs to assist with an extra income.

Table 4.34: Post –Hoc Security

Effect	Level 1	Level 2	M_1	M_2	t-Test p	Cohen's d
Gender	Male	Female	3,61	3,14	,001	0,66

In a final attempt to establish a difference, Table 4.35 illustrates that there is a small practical difference (p= 0.001; Cohen's d=0.66) between Security and Attitude towards Technology Acceptance for the both male and female respondents. This finding can be attributed to that male employees are generally more risk averse than their female counterparts. Female respondents are more likely to wait until a technology is mature before they can consider using it when compared with most of their male counterparts.

Table 4.35: ANOVA IV9 – Innovation and Technology

Effect	F-value	D.F.	p	Cohen's d
Gender	0,08	1; 95	,776	n/a
Age	3,24	2; 95	,044	n/a
Years of Service	1,74	2; 95	,180	n/a
Job Level	0,97	2; 95	,381	n/a
Education Level	0,07	1; 95	,795	n/a

However the ANOVA tests conducted (Table 4-36) indicate a difference p=0.044) between the respondents' age and IV9: Innovation and Technology.

Table 4.36: Post Hoc – Innovation and Technology

Effect	Level 1	Level 2	M_1	M_2	Scheffé p	Cohen's d
Age	18 - 35 years	36 - 45 years	3,93	3,56	,004	0,78
	18 - 35 years	46 - 65 years	3,93	3,70	,188	0,49
	36 - 45 years	46 - 65 years	3,56	3,70	,520	0,28

In a final attempt to establish a difference, Table 4.27 illustrates that there is a small statistical significance and moderately practical significance (p= 0.004; Cohen's d=0.78) between Innovation and Technology and Attitude towards Technology Acceptance for the respondents in the 18 – 35 years as compared to the 36 – 45 years age group. This finding can be attributed to the fact that younger respondents are exposed to technology and are open to experimenting with new technology. This can be further attributed to the fact that most of the younger employees are already using smart phones for social media purposes and are familiar with modern technologies as opposed to the older respondents.

4.10.4 New Conceptual Model

A new conceptual model was identified and will be presented in this section. The conceptual framework is based on the reviewed literature and was identified in Chapter 3. This conceptual framework identified the dependent variable, *Attitude* *towards Technology Acceptance* and the independent variables *Training and Development, Individual Characteristics, Trust, Organisational Culture, Resources and Costs, Job Security, Security and International / National Standards* and *Parent Company.*

An exploratory factor analysis was conducted which indicated that a three-factor model was deemed to be a feasible solution for measuring the *Attitude towards Technology Acceptance Smart Factory*. The three factors analysed were: *Attitude towards the Technology Implementation, Technology Averse* and the *Attitude towards the Automation and Support*. Independent variable *Skills and Training* was analysed by a two factor model and independent variables *Organisational Support* and *Training* were identified. Independent variable *Trust* came out as two independent variables *Peer Support* and *Trust* from the two-factor model. Independent variable *Security and National /International Standards* was analysed by exploratory factor analysis and two independent variables were identified as *Security* and *Government Laws and Regulations*

The new conceptual model is indicated in Figure 4.17.

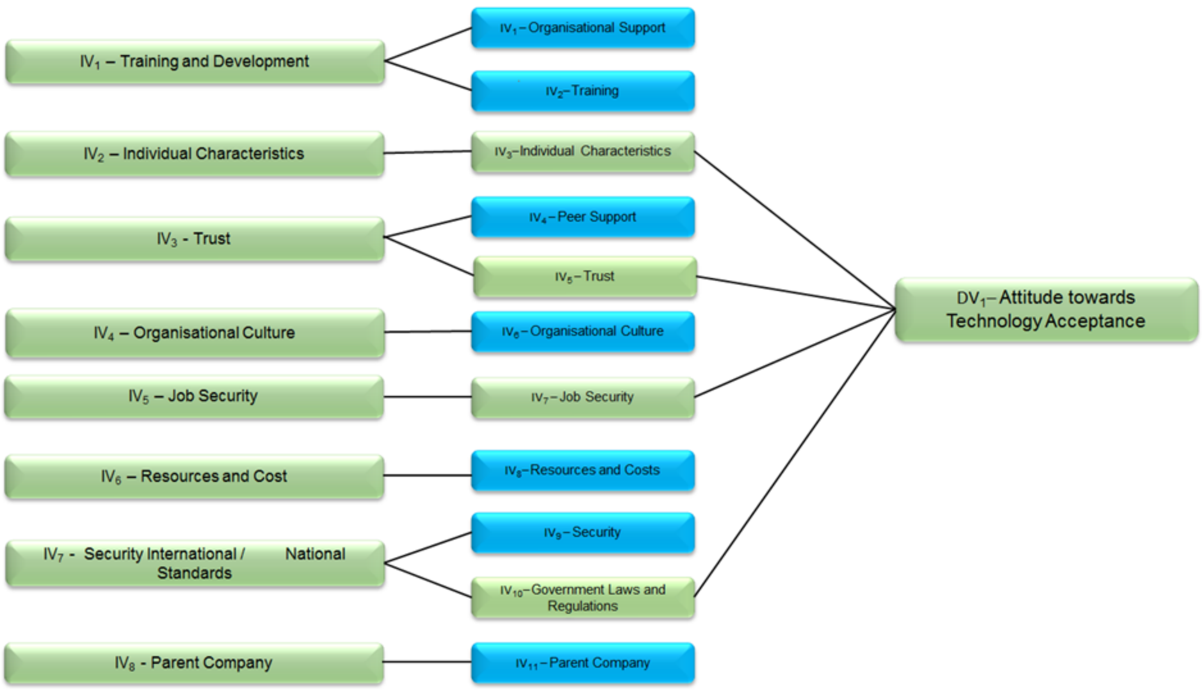

Figure 4.17: New Conceptual Model

4.13 CHAPTER 4 CONCLUSIONS

The chapter addressed RQ_4 which states “What factors influence the attitudes towards technology acceptance at pharmaceutical manufacturing organisation?” and RQ_5 which states; “What is the importance of the identified factors as perceived by employees and management at the pharmaceutical factory?” This chapter achieved the research objective of evaluating the conceptual model for the attitudes towards technology acceptance and established the correlation of the identified factors in the proposed technology acceptance (RO_4); it also established the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing organisation (RO_5).

Some of the findings were that the younger employees were more open to accept technology as opposed to the older employees and this was attributed to the current technology exposure of the two groups. Male respondents were found to value their job security more than the female respondents and this was attributed to the fact that most males are the bread winners in the South African society were the research was conducted. Technology Agreeable, Training, and Trust were found to be the most significant factors that the organisation should focus on for acceptance of technology. On the other hand, Organisational Culture, Job Security and Government Laws and Regulations were found to be the least significant factors in order of importance.

The hypothesis testing accepted the independent variables, Individual Characteristics, Trust, Job Security and National / International Standards whilst Training and Development, Organisational Culture, resources and Costs and Parent Company were rejected in relation to the dependent variable Attitude towards Technology Acceptance. Perceptions of management and employees were found to be statistically and practically significant on factors like Training and Development, Individual Characteristics, Trust and Technology Averse. This was attributed to the fact that managers have an organisational overview and are more likely to look at factors that are holistic and team centred as opposed to employees who are more likely to value more self-centric factors.

In the next chapter the main research objective (RO_M) will be discussed. The research questions will be answered by presenting a summary of the main findings. The knowledge gained from the study will be presented. The future research possibilities will be discussed and the possible limitations recognised. Recommendations for the pharmaceutical manufacturing sector will be offered which are based on the literature and analysis of this study.

CHAPTER 5

FINDINGS, RECOMMENDATIONS AND CONCLUSIONS

5.1 INTRODUCTION

Chapter 4 presented, analysed and discussed the results of the empirical study. The chapter concluded with a conceptual model for Attitudes towards Technology Acceptance. The chapter further addressed RQ_5: What is the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing organisation? RO_5: Establish the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing factory.

The Chapter outline is illustrated in Figure 5.1.

Figure 5.1: Chapter 5 Overview

5.2 SUMMARY OF RESEARCH QUESTIONS AND OBJECTIVES

The research questions and objectives were discussed in the various chapters as the research progressed. Subsections 5.2.1 to 5.2.5 give an overview of the chapters.

5.2.1 Chapter 1: Introduction and Problem Statement

Chapter 1 introduced the treatise, provided an overview of the study, its purpose and the research significance and delimitation. The problem statement: *The factors influencing employees and managers' attitudes towards a smart factory have not been adequately researched in the pharmaceutical sector in South Africa* was further outlined. Additionally, it defined the *RO_M: To identify the factors which influence technology adoption and measure the perception of employees and management regarding smart factories in the pharmaceutical manufacturing industry.* This corresponded with the *RQ_M: What are the differences between the perceptions of management and employees of the factors which influence the attitudes towards smart factories within the pharmaceutical manufacturing sector?* The chapter concluded with the Research Alignment Plan, which guided the researcher throughout the treatise.

5.2.2 Chapter 2: Literature Review

Various academic resources such as journal articles, books and dissertations were explored and analysed in Chapter 2 to address the first two secondary research questions. These were: *RQ_1: What are the characteristics of smart factories in the manufacturing industry?* This addressed *RO_1: Identify the characteristics of smart factories industry.*

The smart factory concept is intended to enable extremely flexible production and self-adaptable production processes with machines and products that act both intelligently and autonomously (Syberfeldt, Danielsson & Gustavsson, 2017; Liu, 2016). The literature review further identified a smart factory as a factory that is autonomous and processes are repeatable according to a set standards and data are collected and processed to support automation and robotisation of production processes (Pham et al., 2008 ; Odwazny, 2018).

Manyika et al., (2017) describe a smart factory as highly integrated, has improved control and coordination for sustainable competitive edge that is not possible from individual systems. Technologies such as IOT, CPS, Block-chain, Big Data Analytics, Cobots and Cloud Computing were identified as central characteristics to the creation of smart factories.

The literature reviewed identified the different theories related to technology acceptance and TAM was identified as the most common academic theory. Chapter 2 discussed other technology acceptance theories however this study used TAM to explain and understand factors influencing technology acceptance. *RQ_2: What factors need to be included in the proposed model to measure the perceptions of employees and management on the factors influencing the attitudes towards smart factories within the pharmaceutical manufacturing sector?* This addressed *RO_2: Identify the factors influencing the attitudes towards smart factories within the pharmaceutical manufacturing sector.*

The literature reviewed identified training and development of employees as an important factor as skilled and well-educated employees are the greatest driver of competitiveness in manufacturing (Kagermann, Wahlster & Helbig, 2013). The findings of this research however, did not identify Training and Development as an important variable influencing the acceptance of technology.

Organisational culture was one of the independent variables identified as important for technology acceptance in the literature review. A company with a strong support culture will be able to implement the smart manufacturing technologies with relative ease as the employees will be willing to support management (Denison, Hooijberg, Lane & Lief, 2012). The findings of this research however revealed that organisational culture is not a significant variable for the in the acceptance of technology. This finding was not in line with reviewed literature.

Job Security was identified as an important variable in the reviewed literature. Studies done in the USA and Europe in 2013 showed that some jobs will not be required in the near future, resulting in renewed concerns that automation and digitalisation might result in a jobless future (Arntz, Gregory & Zierahn, 2016).

Employees are bound to be wary of the potential risks to their employment and therefore their livelihoods if technology is adopted.

Chapter 2 concluded with a proposed conceptual model that formed the foundation of the questionnaire developed for the empirical study as shown in Figure 5.2

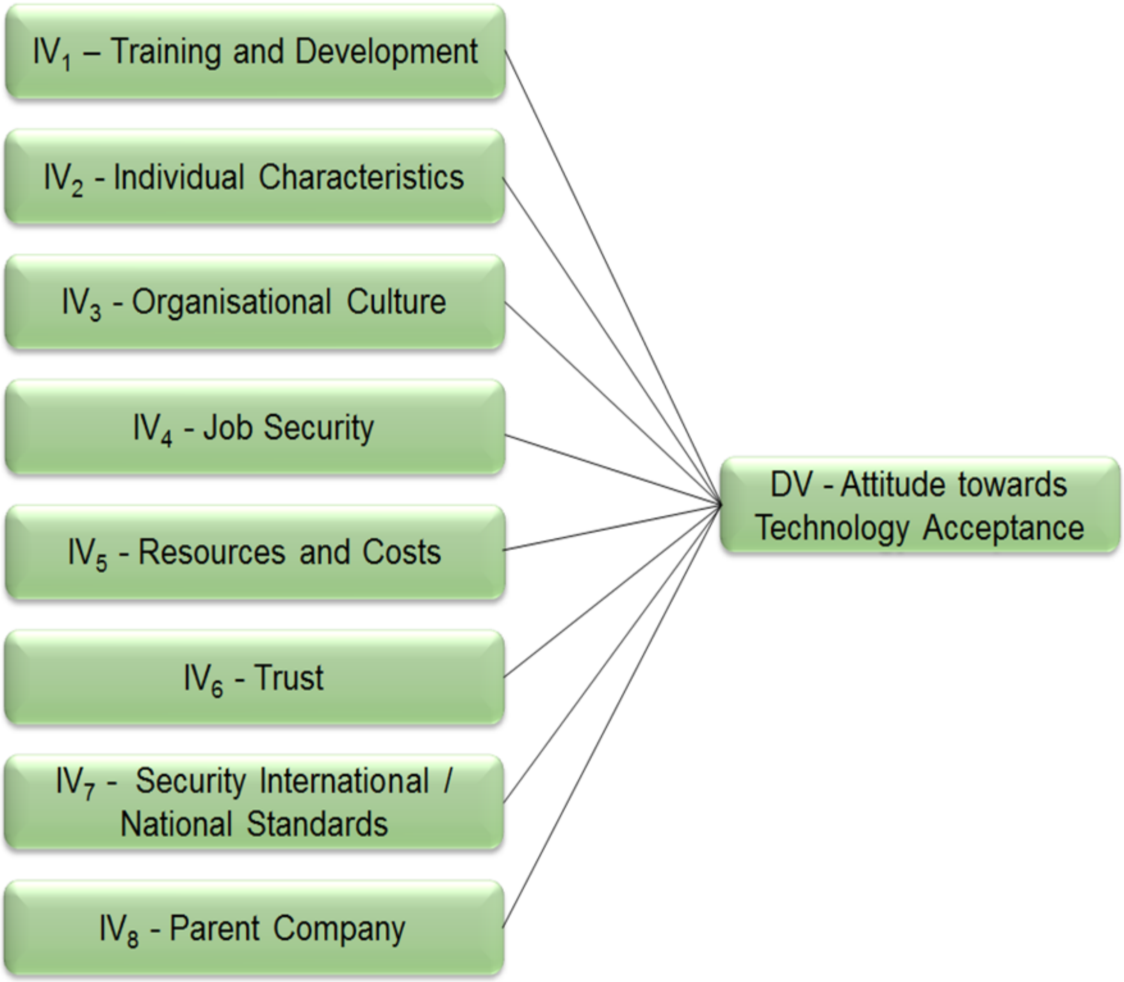

Figure 5.2: Attitude towards a Smart Factory Implementation Conceptual Model.

5.2.3 Chapter 3: Research Design and Methodology

Chapter 3 discussed the various research philosophies and approaches and explained the research methodology used in this study. The research philosophy, approach and paradigm were discussed in Chapter 3 and this research was identified as a Positivistic study using quantitative methods of data collection. This research used the quantitative methods and is a positivistic study.

A questionnaire was designed and data collected where respondents were to give responses about their demographics and relation to the independent variables as shown in Figure 5.2. Additionally, Chapter 3 discussed the operationalisation of the questionnaire from literature review. The reliability and validity of the questionnaire used in the study were discussed.

Data analysis tests and required ranges which were used to analyse the data collected in Chapter 4 were determined in Chapter 3. This chapter addressed *RQ_3: What research design and methodology can be followed to better understand and reproduce this research study in future?* This corresponded to *RO_3: Justify and explain the research design and methodology used for this treatise with sufficient information for future reproduction.* The positivistic paradigm was chosen as the best research method as it allows a large sample to be examined and conclusions on the population to be inferred from statistical analyses. The researcher does not influence the results with a personal worldview in the quantitative study philosophy.

5.2.4 Chapter 4: Results

Data from the survey the pharmaceutical organisation's employees and management was presented, discussed and analysed in Chapter 4. Descriptive and inferential statistics and Exploratory Factor Analysis were conducted. Various relationships between selected variables and demographic information were explored.

The conceptual model from Chapter 2 was tested and Chapter 4 concluded with a tested model for measuring the DV: *Attitude Towards Technology Acceptance*. Therefore, *RQ_5: What is the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing factory?* This matches *RO_5*: *Evaluate the conceptual model for the Attitudes towards Technology Acceptance in the pharmaceutical manufacturing sector was* addressed in Chapter 4. *RO_5*: *To identify the factors which influence technology adoption and measure the perception of employees and management regarding smart factories in the pharmaceutical manufacturing industry* was also addressed in Chapter 4.

In order to effectively address the research question *RQ_5, Chapter* 4 explained the various univariate and multivariate data analyses together with the interpretation methods which were applied in this study. The computer software programme STATISTICA was used to analyse and interpret the data that were used to conduct the empirical study. Bar charts, pie charts and tables were used to present the collected data for both descriptive and inferential statistics. Additionally, exploratory factor analysis was employed to ensure the construct validity of the instrument and identify items which should be removed. Some of the findings were that the younger employees were more open to accept technology as opposed to the older employees and this was attributed to the current technology exposure of the two groups.

Male respondents were found to value their job security more than the female respondents and this was attributed to the fact that most males are the bread winners in the South African society were the research was conducted. Technology Averse, Training, and Trust were found to be the most significant factors that the organisation should focus on for acceptance of technology. On the other hand, *Organisational Culture, Job Security and Government Laws and Regulations* were found to be the least significant factors in order of importance.

The hypothesis testing accepted the independent variables *Individual Characteristics, Trust, Job Security and National / International Standards* whilst *Training and Development*, *Organisational Culture, Resources and Costs* and *Parent Company* were rejected in relation to the dependent variable Attitude towards Technology Acceptance Perceptions of management and employees were found to be statistically and practically significant on factors like Training and Development, Individual Characteristics, Trust and Technology Agreeable. This was attributed to the fact that that managers have an organisational overview and are more likely to look at factors that are holistic and team centred as opposed to employees who are more likely to value more self-centric factors.

5.2.5 Chapter 5: Findings, Recommendations and Conclusions

Chapter 5 serves as a summary of the entire study, presents the key findings from the literature and the empirical study and addresses any gap between the literature and the results. The implications of the study and managerial recommendations are discussed and limitations to the study and a call for future research are made. Finally, conclusions are made based on the research findings. Therefore, the *RQ_M: Interpret empirical results of the importance of the identified factors as perceived by employees and management at the pharmaceutical manufacturing company and provide managerial conclusions. This* is linked to *RO_M: To identify the factors which influence technology adoption and measure the perception of employees and management regarding smart factories in the pharmaceutical manufacturing industry,* therefore, correlation is addressed.

The statistical analysis showed that a different model was required to answer the main research question. Individual Characteristics, Trust, Job Security and Government Laws and Regulations were found to be the main factors influencing Technology Acceptance in a Pharmaceutical manufacturing factory. Furthermore to the factors, the finding also indicated that the perceptions of management and employees were found to be statistically and practically significant on factors like Training and Development, Individual Characteristics, Trust and Technology Agreeable. This was attributed to the fact that managers have an organisational overview and are more likely to look at factors that are holistic and team centred as opposed to employees who are more likely to value more self-centric factors.

5.3 KEY FINDINGS OF THE STUDY

This research made the following contributions to the existing body of knowledge on the subject of technology acceptance in the pharmaceutical manufacturing sector by making the following contributions:

- A new proposed model was presented for the *Attitudes towards Technology Acceptance* in the pharmaceutical sector. The model is based on reviewed literature on smart factories, technology acceptance theories and factors influencing technology acceptance;
- A method to measure the Attitudes towards Technology Acceptance in the pharmaceutical manufacturing sector was developed; - Misalignment between internal perceptions of employee’s attitudes towards technology acceptance;

- Misalignment between the perceptions of employees and management regarding factors influencing the acceptance of technology were identified. Corrective actions were recommended;
- The researcher used non-probability (convenience) sampling in order to expedite the return of questionnaires, therefore the results cannot be generalised to the population as a whole.
- The respondents of this study were concentrated in South Africa, in one pharmaceutical manufacturing factory , due to the time constraints, location of the researcher and the ability to reach the employees of the organisation. If the study were to be repeated in another geographic location the results may differ;

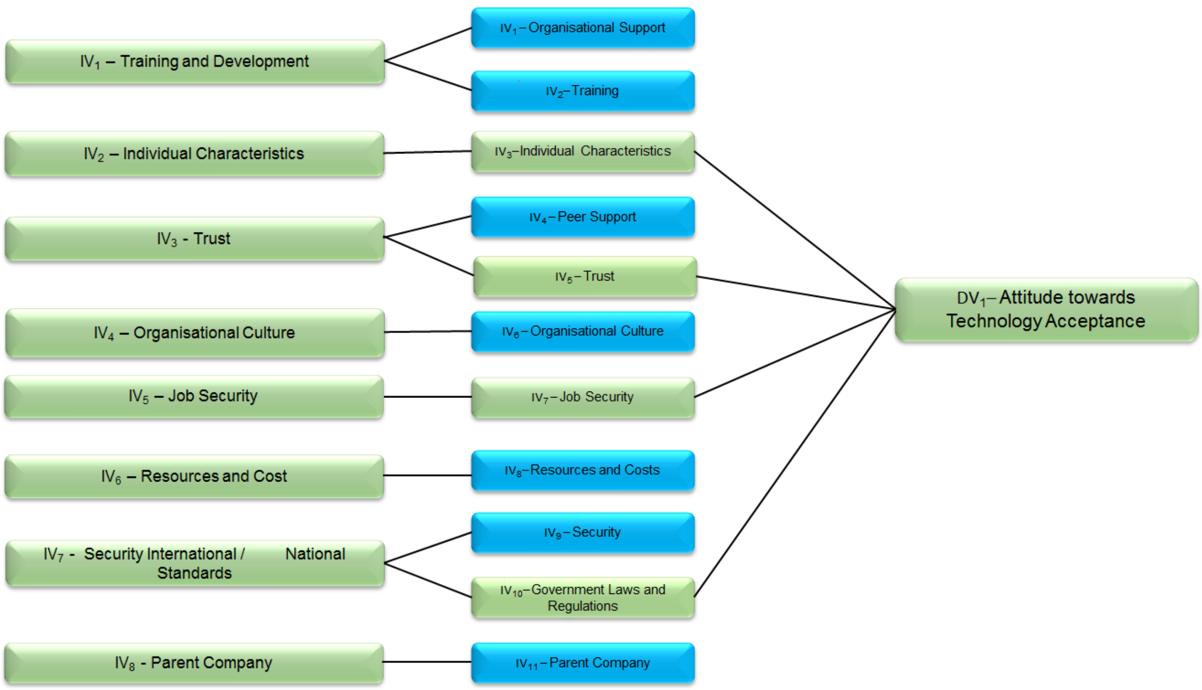

Figure 5.3: The final model

Collis and Hussey (2014) describe a limitation as a weakness or deficiency in the research study. In the research study, the following have been identified as limitations:

- The questionnaire was designed to keep the number of questions to a minimum to maintain each respondent's willingness to answer the questions;

- The scope of the study was limited to focus on only selected factors influencing the attitudes towards technology acceptance, and did not consider all the factors influencing these variables. Future studies could present a broader view on the subject matter by investigating all of the factors; and
- This study was limited to the employees of a pharmaceutical manufacturing factory. It is possible that the outcome of this study might be different if a similar study were performed on employees of another organisation.

5.4 MANAGERIAL RECOMMENDATIONS FOR THE PHARMACEUTICAL MANUFACTURING SECTOR

In this research study, the following practical business recommendations were identified for the pharmaceutical manufacturing sector. These recommendations are based on the literature reviewed and the statistical analysis of the results.

5.4.1 Importance of the Identified Factors in the Attitudes towards Technology Acceptance Model

Pearson's Product Moment correlation coefficient was used to measure the linear relationships between independent variables. *Individual Characteristics, Trust, Job Security* and *Government Laws and Regulations* were found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.*

Independent variables *Training and Development, Organisational Culture, Resources and Costs* and *Parent Company* showed that there is no relationship with the dependent variable *Attitude towards Technology Acceptance.*

5.4.1.1 Individual Characteristics

The independent variable *Individual Characteristics* was found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* This finding is important for management decision making when building teams for Smart Manufacturing. Individual Characteristics were identified by the literature reviewed as an important factor influencing adoption of technology. Individual technology acceptance is based on a number of factors; chief amongst them being attitude, subjective norm, self-efficacy, innovativeness and technological experience which were identified as individual context factors (Talukder, 2012). This was in line with the finding of this research.

A study on smart factories in the automotive sector also found out that individual characteristics are positively correlated with adoption of technology (Leo, 2017). This finding can also be important in terms of the recruitment processes that organisations can implement in order to identify those employees who are more likely to accept technology in their daily routines. This finding supports the reviewed literature that employees who are appreciative of technology are more likely to acceptance technology implementation. A further management recommendation will be that organisations should identify those employees who have an affinity for technology for trials in the implementation of technology as they are more likely to accept the new technology and later influence their peers.

5.4.1.2 Trust

The independent variable *Trust* was found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* Employees want to feel that they can trust the technology to be implemented without worrying about their safety.

Bloss (2016) argued that the era of cobots has brought about some misgivings from some employees due to lack of trust. The literature review identified trust as an important independent variable for successful technology acceptance. Cobots require human-machine interaction and this requires certain levels of trust in terms of employee safety and acceptance (Bogue, 2016). Employees are more inclined to accept and adopt a technology they trust and will not readily accept technologies they do not trust (Daudt & Willcox, 2018). The reviewed literature was found to be in line with the findings of this research as trust was found to be a variable on the technology acceptance model. Trust improves teamwork and collaboration, as well as the quality of relationships within a team (Griffiths, 2006; De Bruyn, 2017).

Trust can be based on either experience or recommendation and is demonstrated by confidence in the goodwill of others, which is produced through interpersonal interactions dealing with matters of uncertainty or risk (Ring & Van der Ven, 1994). Acceptance, approval, confidence or respect can be practical ways of showing trust.

In business, any commercial entity would like its customers to believe in its products without a shade of doubt (Prieto, 2009; De Bruyn, 2017). According to Mayer, Davis and Schoorman (1995), the influence of trust in technology has been widely researched in the e-commerce space. In other studies, trust has been seen as an important element in strengthening organisational commitment and can increase productivity (Lee & See, 2004). In another study on smart factories in the automotive industry, Leo (2017) found out that trust was considered an important factor by both management and employees. This finding is in line with the results of this study.

Technology alone may not be a source of competitive advantage therefore it is recommended that management implement only those technologies that have been tried and tested to improve the chances of the technology being accepted. Employees are more likely to accept technologies that are reliable and secure as this will facilitate acceptance and buy-in from the employees. The organisation can offer support and encouragement to employees with innovative ideas as well as offer training and information forums in order for the employees to have a better understanding of the technologies.

5.4.1.3 Job Security

The independent variable *Job Security was* found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* Management in the pharmaceutical manufacturing organisation should be aware that employees view job security as very important and therefore should exercise caution in the implementation of technology. The finding was in line with reviewed literature that identified job security not only as a technological challenge but rather as a socio-economic challenge in the current South African climate. It is recommended that management offer training or information sessions on the advantages of technology implementation to the business industry and show that technology implementation is not a threat to the employees' jobs.

Employees always fear for the continued existence of their jobs and they are bound to have subjective perceptions of whether they will keep their jobs or lose them in the long term (Witte, 2005). There is a prevalent perception that human substitutability by machines has reached unprecedented proportions and employment is susceptible to computerisation (Frey & Osborne, 2013). Studies done in the USA and Europe in 2013 showed that some jobs will not be required in the near future, resulting in renewed concerns that automation and digitalisation might result in a jobless future (Arntz, Gregory & Zierahn, 2016). their future prospects in the organisation once technology has been adopted.

Smart factories go through some changes in operation resulting in the realignment of roles in supporting new processes (Deloitte University Press, 2017). Some roles will become redundant due to new process capabilities such as virtual / augmented reality. The implementation of a smart factory will bring about changes where people's old roles are affected, bringing about a sense of resistance and mistrust from employees. Employees will need to be trained how to work around cobots in order to secure their jobs. However the menial and repetitive tasks will be done by cobots (Bloss, 2013). Cobots work with precision (Collaborative Robot Buyer's Guide, 2018) and they offer the consistent quality required in the pharmaceutical manufacturing industry.

The South African job market is under severe stress and that can be attributed as a reason why employees view job security as an important factor in relationship to technology acceptance. Management should educate employees on the advantages of technology acceptance and make employees understand that technology will not replace employees in order to increase the chances of technologies being accepted in the organisation. Management should give special attention to the future roles of employees in a technology- enhanced manufacturing environment in order to allay the fears of job losses. It is further recommended that management should approach technology acceptance in a transparent and engaging manner with employees as this is more likely to improve the levels of acceptance of a technology.

5.4.1.4 Government Laws and Regulations

The independent variable *Government Laws and Regulations* was found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* The research showed that government laws and regulations can affect technology acceptance by employees in an organisation. The reviewed literature showed that when governments are in support of technology and innovation, employees are more likely to accept technology in their organisations. The literature review identified that a smart factory is created through the integration of a number complex physical components as well as IT standards and protocols. By design, a smart factory brings a number of technologies together and these technologies are governed by international and sometimes national standards (Fulton & Hon, 2010).

The management review recommendation is that organisations should engage more with relevant government departments in order to influence government policies on technology adoption. Furthermore it is recommended that management in organisations should influence acceptance through sponsorships and involvement of schools and government technology-awareness programmes. Literature reviewed showed that governments that have pushed for technology-driven manufacturing have had tremendous support from their companies and in turn has made them world leaders in technology. The management recommendation is for the companies to take a leading role in engaging with government departments with a view to be actively involved in the strategic-technology policy direction of the country.

5.4.1.5 Training and Development

The independent variable *Training and Development* was not found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* This finding was not in line with reviewed literature. Training equips employees with relevant knowledge and therefore takes away the ambiguity that can potentially be a barrier to adoption and acceptance of technology (Erumban & de Jong , 2006). Employees often judge themselves through self-efficacy which is defined as a person's belief regarding his or her capacity to carry out a specific task using technology (Scannell, Calantone & Melnyk, 2012; Dajani, 2016).

Employees often judge themselves through self-efficacy defined as a person's belief regarding his or her capacity to carry out a specific task using a technology (Scannell, Calantone & Melnyk, 2012; Dajani, 2016). Training within an organisation should be given to boost the self-efficacy of employees (Bogue, 2016). Industry 4.0 has brought about a deliberate shift from a product-based economy to a knowledge-based economy (Onga, Laia, & Wang, 2004). Hence organisations are required to educate and train their employees so that they are ready to work with smart technologies thus improving their acceptance levels of the new technology. Onga et al. (2004) aver that organisations need to train employees from anywhere within the organisation using asynchronous e-learning. Asynchronous learning saves on time and costs as well as reaps benefits associated with employee retention, improved compliance and meeting business needs (Onga et al., 2004). Training of employees should be done to expose the employees to the usefulness of technology and this will increase their acceptance of the technology (King & He, 2006). Leo (2017) in the research in automotive manufacturing found out that training was an important factor as perceived by employees however this was not in line with the findings of this research

The management recommendation is that the organisation should not focus on the training and development aspect as this was found not to positively influence technology acceptance. If management decides to do training, the training should be tied to the positive factors namely *Trust, Individual Characteristics, Job Security and Government Laws and Regulations*.

5.4.1.6 Organisational Culture

The independent variable *Organisational Culture* was not found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* Reviewed literature identified culture as an important variable in the acceptance of technology. A company with a strong support culture will be able to implement smart manufacturing technologies with relative ease as the employees will be willing to support management (Denison, Hooijberg, Lane & Lief, 2012). Technology adoption in any organisation requires some internal changes to support or implement the new technology. The company should be able to have a culture that supports the changes from a management and employees point of view.

The prevalent culture in an organisation can either encourage or impede technology adoption (Corfield & Paton, 2016). A company with a strong support culture will be able to implement the smart manufacturing technologies with relative ease as the employees will be willing to support management (Denison, Hooijberg, Lane & Lief, 2012). The organisational culture can also affect resource allocation in an organisation (Elias et al., 2011; Sharp, Lyer & Brush, 2017).

Research has shown that some cultures such as the German and Japanese readily accept technology and this has been a critical success factor in organisations operating within these cultures (Gu, Cao & Duan, 2012). This finding was not in line with the reviewed literature that stated that organisational culture is a vital variable in the acceptance of technology. The management recommendation is that the organisation should not focus on the culture but rather on the other variables in order to increase the chances of acceptance of technology. An innovative culture however is recommended as it can potentially produce other variables like identification of those who have innovative, individual characteristics.

5.4.1.7 Resources and Costs

The independent variable *Resources and Costs* was not found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* This finding was not in line with the reviewed literature that stated that those organisations with more access to resources and the financial muscle to execute have a better chance of having technology accepted. Migration from an automated factory to a smart factory is no easy feat in terms of financial and time resources.

An organisation needs to invest a substantial amount of money to realise the smart - factory dream (Arntz, Gregory & Zierahn 2016; Bogue, 2016). Daudt and Willcox, (2018) argued that technical talent is a scarce resource that costs a lot of money. An organisation needs to have the financial muscle to bring the scarce human talent together to run a smart factory. More often than not highly technical resources are not always found in the same area and it takes a lot of money to bring them into one area.

The research showed that the financial resources of an organisation are not as important as employees but management are more concerned with other variables. The management recommendation is that the organisation should rather focus on other variables instead of the financial aspects for success in technology acceptance. Resources and costs are important for execution, however, acceptance is more to do with other factors.

5.4.1.8 Parent Company

The independent variable *Resources and Costs* was not found to have a positive relationship with the dependent variable *Attitude towards Technology Acceptance.* This finding was not in line with the reviewed literature that stated the parent company was important in the acceptance of technology as employees were more likely to accept technology based on the knowledge that their parent company had accepted or uses the same technology.

Adoption of smart factory technology can be viewed as more of a corporate-governance function as opposed to that of local management of the company due to other factors involved like costs, communication with other sister factories and the supply chain (Burke et al., 2017; Hill & Hult, 2017). In their study on the relationship between the spill over of benefits to local companies from the multinational companies, Belderbos, Van Roy and Duvivier, (2012) concluded that affiliates of foreign multi-national enterprises have higher productivity levels, which can be attributed to the transfer of superior technologies.

Management's recommendation is that, in as much as it is important to make employees aware of the adoption of a new technology by the parent company, it is not very important for the employees and should not be a focus area. It is further recommended that management could send some of the employees to the parent company, especially those whose individual characteristics are more technology averse.

5.5 DIFFERENCES IN PERCEPTION BY EMPLOYEES AT DIFFERENT JOB LEVELS

Table 4:29 showed the differences in perception between management and employees on the various factors. *Training, Individual Characteristics, Trust and Technology Averse* were found to have a significant statistical and a large practical different between management and employees. The perception of management and employees had a medium statistical and practical significance on R*esources and Costs, Innovation and Technology, Automation and Support* as well as *Parent Company.*

Both management and employees had the same perceptions on *Organisational Support, Peer Support, Organisational Culture and Job Security* showing that they felt that these factors affect them in the same way in relation to acceptance of technology. It is recommended that the organisation should treat the management and employees in the same manner regarding common variables namely *Organisational Support, Peer Support, Organisational Culture and Job Security.*

5.5.1 Organisational Support

The organisation should make sure that both management and employees are accorded the same level of support from an organisational point of view. New technology acceptance can be a daunting process with a number of unknown factors. It is recommended that the organisation should look at ways of giving management and employees alike much support during the new technology process. It is recommended that the organisation should have a technology transfer team dedicated to assisting employees during the process in order to increase the chances of technology acceptance by both management and employees.

5.5.2 Peer Support

Both management and employees valued peer support during technology transfer in the same manner. It is recommended that the organisation should allow for work groups of employees and management from varied fields of expertise to work together and learn together during the process of a new technology. Employees and management should be allowed to work together with peers to improve the chances of a new technology being accepted. It is further recommended that the organisation should capacitate peer groups and encourage employee participation and make available platforms for the peer groups to thrive.

5.5.3 Organisational Culture

The research showed that both management and employees perceive *Organisational Culture* in the same way in relation to *Attitude towards Technology Acceptance*. The organisation should therefore treat management and employees in the same way in terms of inculcating a technology-friendly culture. It is recommended that the organisation include both management and employees in any programmes that promote a technology-driven culture in the same way.

5.5.4 Job Security

The research showed that both management and employees perceive *Job Security* in the same way in relation to *Attitude towards Technology Acceptance*. This can be attributed to the fact that jobs are scarce in the current environment where the research was conducted. Both management and employees view their job security as important as there are no abundant opportunities in the market. The other factor could be that the pharmaceutical manufacturing sector is highly specialised and some of the employees and management might have invested heavily in specialist skills and share the fears of being laid off from the organisation. It is recommended that the organisation should give as much attention as is possible to assuring both management and employees of their job security.

5.5.5 Government Laws and Regulations / Security

The research showed that there is a very small difference in the perception of management and employees where *Government Laws and Regulations* and *Security* are concerned. This is an area where the organisation should assure both management and employees how the new technology will be secure and is in line with the government's laws and regulations in the same manner. The perceptions were marginally different hence insignificant on these two factors.

5.5.6 Training

The research showed that there is a significant difference between how management and employees perceive training in relation *Attitude towards Technology Acceptance*. Employees place high value in training for a new technology whereby management views other factors as more important. The management recommendation for the organisation is that employees should be accorded more training time and opportunity in the face of a new technology but not management. It is further recommended that management should be made aware of the need for training by the employees as management play a pivotal role in making available training opportunities to employees.

5.5.7 Individual Characteristics

The research showed that there is a significant difference between how management and employees perceive *Individual Characteristics* in relation to *Attitude towards*

Technology Acceptance. Employees place a lot of emphasis on their individual characteristics in relation to acceptance of a new technology however management placed importance on other factors. This might be due to the fact that employees generally look at themselves as individuals and are more concerned with achieved individual goals. On the other hand management are more concerned with delivery of overall business goals therefore they place their emphasis on team-related factors more than on individual goals and capabilities. The management recommendation is that the organisation should focus on fostering team work especially on the employees' levels in order to make employees aware that team goals are important.

5.5.8 Trust

The research showed that there is a significant difference between how management and employees perceive *Trust* in relation to Attitude towards Technology Acceptance. Employees put a lot of emphasis on trust in their responses. The employees' responses could be attributed to the high levels of job losses being experienced around South Africa and automation has been cited by Workers' Union bodies as one of the drivers of employees' layoffs. Management on the other hand perceive trust lowly when compared to employees.

The management recommendation is that the organisation should include the employees, get to understand their concerns about technology and try to get their buy-in before trying to adopt a new technology. It is further recommended that employee involvement should come early in the process so as to remove any doubts and allay any fears. It is further recommend that the organisation should adopt an inclusive process to improve on early commitment to the technology so as to improve the chances of acceptance of the technology.

5.6 CHAPTER 5 SUMMARY

The main research objective of this research was to identify the factors which influence attitude towards technology acceptance and measure the perception of employees and management in the pharmaceutical sector. The following deliverables were achieved:

- A literature review was conducted in order to establish the characteristics of smart factories;
- Identification of factors influencing attitude towards technology acceptance within smart factories;
- A proposed model on attitudes towards technology acceptance was developed based on the reviewed literature;
- The research design and methodology used for this study was explained with sufficient detail to allow it to be reproduced in future;
- Evaluation of the proposed model of the attitude towards technology acceptance in the pharmaceutical sector; and
- The significance placed on various factors affecting technology acceptance between management and employees was established in the pharmaceutical sector.

In conclusion, a technology acceptance model in the pharmaceutical sector was developed specifying what factors are of importance in technology acceptance. This research addressed the main problem, namely what are the factors influencing the attitudes towards a technology acceptance as perceived by the employees and management. This has been effectively addressed. Recommendations were made about areas where the model could be improved, opportunities for further research were outlined, limitations of this study were identified and managerial recommendations based on this study were made.

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ANNEXURE A: TURNIT IN REPORT

Technology Acceptance in Pharmaceutical Factory

ORIGINALITY REPORT

25%	16%	9%	16%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Nelson Mandela Metropolitan University Student Paper	9%
2	www.emeraldinsight.com Internet Source	1%
3	www.ijikm.org Internet Source	<1%
4	www.docstoc.com Internet Source	<1%
5	uir.unisa.ac.za Internet Source	<1%
6	Submitted to University of Cape Town Student Paper	<1%
7	core.ac.uk Internet Source	<1%
8	pdfs.semanticscholar.org Internet Source	<1%
9	www.tandfonline.com	

ANNEXURE B: ETHICS CLEARANCE – FORM E

FORM E

NELS N M NDELA
UNIVERSITY

ETHICS CLEARANCE FOR TREATISES/~~DISSERTATIONS/THESES~~

Please type or complete in black ink

FACULTY: BUSINESS AND ECONOMIC SCIENCES

SCHOOL/DEPARTMENT: BUSINESS SCHOOL

I, (surname and initials of supervisor) Prof A. P. Calitz

the supervisor for (surname and initials of candidate) B. MUGWAGWA

(student number) 213551055

a candidate for the degree of MBA

with a treatise/dissertation/thesis entitled (full title of treatise/~~dissertation/thesis~~):

A MODEL FOR SMART FACTORIES IN THE PHARMACEUTICAL MANUFACTURING SECTOR

considered the following ethics criteria *(please tick the appropriate block)*:

	YES	NO
1. Is there any risk of harm, embarrassment of offence, however slight or temporary, to the participant, third parties or to the communities at large?		X
2. Is the study based on a research population defined as 'vulnerable' in terms of age, physical characteristics and/or disease status?		X
2.1 Are subjects/participants/respondents of your study:		
(a) Children under the age of 18?		X
(b) NMMU staff?		X
(c) NMMU students?		X
(d) The elderly/persons over the age of 60?		X

(e) A sample from an institution (e.g. hospital/school)?		X
(f) Handicapped (e.g. mentally or physically)?		X
3. Does the data that will be collected require consent of an institutional authority for this study? (An institutional authority refers to an organisation that is established by government to protect vulnerable people)		X
3.1 Are you intending to access participant data from an existing, stored repository (e.g. school, institutional or university records)?		X
4. Will the participant's privacy, anonymity or confidentiality be compromised?		X
4.1 Are you administering a questionnaire/survey that:		X
(a) Collects sensitive/identifiable data from participants?		X
(b) Does not guarantee the anonymity of the participant?		X
(c) Does not guarantee the confidentiality of the participant and the data?		X
(d) Will offer an incentive to respondents to participate, i.e. a lucky draw or any other prize?		X
(e) Will create doubt whether sample control measures are in place?		X
(f) Will be distributed electronically via email (and requesting an email response)?		X
Note: • If your questionnaire **DOES NOT** request respondents' identification, is distributed electronically and you request respondents to return it *manually* (print out and deliver/mail); **AND** respondent anonymity can be guaranteed, your answer will be NO. • If your questionnaire **DOES NOT** request respondents' identification, is *distributed via an email link and works through a web response system (e.g. the university survey system);* ***AND*** respondent anonymity can be guaranteed, your answer will be NO.		

Please note that if ANY of the questions above have been answered in the affirmative (YES) the student will need to complete the full ethics clearance form (REC-H application) and submit it with the relevant documentation to the Faculty RECH (Ethics) representative.

and hereby certify that the student has given his/her research ethical consideration and full ethics approval is not required.

A. Collitz
SUPERVISOR(S)

24 April 2018
DATE

p.p. N. Jl
HEAD OF DEPARTMENT

10 May 2018
DATE

Mqwaqwa
STUDENT(S)

19 Apr 2018
DATE

Student(s) contact details (e.g. telephone number and email address):

basilmqwaqwa@gmail.com - 071 051 2889

Please ensure that the research methodology section from the proposal is attached to this form.

ANNEXURE C: QUESTIONNAIRE

Please place a tick for each selection, one tick per question. Please complete all questions.							
1. Demographics							
1.1	**Gender**	**Male**	**Female**				
1.2	**Age**	**18 - 25 Years**	**26 - 35 Years**	**36 - 45 Years**	**46 - 55 Years**	**56 - 65 Years**	
1.3	**Years of Service**	**Less Than 2 Years**	**2 - 4 Years**	**5 - 9 Years**	**10 Years+**		
1.4	**Job Level**	**Grade 1 - 6**	**Grade 8 - 9**	**Grade 10 - 11**	**Grade 12 - 14**	**Grade 15 - 16**	
1.5	**Education level**	**Below Matric**	**National Diploma**	**Undergraduate Degree**	**Post Graduate Degree**		
1.6	**Department**	**Production**	**IT & Engineering**	**Quality Assurance**	**Validation**	**Warehousing**	**Support Services**

In the following sections, please indicate by circling the appropriate number, the extent to which you agree with the following statements.

Please give a response for each statement.

No.	Skills and Training	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
2.1	Training is important when new technologies are implemented.	1	2	3	4	5
2.2	In my organisation, adequate training is provided when new technologies are introduced.	1	2	3	4	5
2.3	Training enhances my interest in new technologies.	1	2	3	4	5
2.4	New skills are required when technologies are implemented.	1	2	3	4	5
2.5	In my organisation, there is continuous investment in the improvement of my skills.	1	2	3	4	5
2.6	My organisation supports my learning and capability development.	1	2	3	4	5

No	Individual Characteristics	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
3.1	I trust my abilities to perform my organisational duties.	1	2	3	4	5
3.2	I easily adapt when new technologies are implemented.	1	2	3	4	5
3.3	Innovation / new technologies enhances my job performance.	1	2	3	4	5
3.4	I perceive new technologies as being easy to understand and use.	1	2	3	4	5
3.5	I take initiative in implementing new ideas or technologies.	1	2	3	4	5
3.6	I feel empowered to implement new ideas or innovation.	1	2	3	4	5
3.7	I view adaptability as important for new technologies.	1	2	3	4	5
No	**Trust**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
4.1	In my organisation, new technologies are reliable.	1	2	3	4	5
4.2	Good communication aids trust with new technologies.	1	2	3	4	5
4.3	My innovative ideas are taken seriously.	1	2	3	4	5
4.4	I get the support required to implement innovative ideas.	1	2	3	4	5
4.5	I rely on and trust automation.	1	2	3	4	5
4.6	I view my personal safety as an important factor when technologies are implemented.	1	2	3	4	5
4.7	I accept new technologies more readily from people I trust.	1	2	3	4	5
No	**Organisational Culture**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
5.1	The culture within my organisation actively encourages innovation and technology adoption.	1	2	3	4	5
5.2	The culture within my organisation is open and supports new innovative ideas.	1	2	3	4	5
5.3	An entrepreneurial-style culture is nurtured within my organisation	1	2	3	4	5
5.4	I am involved in the decision making process when innovation or new technologies are implemented.	1	2	3	4	5
5.5	Organisational culture supports innovation or new technologies adoption.	1	2	3	4	5
5.6	The new MES leadership culture will positively influence innovative / new technologies adoption.	1	2	3	4	5

No	Resources	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
6.1	Basic infrastructure exists to enable advanced technologies adoption.	1	2	3	4	5
6.2	My organisation has the required IT resources to adopt innovation and new technologies.	1	2	3	4	5
6.3	In my organisation, the IT department drives innovation.	1	2	3	4	5
6.4	Cost for innovation/new technologies is justified.	1	2	3	4	5
6.5	My organisation has the financial resources to adopt innovation or new technologies.	1	2	3	4	5
6.6	The benefits of innovation is greater than the cost of implementing new technologies.	1	2	3	4	5
No	**Job Security**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
7.1	I feel my job is secure, regardless of new technologies being implemented.	1	2	3	4	5
7.2	Job security is impacted negatively when new technologies are implemented.	1	2	3	4	5
7.3	My job security is more important than using new technologies.	1	2	3	4	5
7.4	Implementation of new technologies leads to job losses.	1	2	3	4	5
No	**Technology Acceptance**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
8.1	The implementation of innovation / technology will lower the cost within the organisation.	1	2	3	4	5
8.2	The implementation of innovation / technology will improve the productivity within the organisation.	1	2	3	4	5
8.3	The implementation of innovation / technology will improve the quality of products within the organisation.	1	2	3	4	5
8.4	The use of information will improve the organisation capabilities.	1	2	3	4	5
8.5	Innovation / new technologies will allow the organisation to gain and maintain a competitive advantage.	1	2	3	4	5
8.6	Training on the use of new technologies enhances my career opportunities.	1	2	3	4	5
8.7	Automation improves my job performance.	1	2	3	4	5
8.8	Innovation / new technologies increase complexity in my work environment.	1	2	3	4	5
8.9	Poor communication negatively influences new technology adoption.	1	2	3	4	5

8.10	Innovation / new technologies negatively impact career opportunities and development.	1	2	3	4	5
8.11	My job performance is affected negatively when innovation / technologies are implemented.	1	2	3	4	5
8.12	General support of colleagues is important for new technologies adoption.	1	2	3	4	5
8.13	New technologies increase the risk of cyber threats.	1	2	3	4	5
No	**Security International / National Standards**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
9.1	My organisation's information is secure when using new technologies (e.g. cloud computing)	1	2	3	4	5
9.2	The current laws and regulations are sufficient to protect the use of cloud computing.	1	2	3	4	5
9.3	International standards hinder the implementation of innovation and new technologies.	1	2	3	4	5
9.4	In general, new technologies (e,g. cloud computing) are more secure than traditional methods / technologies.	1	2	3	4	5
9.5	Government policies and initiatives encourage companies to adopt advanced technologies (e.g. Internet of Things)	1	2	3	4	5
No	**Parent Company**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
10.1	The parent company supports the adoption of new technologies in local subsidiary.	1	2	3	4	5
10.2	The parent company has implemented superior technologies.	1	2	3	4	5
10.3	Advanced technologies implemented within the parent company benefit the local subsidiaries.	1	2	3	4	5
10.4	The parent company supports new ideas in the subsidiaries.	1	2	3	4	5
10.5	The parent company understands local conditions when implementing new technologies.	1	2	3	4	5

ANNEXURE D: DISCRIPTIVE STATISTICS

Table D1: Dependent Variable Organisational Support by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,55**	**0,78**
Gender	Male	60	58%	3,53	0,85
	Female	44	42%	3,57	0,70
Age	18 - 35 years	38	37%	3,79	0,73
	36 - 45 years	42	40%	3,50	0,79
	46 - 65 years	24	23%	3,25	0,76
Years of Service	Less than 5 years	33	32%	3,74	0,71
	5 - 9 years	29	28%	3,59	0,81
	10 years or more	42	40%	3,37	0,80
Job Level	Grade 1 - 9	51	49%	3,60	0,77
	Grade 10 - 11	27	26%	3,70	0,62
	Grade 12 - 16	26	25%	3,28	0,91
Education Level	Not a degree	63	61%	3,58	0,79
	Under or Post Graduate Degree	41	39%	3,50	0,79

Table D2: Dependent Variable Training by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**4,48**	**0,52**
Gender	Male	60	58%	4,51	0,53
	Female	44	42%	4,44	0,50
Age	18 - 35 years	38	37%	4,50	0,46
	36 - 45 years	42	40%	4,50	0,48
	46 - 65 years	24	23%	4,42	0,66
Years of Service	Less than 5 years	33	32%	4,51	0,53
	5 - 9 years	29	28%	4,41	0,51
	10 years or more	42	40%	4,51	0,52
Job Level	Grade 1 - 9	51	49%	4,43	0,53
	Grade 10 - 11	27	26%	4,56	0,37
	Grade 12 - 16	26	25%	4,50	0,63
Education Level	Not a degree	63	61%	4,44	0,50
	Under or Post Graduate Degree	41	39%	4,55	0,55

Table D3: Dependent Variable Peer Support by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,53**	**0,60**
Gender	Male Female	60 44	58% 42%	3,55 3,49	0,58 0,64
Age	18 - 35 years 36 - 45 years 46 - 65 years	38 42 24	37% 40% 23%	3,68 3,42 3,47	0,54 0,65 0,58
Years of Service	Less than 5 years 5 - 9 years 10 years or more	33 29 42	32% 28% 40%	3,56 3,64 3,42	0,67 0,51 0,61
Job Level	Grade 1 - 9 Grade 10 - 11 Grade 12 - 16	51 27 26	49% 26% 25%	3,50 3,69 3,41	0,58 0,55 0,69
Education Level	Not a degree Under or Post Graduate Degree	63 41	61% 39%	3,57 3,46	0,57 0,65

Table D4: Dependent Variable Trust by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**4,17**	**0,43**
Gender	Male Female	60 44	58% 42%	4,19 4,14	0,42 0,44
Age	18 - 35 years 36 - 45 years 46 - 65 years	38 42 24	37% 40% 23%	4,18 4,17 4,17	0,46 0,39 0,45
Years of Service	Less than 5 years 5 - 9 years 10 years or more	33 29 42	32% 28% 40%	4,25 4,18 4,09	0,36 0,51 0,41
Job Level	Grade 1 - 9 Grade 10 - 11 Grade 12 - 16	51 27 26	49% 26% 25%	4,17 4,10 4,24	0,47 0,33 0,43
Education Level	Not a degree Under or Post Graduate Degree	63 41	61% 39%	4,20 4,12	0,40 0,47

Table D5: Dependent Variable Organisational Culture by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,46**	**0,65**
Gender	Male	60	58%	3,50	0,69
	Female	44	42%	3,40	0,60
Age	18 - 35 years	38	37%	3,66	0,54
	36 - 45 years	42	40%	3,43	0,67
	46 - 65 years	24	23%	3,18	0,69
Years of Service	Less than 5 years	33	32%	3,51	0,63
	5 - 9 years	29	28%	3,57	0,68
	10 years or more	42	40%	3,34	0,64
Job Level	Grade 1 - 9	51	49%	3,45	0,60
	Grade 10 - 11	27	26%	3,64	0,62
	Grade 12 - 16	26	25%	3,28	0,75
Education Level	Not a degree	63	61%	3,45	0,64
	Under or Post Graduate Degree	41	39%	3,47	0,67

Table D6: Dependent Variable Resources and Costs by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,75**	**0,56**
Gender	Male	60	58%	3,76	0,51
	Female	44	42%	3,73	0,64
Age	18 - 35 years	38	37%	3,75	0,70
	36 - 45 years	42	40%	3,71	0,49
	46 - 65 years	24	23%	3,79	0,45
Years of Service	Less than 5 years	33	32%	3,70	0,73
	5 - 9 years	29	28%	3,79	0,53
	10 years or more	42	40%	3,74	0,44
Job Level	Grade 1 - 9	51	49%	3,79	0,52
	Grade 10 - 11	27	26%	3,81	0,50
	Grade 12 - 16	26	25%	3,60	0,69
Education Level	Not a degree	63	61%	3,82	0,45
	Under or Post Graduate Degree	41	39%	3,63	0,70

Table D7: Dependent Variable Job Security by ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,41**	**0,73**
Gender	Male	60	58%	3,61	0,67
	Female	44	42%	3,14	0,74
Age	18 - 35 years	38	37%	3,61	0,63
	36 - 45 years	42	40%	3,33	0,75
	46 - 65 years	24	23%	3,22	0,81
Years of Service	Less than 5 years	33	32%	3,37	0,77
	5 - 9 years	29	28%	3,49	0,60
	10 years or more	42	40%	3,38	0,79
Job Level	Grade 1 - 9	51	49%	3,34	0,76
	Grade 10 - 11	27	26%	3,39	0,76
	Grade 12 - 16	26	25%	3,56	0,65
Education Level	Not a degree	63	61%	3,29	0,76
	Under or Post Graduate Degree	41	39%	3,59	0,66

Table D8: Dependent Variable Innovation and Technology Implementation ANOVA Factors

Factor	Level	n	Perc.	Mean	Std.Dev.
Total		**104**	**100%**	**3,73**	**0,50**
Gender	Male	60	58%	3,76	0,51
	Female	44	42%	3,67	0,50
Age	18 - 35 years	38	37%	3,93	0,45
	36 - 45 years	42	40%	3,56	0,50
	46 - 65 years	24	23%	3,70	0,50
Years of Service	Less than 5 years	33	32%	3,91	0,58
	5 - 9 years	29	28%	3,75	0,43
	10 years or more	42	40%	3,56	0,43
Job Level	Grade 1 - 9	51	49%	3,72	0,51
	Grade 10 - 11	27	26%	3,67	0,51
	Grade 12 - 16	26	25%	3,80	0,50
Education Level	Not a degree	63	61%	3,68	0,46
	Under or Post Graduate Degree	41	39%	3,79	0,56

ANNEXURE E: FREQUENCY DISTRIBUTION

Training and Development	Strongly Disagree		Disagree		Undecided		Agree		Strongly Agree	
Training is important when new technologies are implemented.	7	7%	0	0%	0	0%	15	14%	84	79%
In my organisation adequate training is provided when new technologies are introduced.	2	2%	16	15%	9	8%	67	63%	12	11%
Training enhances my interest in new technologies.	1	1%	1	1%	0	0%	67	63%	37	35%
New skills are required when technologies are implemented.	0	0%	0	0%	1	1%	44	42%	60	57%
In my organisation there is continuous investment in the improvement of my skills.	3	3%	19	18%	19	18%	57	54%	8	8%
My organisation supports my learning and capability development.	2	2%	16	15%	21	20%	59	56%	7	7%
Individual Characteristics	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
I trust my abilities to perform my organisational duties.	0	0%	0	0%	0	0%	67	64%	38	36%
I easily adapt when new technologies are implemented.	0	0%	4	4%	4	4%	70	66%	28	26%
Innovation / new technologies enhance my job performance.	1	1%	0	0%	3	3%	78	74%	24	23%
I perceive new technologies as being easy to understand and use.	0	0%	6	6%	7	7%	78	74%	15	14%
I take initiative in implementing new ideas or technologies.	0	0%	4	4%	11	10%	76	72%	15	14%
I feel empowered to implement new ideas or innovation.	2	2%	9	8%	10	9%	67	63%	18	17%
I view adaptability as important for new technologies.	0	0%	0	0%	0	0%	42	40%	64	60%
Trust	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
In my organisation, new technologies are reliable.	1	1%	4	4%	18	17%	80	75%	3	3%
Good communication aids trust with new technologies.	0	0%	0	0%	1	1%	54	51%	50	48%
My innovative ideas are taken seriously.	0	0%	16	15%	34	32%	51	48%	5	5%
I get the support required to implement innovative ideas.	2	2%	18	17%	27	25%	57	54%	2	2%
I rely on and trust automation.	0	0%	6	6%	18	17%	71	67%	11	10%
I view my personal safety as an important factor when technologies are implemented.	0	0%	1	1%	1	1%	47	44%	57	54%
I accept new technologies more readily from people I trust.	0	0%	4	4%	2	2%	72	69%	27	26%

Organisational Culture (n = 106)	Strongly Disagree		Disagree		Undecided		Agree		Strongly Agree	
The culture within my organisation actively encourages innovation and technology adoption.	1	1%	7	7%	15	14%	74	70%	9	8%
The culture within my organisation is open and supports new innovative ideas.	1	1%	15	14%	9	8%	73	69%	8	8%
An entrepreneurial-style culture is nurtured within my organisation.	2	2%	20	19%	28	26%	49	46%	7	7%
I am involved in the decision making process when innovation or new technologies are implemented.	14	13%	42	40%	10	9%	39	37%	1	1%
Organisational culture supports innovation or new technologies adoption.	1	1%	6	6%	23	22%	73	69%	3	3%
The new leadership 2020 culture will positively influence innovative / new technologies adoption.	0	0%	2	2%	30	28%	61	58%	13	12%
Resources and Costs	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
Basic infrastructure exists to enable advanced technologies adoption.	0	0%	5	5%	14	13%	74	70%	13	12%
My organisation has the required IT resources to adopt innovation and new technologies.	0	0%	9	9%	9	9%	69	66%	18	17%
In my organisation, the IT department drives innovation.	3	3%	12	11%	29	28%	54	51%	7	7%
Cost for innovation/new a technology is justified.	1	1%	6	6%	24	23%	68	65%	6	6%
My organisation has the financial resources to adopt innovation or new technologies.	0	0%	3	3%	10	10%	47	45%	45	43%
The benefits of innovation are greater than the cost of implementing new technologies.	0	0%	1	1%	21	20%	41	39%	43	41%
Job Security	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
I feel my job is secure regardless of new technologies being implemented.	4	4%	11	10%	23	22%	54	51%	13	12%
Job security is impacted negatively when new technologies are implemented.*	6	6%	15	14%	29	27%	50	47%	6	6%
My job security is more important than using new technologies.	1	1%	20	19%	9	9%	49	47%	26	25%
Implementation of new technologies leads to job losses.*	1	1%	28	26%	22	21%	52	49%	3	3%
Technology Acceptance	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
The implementation of innovation / technology will lower the cost within the organisation.	0	0%	5	5%	19	18%	65	61%	17	16%

The implementation of innovation / technology will improve the productivity within the organisation.	0	0%	1	1%	11	10%	75	71%	19	18%
The implementation of innovation / technology will improve the quality of products within the organisation.	0	0%	5	5%	6	6%	74	70%	21	20%
The use of information will improve the organisation capabilities.	0	0%	1	1%	1	1%	47	44%	57	54%
Innovation / new technologies will allow the organisation to gain and maintain a competitive advantage.	0	0%	0	0%	8	8%	40	38%	57	54%
Training on the use of new technologies enhances my career opportunities.	0	0%	0	0%	3	3%	73	70%	29	28%
Automation improves my job performance.	0	0%	1	1%	13	12%	68	64%	24	23%
Innovation / new technologies increase complexity in my work environment.*	5	5%	29	28%	42	40%	28	27%	1	1%
Poor communication negatively influences new technology adoption.	1	1%	0	0%	1	1%	35	33%	68	65%
Innovation / new technologies negatively impact career opportunities and development.*	1	1%	10	10%	17	16%	65	62%	12	11%
My job performance is affected negatively when innovation / technologies are implemented.*	0	0%	7	7%	14	13%	77	73%	8	8%
General support of colleagues is important for new technologies adoption.	0	0%	0	0%	6	6%	74	70%	26	25%
New technologies increase the risk of cyber threats.*	9	8%	61	58%	12	11%	22	21%	2	2%
Security International / National Standards	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
My organisations information is secure when using new technologies.	0	0%	4	4%	30	28%	42	40%	30	28%
The current laws and regulations are sufficient to protect the use of cloud computing.	1	1%	4	4%	74	70%	27	25%	0	0%
International standards hinder the implementation of innovation and new technologies.*	0	0%	27	25%	28	26%	48	45%	3	3%
In general new technologies are more secure than traditional methods / technologies.	1	1%	11	10%	29	27%	63	59%	2	2%
Government policies and initiatives encourage companies to adopt advanced technologies.	1	1%	12	11%	63	60%	27	26%	2	2%
Parent Company	**Strongly Disagree**		**Disagree**		**Undecided**		**Agree**		**Strongly Agree**	
The parent company supports the adoption of new technologies in local	0	0%	0	0%	25	24%	80	75%	1	1%

subsidiary.										
The parent company has implemented superior technologies.	0	0%	3	3%	57	54%	40	38%	6	6%
Advanced technologies implemented within the parent company benefit the local subsidiaries.	0	0%	2	2%	30	29%	69	66%	4	4%
The parent company supports new ideas in the subsidiaries.	0	0%	2	2%	23	22%	78	74%	2	2%
The parent company understands local conditions when implementing new technologies.	2	2%	13	12%	27	25%	64	60%	0	0%