The effect of investments in digital assets on the performance of the company

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ABSTRACT

The fourth industrial revolution (4IR) has been topical for South Africa as one of the strategies to gain a competitive advantage as a country. 4IR comprises artificial intelligence (AI), the internet of things (IoT), virtual and augmented reality, 3D manufacturing, and blockchain. Due to an increase in data volumes, the need for storage capacity and computational power, business intelligence, and cloud computing are also regarded as foundational technologies influencing trends. This study focuses on three categories of 4IR technologies namely, artificial intelligence, business intelligence (BI) & data sciences, and cloud computing to investigate the share price performance of companies listed on the Johannesburg Stock Exchange (JSE)

Using a quantitative design, an events study methodology is used based on the efficient market hypothesis. This determines whether public announcements made through the stock exchange news service (SENS) result in an increase in the share price and correspondingly market value measured through abnormal returns. The news tested was for a JSE listed company purchase of a target company to acquire digital fourth industrial revolution assets.

Four hypotheses were tested, whether share price showed any response to 4IR technology investments. Second, whether share price increase within three days after an announcement. Third, increase in abnormal returns on the day of the news release, and fourth, enquiry into increased abnormal returns three days after the announcement date. Empirical evidence failed to support hypotheses 1, 2, and 4, whereas hypothesis 3 was supported.

Significantly, BI data science related announcements could predict an increase in abnormal returns on the day of the announcement as well as the debt ratio. Whilst the adoption of 4IR technologies in South African corporates have increased, from the study one can infer that investors do not perceive a positive effect on wealth and value increase from these investments with the exception of business intelligence and data science investments.

KEY WORDS: Fourth industrial revolution technologies; abnormal returns, Event study

DECLARATION

I, *Senzekile Mofokeng*, declare that this research report is my own work except as indicated in the references and acknowledgments. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: *Senzekile Mofokeng* Signature: 

Signed at …*Ermelo*……

On the …*19*…… day of …*February*… 2021…

DEDICATION

I dedicate this research to my Divine Helper, God the Creator of heaven and earth, my husband: Frank Mofokeng, and my children: Ofenste, Nonala, and Nthabiseng Mofokeng.

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3D- Three dimension

4D- Four dimension

4IR- Fourth Industrial Revolution

AR- Augmented Reality

AI- Artificial Intelligence

BC- Block Chain

BI- Business Intelligence

JSE- Johannesburg Stock Exchange

IoT- Internet of Things

ICT- Information Communication Technology

RAISA- Robotics, Artificial Intelligence, and Service

SA- South Africa

VR- Virtual Reality

CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

The purpose of the study is to assess shareholder's reactions upon the announcement of news by a listed company (Purchaser) for the purchase of a company (Target) with digital assets specifically fourth industrial revolution technologies. The Purchaser's shareholder response is signalled through the share price of a firm. This study is a quantitative enquiry and employs event study methodology to measure significance of share price movement and/or abnormal returns in the purchasing company's listed stock.

1.2 Context of the study

The fourth industrial revolution has resulted in a change in the manner in which investors attribute value to companies. This is shown by the churn of companies within stock exchanges. Changes in technologies have shortened the life cycles of many companies. Companies that have not anticipated nor responded to society's demands in response to changing technologies have lost competitive advantage and some have exited the market.

In the late 1990s, it was noted that the technology industry had taken the dominant lead in global stock exchanges. In terms of market capitalisation, the highest valued company was Microsoft, then valued, at $ 538 billion. From 2014 technology companies picked up again as the market leaders, with Apple leading the pack at a market capitalisation of $ 560 billion (Desjardins, 2019). Up until 2019, the market remained in the digital era, and the 5 top companies in terms of market capitalisation are technology companies (see Figure 1).

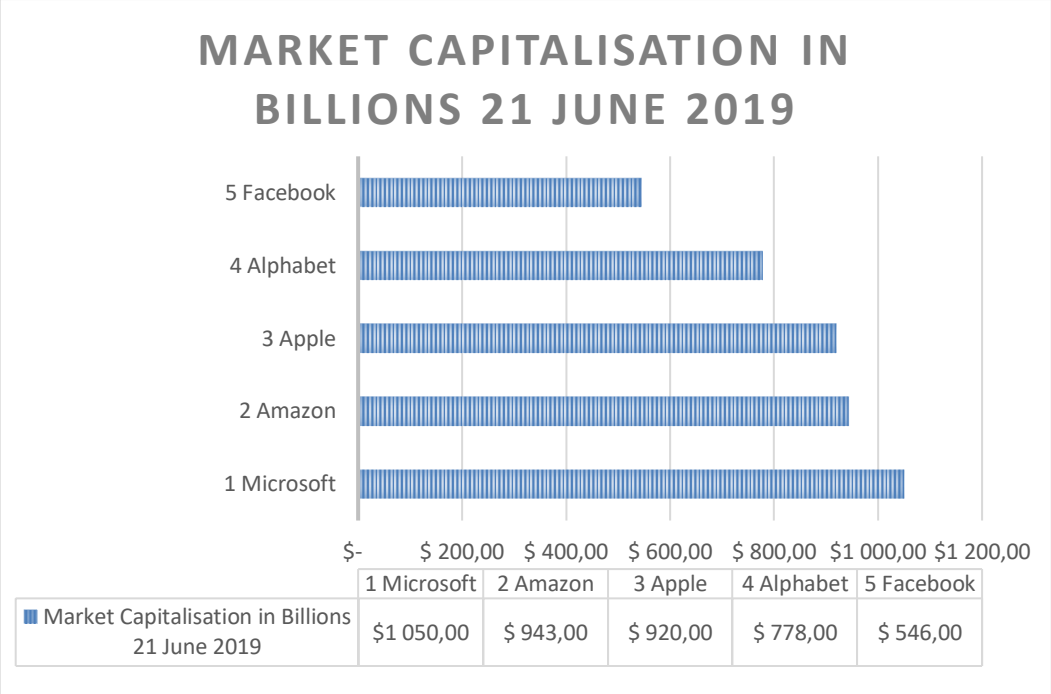

Figure 1: Visual capitalist top 5 market capitalisation Adapted from (Desjardins, 2019)

The top 5 companies in Figure1 were created during the digital era therefore; they have more digital assets than traditional companies do. Although these companies have high market values, their earnings do not justify these high market values. This is revealed by their high Price Earnings (P/E) ratios, which indicate high share prices but with low earnings.

A study on Google and Facebook argued that customers intrinsically value these companies highly despite customers using the platforms for free as these companies rely on the prospect of future revenue from advertising (Herzog, 2018).

Another view introduced the rise of super-firms depicted by high market concentration, high profitability and low labour share. The rationale for the concentration is that these firms have high investments in technology; consumers are price-sensitive as they can compare prices on the internet; customised products and increased network effect (Autor et al., 2017).

Digital technology has enabled organisations to compete globally, thus increasing the customer base or the network in which the product can be consumed. The

scale at which revenue grows for these companies is accelerated in that they have a global network in which business is effectively carried out. With the benefit of digitization towards cost reduction and increased revenues, both market and book values of organisations with digital capital are expected to be high. However, the book values or accounting indicators appear to be lower than expected.

In relation to the investment in digital technologies, a study on 184 listed companies concluded that companies with high digital intensity (investments in digital technologies intended to improve business operations) and high transformation management intensity (investments in leadership, governance, and business/IT networks) perform higher than their peers by outperforming the industry by an average of 6-9%. Further, the study proposes that a high percentage of information technology companies are the drivers for digital transformation (Westerman & McAfee, 2012).

The rise of digitisation has intensified in the fourth industrial revolution (4IR), causing the gap to widen between the value reported by organisations and the value quoted on financial markets or stock exchanges. One reason presented for the gap pertains to intangible assets, such as brand equity, intellectual capital, technology, patents, and client portfolios.

Another attribution relates to differences between the new economy which is knowledge-based, promoting increased regard of intangible assets whereas, the old advocated for more tangible assets (Gouveia, Silva, Szuster, & Szuster, 2018) The gap between the book value of the organisation and the market cannot be explained by any finance theory but by shareholder sentiment (Brown & Cliff, 2005).

Digital capital manifests in the form of tangible and intangible assets, meanwhile, only tangible assets are stated on the company's financial statements. The intangible assets include, but are not limited to, monetising data analytics and enhancing customer experience through intelligent capture of user behaviour. Intangible digital assets are largely unaccounted for, yet they are strategic assets

that can unlock competitive advantage and growth (Bughin & Manyika, 2013). A mind-set shift is needed among decision makers to expand understanding of optimal investment into digital assets. Currall, Johnson, & McKinney (2008) state that one should understand the value of the digital asset, the technological fragility, and the need for support to ensure that the asset is preserved.

From a quality perspective, the asset ratios of these companies are significantly low compared to the income generated. One of the explanations is that this gap is caused by the differences in which accounting standards account for digital assets on the balance sheet, for example, research and development are expensed instead of capitalised (Gouveia et al., 2018). Evidently, accounting, finance, and economic valuation methods have been lagging in identifying the true value of digitalisation (Bughin & Manyika, 2013).

The introduction of digital technology has lowered the cost of research, replication, transportation, tracking, and verification. All these costs are necessary for attracting customers, either by increasing revenue or reducing the cost of doing business and in turn, increasing profitability. Digitisation has changed how business is conducted both from a customer perspective and for organisations. For example, digital competency has increased the provision of free services to the customers, as well as accelerating the speed of business adjusting product lifecycles (Goldfarb & Tucker, 2019). Therefore, the market can no longer rely on accounting principles alone to measure the value of an investment in digital technology. An alternative method to evaluate the investment in digital assets is the stock market.

Globally, specifically in more advanced digital countries such as Israel, Japan, Sweden, the United Kingdom, and the United States; digital capital is rapidly growing and contributes approximately 8,5 percent of nominal gross domestic product (Du Rausas et al., 2011). This contribution can be traced back to increased economic productivity as a result of the use of technology thus changing the manner of work for human resources, promoting more skilled labour (Du Rausas et al., 2011).

The author concludes that digital capital is a source of wealth however, the distribution of income created by digital capital still needs to be debated (Du Rausas et al., 2011).

The rise of digital economics especially in the United States resulted in several investment capital deals and the founders and shareholders of those organisations were made wealthy. In the South African context, 4IR issues have been topical and explained as to how society engages and uses technology for the country's competitive advantage (Ntsabo, 2019). This trend can be assessed using companies listed on the Johannesburg Stock Exchange (JSE). It is expected that the ICT industry will be the leader in implementing this technology as they provide thought leadership and consulting services to other firms listed on the JSE.

1.3 Research problem

1.3.1 *Effect of announcements of technology investments.*

It has been difficult to prove that investments in technology have a direct impact on the performance of firms. Studies within finance and IT have used the event study method to predict a relationship between technology investments and company performance. An analysis of twenty-four studies where researchers measured the effect of information technology investments on the performance of the company using events studies was carried out. The results proved that there was a relationship (positive, indifferent, or adverse) between the investment in technology and the performance of an organisation's share price (Roztocki & Weistroffer, 2009).

However, listed companies within the South African context have not performed similar studies for announcements on purchases of digital technology. This is particularly relevant within the 4IR in that the consolidation of digital assets has resulted in digital technologies that have transformed how society interacts with technology, consumes information, and purchases products.

Elsewhere, companies that have been efficient in understanding society's demands have been seen to dominate stock markets. This study seeks to determine whether announcements for the purchase of digital assets in the target company result in an increase in share price and an increase in abnormal returns for the purchaser.

1.3.2 *Effect of announcing technology purchases on share price*

The debate on whether accounting income has an impact on the share price began in the 1960s. It was proven that the relationship between accounting income and the share price reflected economic relevance rather than statistical relevance, however, economic information needed to be used (Ball & Brown, 1968; Ball, Ray & Brown, 2014).

This birthed the theory of efficient market which advocates that the market price of a share reflects all available and relevant information for the firm (Fama, 1970b; 1991). Fama (1991) describes three degrees of efficiency, weak, semi-strong, and strong. In a weak market, efficient share prices reflect current market information and cannot predict future price movements. The semi-strong market information reflects publicly available information therefore no returns can be obtained from trading the information. While in a strong market, the share price reflects all private and publicly available information and at this point, abnormal returns are nullified.

The effect of an announcement will affect the share price either positively or negatively depending on the type of announcement. For example, bad news- that is news that will decrease the future cash flows of the company - will affect the share price negatively. Whereas good news, that is news that will increase the future cash flows of the company, will have a positive share price impact resulting in abnormal returns. Empirical evidence has been obtained through JSE studies on the impact of announcements on dividends (Wesson, Smit, Kidd, & Hamman, 2018), share buybacks (Punwasi & Brijlal, 2016), earnings (Maraisane, 2016), and Broad-based economic empowerment announcements (Ward & Muller, 2010).

1.4 Research objectives

The objective of this study is to evaluate the effect of digital assets investments, within the fourth industrial revolution, on firms. Performance of these activities will be evaluated through changes in the share price and whether there are significant abnormal returns because of announcements made by the purchasing company.

1.5 Research questions

1. What is the effect of investments in fourth industrial revolution digital assets on the share price of the purchaser?

2. Which of the fourth industrial revolution technologies have more effect on changes in share price?

3. Is there an increase in abnormal returns as a result of the announcements made for investments in fourth industrial revolution technologies?

1.6 Hypotheses

In order to achieve the objective, the following hypotheses were formulated, the null hypothesis (H0) and the alternative hypothesis (H1) which may be described as follows:

Hypothesis 1: Increase in the share price on the day of the announcement

H0: There is no significant increase in the share price for the purchaser on the day of the announcement of the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in the share price for the purchaser on the day of the announcement of the purchase of digital assets used in the fourth industrial revolution in the target company.

Hypothesis 2: Increase in share price three days after the announcement date

H0: There is no significant increase in the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company.

Hypothesis 3: Increase in abnormal returns on the day of the announcement

H0: There is no significant increase in abnormal returns on the share price for the purchaser on the day of the announcement of the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in abnormal returns on the share price for the purchaser on the day of the announcement of the purchase of digital assets used in the fourth industrial revolution in the target company.

Hypothesis 4: Increase in abnormal returns three days after the announcement date

H0: There is no significant increase in abnormal returns on the share price for the purchaser three days after the announcement date of purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in abnormal returns on the share price for the purchaser three days after the announcement date of purchase of digital assets used in the fourth industrial revolution in the target company.

1.7 Significance of the study

Digitally led economies have changed how businesses are carried out. Specifically, the way society interacts, and the mode in which wealth is created and distributed. Financial Statements do not reflect all available and relevant information. This information needs to be combined with public and other private information for shareholders to make informed decisions.

According to the efficient market hypothesis (EMH) theory, this information is encapsulated in the share price. It is therefore imperative to understand whether the purchase of digital technology affects the share price. The findings from this study will assist in understanding whether investors see value in digital investments. Abnormal returns will be calculated to identify whether digital investments result in economic benefit for shareholders.

1.8 Delimitations of the study

The fourth industrial revolution technologies are still in an infancy state in South Africa and yet set to serve as a tool to obtain a competitive advantage. Therefore, it may be assumed that some companies may not want to disclose the implementation of these technologies to be the first movers within the industry and thus capture maximum return on investments.

1.9 Definition of key terms

Announcement – Acquisition declaration made by the company communicated to shareholders through stock exchange news service (SENS).

Company- A Company is defined in section 1 of the Income Tax Act No. 58 of 1962 as including any association, corporation or company incorporated, formed or established by or under any law enforcement or previously so in South Africa or established under the law of any country other than South Africa.

Event day- The day of the acquisition/ merger announcement as published on SENS.

Event window period- The period from announcement day up to three days after the announcement day.

Share price- the price of a particular company's shares (Cambridge Dictionary, 2020). In this study, a share price indicates a unit price for an individual share of an ICT company listed on the JSE.

Share price reaction- The increase or decrease of the share price because of the acquisition announcement.

Intrinsic value- The perceived or calculated value of a company, including tangible and intangible factors, using fundamental analysis.

Johannesburg Stock Exchange (JSE)- The JSE was established in late 1887 and began as an institution to source finance for the gold mining sector (Lukasiewicz, 2017).

1.10 Assumptions

The assumptions will be based on the factors that affect the efficiency of a market as per the EMH theory. Firstly, the market must have a large number of participants such as investors, analysts, and traders. Secondly, information is readily available. Thirdly, there are price differences between markets, which enables a shareholder to buy a share in one market and sell at a higher price in another; this means that there are no inhibitions to buying and selling a share. Fourthly, the cost of transacting is low. The existence of these factors means that share prices will respond straightaway with the release of any new information (Zhou, 2018).

An underlying assumption of this study is that the JSE meets all the above factors and therefore it is an efficient market.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The literature review will commence with a history of the fourth industrial revolution and how it has changed organisations and societies. The dominant technologies are defined, their application, and their impact on the business environment discussed. Data on how the technology is being integrated to provide services or used in applications is also included.

Thereafter the literature will discuss the base theory of efficient markets followed by a review of the character and effects of fourth industrial revolution technologies on the market valuation of the firm.

2.2 Background discussion

The objective of this paper is to identify whether the investment in digital technology affects the share price of a company. The performance of the company will be measured by changes in the share price of the purchasing company on the stock market.

The first phase in investigating the phenomenon is to understand the context and characteristics of digital assets and technology.

The first computer was designed in 1939 with the primary purpose of enabling large computations (Brynjolfsson & Hitt, 2000). This was followed by the development of an electronic computer without moving parts designed in 1943 which required smaller storage space and reduced energy utilisation (Brynjolfsson & Hitt, 2000). An acceleration in technology development occurred during World War II, which resulted in the launch of the first digital computer (Brynjolfsson & Hitt, 2000). This digital technology formed the basis of storage, retrieval, organisation, transmission, and transformation of any digital information to numbers, text, video, music, speech, and programs (Brynjolfsson & Hitt, 2000).

As time passed computers became more powerful and cheaper enabling businesses to utilise them to solve problems and thus become more efficient at realising value for the business. The cost-benefit of digital technology stems from a reduction in coordination, communication, and information processing costs, which results in higher productivity and organisational transformation. The author concludes that measuring intangible assets arising from information technology complementary products is a gap that requires further research (Brynjolfsson & Hitt, 2000).

Brynojolfsson & Hitt (2000) document the genealogy of digital technology. Goldfarb & Tucker (2019) who highlight that digital technology results in lower marginal costs of reproducing information enhanced this. The authors underscore the fact that the benefit of digital technology was enhanced by the internet, as it enabled communication across computers thus creating networks. The commercialisation of the internet introduced new technologies and services such as artificial intelligence, block chain, e-commerce, cybersecurity, data analytics, the internet of things, and social media to mention a few current technologies (Goldfarb & Tucker, 2019)

The transition to the information age from the industrial period termed the fourth industrial revolution (4IR), has resulted in value assets changing form, from tangible to intangible (Hsu, Li-Chang; Wang, 2012).

2.2.1 *Digital Technology*

Digital technology is defined as the encoding of analogue information into a digital format being audio, text, and or video format, which can be stored, transferred, traced, and transformed. It has transformed how society interacts as it draws from traditional theories of behavioural sciences and design thinking to solve current issues (Yoo, 2010). Digital technology in a business context categorises digital capital into digital artifacts, digital platforms, and digital infrastructure. Artifacts are components of a product or service defining the functional value to the customer (Nambisan, 2017).

Platforms are the architecture, which encompasses the production, marketing, and distribution, of shared services within the digital ecosystem. Examples include Google and Android. Whereas digital infrastructure is the system that combines different technologies to solve business problems, for example, cloud computing and data analytics (Nambisan, 2017). These technologies have blurred the lines between social, economic, and business disciplines of commerce and as such have provided businesses with a wide spectrum of new opportunities.

Furthermore, digital technology has converged industries yielding the benefit of providing a holistic product to the customer. For example, Amazon operates as an e-commerce retailer but also competes with Google on the provision of business-to-business cloud computing services. The converging of industries has allowed companies to have multiple revenue streams and some to saturate the market gaining higher market shares and creating oligopolistic or monopolistic industries. Socially there are growing concerns of a digital divide. Those with access to digital technology will gain more opportunities to prosper thus widening the inequality gap (Ruotsalainen, Heinonen, Karjalainen, & Parkkinen, 2016).

2.2.2 *Source of value for digital technology*

In the late 1700s, value was defined as the manufacture and trade of goods. The exchange and distribution of goods through exports for a fair value resulted in the economic theory of a firm. In the 1900's physical goods were actively marketed resulting in the economic activity being a hybrid of the sale of physical goods and services thus enhancing customer management. In the late 2000's the source of value was attributed to co-creation through collaboration between customers and value chain partners to create sustained value for all parties within the value chain (Lusch, Robert, Vargo, & O' Brien, 2007). To realise holistic value for digital transformation, organisations need to collaborate with value chain customers and with customers for effective planning.

The revolution occurred in 2010 where the convergence of mobile technology, social media, and analytics was used optimally to benefit commercial activities. Through business model innovation companies were able to disrupt their

industries by providing and extracting more value from customers (Rachinger, Rauter, Müller, Vorraber, & Schirgi, 2019).

Chew et.al. (2013) describes customer value from co-created digital firms to arise from two sources, one being use value and the other being exchange. Use value is the perceived value of a good or service measured by consumer experience from a service or the quality of the product. Whereas exchange value is the monetary value for the purchase of the good or service (Chew, Semmelrock-Picej & Novak, 2013).

From an organisational perspective, the digital technologies through globalisation result in larger networks, which can be translated, to revenue and therefore capital for future investments. The revenue realised from services, intangible assets, produces higher benefits when compared to physical assets.

Brynjolfsoon & Hitt (2000) argue that investment in information technology does not realise the expected benefits if it is not combined with intangible services such as organisational change management or highly skilled employees. It is the combination of the organisations' internal capabilities that enable the investment in digital technology to unlock value.

2.2.3 *Intangible assets complementarities*

The use of digital technologies enables companies to have dynamic capabilities. However, the organisation must complement investment into technology with organisational change processes and structures to realise maximum returns. The existence of intangible assets is evident through high market valuations in the short run and increased economic productivity in the long run. When combined with investments in technology intangible assets became complements that realise synergies. Financial market value is the discounted value in the current period of future returns (Brynjolfsson, Hitt, & Yang, 1998).

Relatedly, accounting theory for measuring assets is aligned to the manufacturing economic era, where tangible assets were reported as capital expenditure and human capital costs were expensed (Damodaran, 2009). This theory did not

consider the investments made in intangible assets such as research and development (R&D). These activities form a major part of the investment into intangible assets; and have caused inconsistencies in accounting for investments in intangible assets. Financial markets are observed to be better at estimating the true value of intangibles as investors know what the firm is investing in to generate future growth and thus guide measure of the correct rate of return on invested capital (Damodaran, 2009).

The nature of the fourth industrial revolution has enhanced the interconnectedness of intangible assets. Investment into digital technologies requires interlinking of resources to realise the financial returns that an organisation requires. However, an increase in company performance cannot be exclusively related to digital technologies, it requires cognisance of the cohesive complement of business assets as a whole (Hsu et al., 2012).

Accounting principles for the presentation and disclosure of intangible assets are also noted to fail in comprehensively reflecting the value of assets within the information economy (Gouveia et al., 2018). Not all intangible assets are recorded in the financial statements of corporates, as they do not qualify to be recorded according to the accounting framework definition and recognition criteria.

The recognition criteria test fails due to uncertainty of future revenues; meanwhile, the cost is expensed in the profit and loss. These result in a mismatch between the revenues generated by the unrecognised assets versus total assets recognised. This is an indication that the accounting framework has not caught up with the digital economy in recognising intangible sources of value. This is an indication that the value of the firm is best measured by market performance, which is the share price.

In conclusion, the study seeks to examine whether investing in digital assets prevalent within 4IR increases company performance measured by the share price or abnormal returns. The literature indicates a sequence of events towards the fourth industrial revolution and the importance of digital technology in enhancing business performance in this era. The cohesive integration of tangible

and intangible resources is discussed. Further highlighting the gap of measuring business performance by traditional accounting measures at it does not take into account intangible assets concluding that the share price captures all value of the organisation.

2.3 The fourth industrial revolution (4IR)

The industrial revolution deals with the invention of innovative technology, which transforms how society conducts business resulting in growth transitions for economies. The first industrial revolution started in 1760 with the invention of the steam engine, this technology transitioned the economy from farming to manufacturing. The second revolution followed in 1900 with the invention of the internal combustion engine resulting in electricity, this rapidly transformed the manufacturing industry to mass production. The third revolution started in 1960 with the invention of digital technologies, which resulted in the use of electronics and information technology to automate production (Xu, David, & Kim, 2018).

Levin & Cunningham (2018) detail the phases of the industrial revolution, the first being the steam engine, followed by electricity, thereafter the fourth-generation. The key drivers of 4IR are an increase in the availability of data, an increase in performance of computers, an increase in connectivity enabled by the network infrastructure, and an increase in human and machine interaction (Levin & Cunningham, 2018)

There is a consensus amongst researchers that the world is in the fourth industrial revolution (Vogelsang, 2010; Makridakis, 2017; Levin & Cunningham, 2018; Xu et al., 2018). However, Makridakis (2017) proposes that 1990 was the beginning of a new revolution, the revolution of intelligence. The author postulates that artificial intelligence machines will replace human tasks as computer algorithms become so advanced as to imitate human reasoning and functions. The term Artificial Intelligence (AI) was first mentioned in 1955 by a math professor, who held a seminar on the subject, this term has evolved to encapsulate machine learning, deep learning, neuro network learning amongst other advancements (Brynjolfsson, & Mcafee, 2017)

Technologies from the first revolution up to the present have transformed how business is conducted. Businesses, which leveraged these technologies, had a competitive advantage and through business, efficiencies realised higher profits. The significant difference with the fourth industrial revolution is the speed at which technologies are being adopted. It took two hundred years to experience the full impact of the first industrial revolution and forty years to experience the impact of the digital revolution.

The AI revolution is estimated to wield full effect in less than 10 years (Makridakis, 2017). This was confirmed by Schwab (2017) who states that the differentiator of the fourth industrial revolution is the speed and the depth of convergence in technologies, industries, and governments.

The quantum impact of these technologies is driven by innovation to invent new products rather than mere access to the new capabilities (Brynjolfsson, & Mcafee, 2017)

2.3.1 *Digital Transformation*

Digital transformation is the process of accelerated global adoption of digital technology by society, businesses, and nations (Khan, 2016). It is the redesign of business operating models through the collaboration of ecosystems to meet similar goals (Berman, 2012; Nachira, 2007). The resulting global collaborations across firms to co-create are set to blur the lines between value chains, industries, and the public sector (Collin et al., 2015). This interconnection of businesses across industries and geographies is necessary to create value for the customer (Rachinger et al., 2019). Additional benefits will also accrue through optimisation of business processes, unlocking efficiencies to realise value for global competitive advantage (Chew, Semmelrock-Picej & Novak, 2013).

2.3.2 *The fourth Industrial Revolution within South African*

The term fourth industrial revolution has been topical in South Africa specifically in the government spheres. Relatedly, digital transformation has become a topical reference in the business environment. The term was first mentioned in

the 1940s and now gaining popularity in South Africa. However advancements into this phase of the revolution remain highly varied globally (Levin & Cunningham, 2018).

The 2016 World Economic Forum Networked Readiness Index estimates the readiness of countries to support fourth industrial technologies. South Africa is ranked 65th out of 70 countries globally. Whilst the country is performing well on rolling out network infrastructure, providing affordable access; conversely, it lacks the innovation and venture capital funding to drive progress (Lanvin et al., 2016).

The ranking does indicate that South Africa is participating in the fourth industrial revolution. However, some challenges must be attended such as high rates of inequality and the readiness indexes may not have factored in the skewed distribution of the infrastructure across the country. The effect on business is that firms within urban metropoles may be advantaged whereas those in small economic centres may not be obtaining benefit at all. The size of the business community also affects access and use of the fourth industrial revolution technologies. In this regard, South Africa has pockets of 4IR level excellence whilst some parts of the country are still in the second revolution as they lack access to basic infrastructure such as electricity (Manda & Backhouse, 2018).

Because the concept of the fourth industrial revolution and digital technologies have not been researched extensively in South Africa, the literature review includes a brief explanation of these technologies.

2.3.3 *The fourth-generation technologies*

Levin & Cunningham (2018) grouped the fourth industrial technologies into seven areas as illustrated in Table 1 below. This study focuses on five technologies namely business intelligence & data analytics; cloud computing and artificial intelligence as these can be used across business sectors. Technologies related to advanced nanomaterials such as block chain, energy capture, storage, transmission are excluded as they are specialised in nature and specific to niche industries.

Table 1: Fourth Industrial Revolution Technologies

Technology	Description	Impact on performance
Artificial intelligence and robotics	Development of machines that can substitute for humans, increasingly in tasks	There is limited research on the effect of investments on AI concerning the performance of the firm. Fethi & Pasiouras, (2010) analysed bank operational effectiveness using AI to augment performance. Part of the factors used to measure effectiveness is size, profitability, capitalisation, loans to assets, and revenues.
Block Chain	Distributed ledger technology based on cryptographic systems that manage, verify, and publicly record transaction data; the basis of "cryptocurrencies" such as bitcoin (Levin & Cunningham, 2018	Zhou, 2018 used the event study methodology to assess the announcement effect of blockchain investment on stock prices for Financial Companies in the Netherlands. The author concludes that blockchain announcements have a positive impact on the share price of smaller firms compared to larger firms. Further, the stage of the project affects the stock price, the new product phase have minimal impact compared to the initiation and continuation phase (Zhou, 2018).
Ubiquitous linked sensors (Internet of Things)	Also known as the "Internet of Things". The use of networked sensors to remotely connect, track and manage products, systems, and grids.	Xu, J., & Jin (2016) investigated the effect of IoT R&D expenditure on the performance of the company but failed to accept the hypothesis that a positive correlation exists between the IoT research and development and the performance of the company.

Virtual and augmented realities	Next-step interfaces between humans and computers involving immersive environments, holographic readouts, and digitally produced overlays for mixed-reality experiences.	Niaki & Nonino, (2017) examined the use of 3D printing on the competitiveness of firms and concluded that 3D improves competitiveness for small to medium-sized enterprises. These businesses become innovative in creating customised products and so they can charge higher prices yielding higher revenues. Customers are serviced better and there is an increase in the speed of products reaching targeted markets. The return on investment is also proven to be higher except for companies using plastic as a raw material that have a longer payback period.
Business Intelligence & Analytics	Business Intelligence is the use of analytical tools to analyse complex operational data to assist businesses to make decisions to improve competitiveness (Negash, S., & Gray, 2008)	Rubin & Rubin, (2013) postulate that investments into business intelligence (BI) reduces stock volatility, thus reducing financial risk. Further, a positive correlation between business performance and investment in BI & analytics has been observed (Torres, Sidorova, & Jones, 2018). BI inputs were in the form of infrastructure, quality management capability, and personal expertise for BI&A management. These investments produce dynamic capabilities, which are sensing, seizing, and process change, which result in functional performance and contributes to the firm's performance. The article proved that there is a positive correlation between inputs and capabilities except for personal expertise with the sensing capability. There is a positive correlation between dynamic capability and functional

		performance and finally a positive correlation between functional performance and firm performance.
Cloud computing	Cloud computing consists of hardware and software services over the internet. Hayes (2008) defines it as the migration of computational activity from geographically based company servers to a remote location and sometimes multiple remote locations where the service/server is shared amongst other users.	(Mahmood, Arslan, Dandu & Udo (2014) used an event study methodology to assess whether there were abnormal returns between adopters of cloud and non-adopters. The author concluded that cloud adopters experience significantly statistical abnormal returns during the announcement period.

2.3.4 *Conclusion on fourth industrial revolution technologies*

The fourth industrial revolution technologies are predicted to provide competitive advantage; change business models; improve customer satisfaction and change how customers interact with businesses through social media. In the literature, it is evident that the technologies do not exist independently but are interconnected. Of the five technologies, artificial intelligence (AI) appears to be an input to virtual and augmented reality (VAR), the internet of things (IoT), and blockchain. The literature also highlights that blockchain is an input to the internet of things. This interaction of the technologies is depicted in Figure 2 below.

Figure 2: Interconnectedness of 4IR Technolog

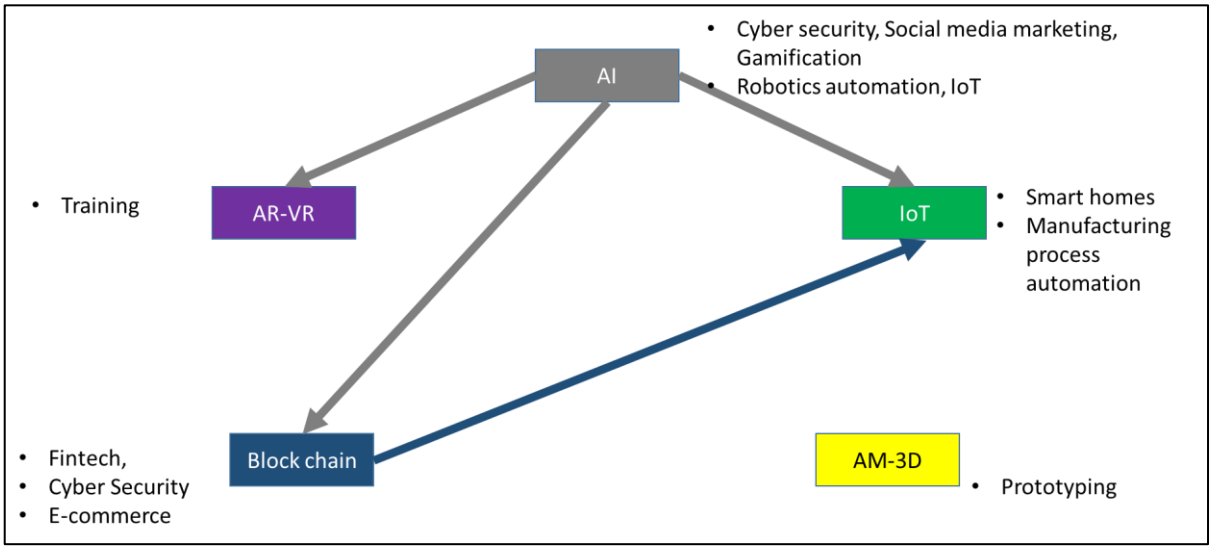

Figure 2: Interconnectedness of 4IR Technologies Source: Researcher

Business intelligence and data analytics as well as cloud computing form the foundation for the five fourth industrial revolution digital technologies. The connection of all the technologies is depicted in Figure 3.

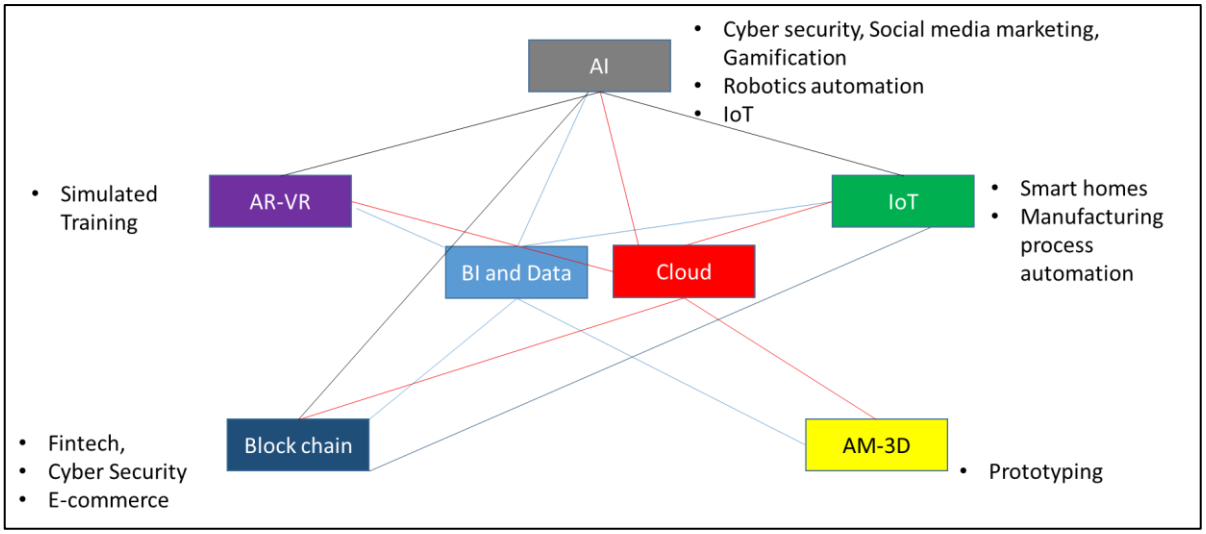

Figure 3: Interconnectedness of 4IR technology including BI & Cloud
Source: Researcher

This study focuses on business intelligence & data analytics; cloud computing and artificial intelligence as these technologies are used as input technologies or are interconnected with more than two fourth industrial revolution technologies.

2.4 Efficient market hypothesis (EMH)

Fama (1995) explains two general approaches of predicting stock markets; one is technical and the other a fundamental perspective. The technical perspective states that historical trends are unlikely to occur in the future. Random walk theory aligns with the technical view which concludes that movements in share price are independent of each other. Specifically, events cannot predict future share prices therefore, an investor cannot use prior knowledge to obtain superior gains (Fama, 1995).

The fundamentalist perception is that a share price has an intrinsic value or an equilibrium price, which depends on the earnings potential of the share. The foundational assumption of the theory is that markets are efficient. The current share price of a stock reflects all available information of events that have occurred or which will occur in the future. This means that the actual price of the share is a good estimate of its intrinsic value or equilibrium price and new information causes the intrinsic value to change (Fama, 1995).

In defining the random walk theory Kendal (1953) proved through statistical modelling that market price movements are independent that historic data cannot predict future share prices. Contrary to this view, however, the theory was empirically tested and it emerged that there is a statistically significant correlation between historic data and future share prices (Fama, 1965). The data indicated that there are trends in the markets and that the past can repeat itself.

As established in the discussion thus far, the theory of efficient markets maintains that share price fully reflects all publicly available information (Fama, 1970a). Investors react instantaneously to market information; therefore, the share price reflects all publicly available information. No profits can be made from new information. Three different market forms emerge:

- A **weak form** in which the share price is a presentation of historic information, new information does not change the share price or provide abnormal returns.
- A **semi-strong** market in which the share price can adjust to new publicly available information such as announcements. The share price reacts at the time of the announcement.
- A **strong form** in this instance there is the inclusion of insider information privy to a few investors.

This study will be based on the semi-strong view, that publicly available information affects the market value of the organisation.

The efficient market hypothesis gave rise to the event study method of assessing the effectiveness of public announcements on share values. Price reactions are measured through abnormal returns, calculated as the difference between normal and market indices returns over the event window (Cowan, 1992). The event window is determined at the discretion of the researcher. Corrado (1989) set precedent for using an event window of one day. Other scholars recommend an ad-hoc flexible method in determining the event period guided by three rules 1) abnormal returns 2) trading activity 3) intraday volatility (Krivin, Patton, Rose, & Tabak, 2003). The authors conclude by proposing that a researcher may use a period in which the market incorporates processed information. Three event

windows are used in this study being three days before the announcement date, day zero being the announcement date and day three being three days after the announcement date. Three days was selected as, after three days the strength of the estimation model is reduced (Lin, Jang, & Chen, 2007; Jacobs, Singhal, & Subramania, 2010).

Shleifer (2000) tested for abnormal returns linked to news of takeover attempts. The study concluded that share price increases before the announcement meant that some news had leaked on the day of the announcement. Investors were noted to react to the announcement and then the share price steadied post the announcement. In the long run, there are no profits as a result of announcements or news (Fama, 1965). In addition, Malkiel (2003) proved that portfolios did not outperform benchmark indices.

In advancing insight into EMH theory, researchers have used neural network technology within artificial intelligence to predict future share prices (Khan, Alin, & Hussain, 2011). The authors stipulate that the reason for seeking to predict stock prices is to yield a higher rate of return on investments above the market rates. The study concludes that the system posed some level of error and would need to be provided with more input to accurately predict stock changes. Relatedly, Nelson, Pereira & de Oliveira (2017) proved that the long-short term memory machine learning algorithm appeared to be more accurate than other neutral network algorithms however, the results still indicated a high variance compared to actual prices

2.5 Technology investments events studies

Investments in IT have been studied in the past however, it has been uncertain whether the investments have tangible payoffs and whether IT factors influence the performance of company share values. The stock market is one of the methods to evaluate company performance using the event study methodology (Roztocki & Weistroffer, 2009) This section of the review discusses scholarly experiences with event studies applied on different 4IR technologies.

2.5.1 *Event study on artificial intelligence*

Intrigued by the rise in artificial intelligence investment over the period 2013 to 2019 on the USA stock exchange, Burnickas (2019) investigated its effects on the financial performance of businesses using an event study methodology. The study explored the existence of abnormal returns between AI and non-AI announcements on the acquirers' share price.

The findings indicate the existence of abnormal returns on the day of announcement for AI related announcements, whilst the opposite occurred for non-AI announcements. A day and two days after the announcements both AI and non-AI targets showed a drop in share prices, thus revealing a negative effect.

2.5.2 *Event study on business intelligence and big data*

Rubin & Rubin (2013) identified an increase in BI expenditure and benefits related to insight captured in decision making and information sharing. The author used an event study format as the method captures impact from both tangible and intangible assets in the market value. The objective of the study was to measure stock return volatility as a result of BI investment announcements. The study was based on 129 BI announcements from 2000-2007, using the generalised auto-regression conditional heteroscedasticity (GARCH) model.

The findings indicate that stock return volatility was lower upon the deployment of BI implying that information access resulted in performance stability. For investors lower volatility means lower risk and an increased likelihood for wealth creation.

Relatedly, Tony, Wang, and Tsai (2016) investigated whether abnormal returns existed as a result of big data investment announcements. The study sampled 40 companies from 2010 to 2015. Eighteen companies had made big data announcements while 22 companies were non-adopting. The study focused on four window periods of reporting, one day, three days, five days, and ten days.

The study proved that the cumulative abnormal returns were not statistically significant for both big data adopting and non-adopting companies. The author postulates the possibility that investors are not well versed about the benefits of big data and therefore do not see value in the technology. Alternatively, it could be that the benefits of big data as an emerging technology are still uncertain (Tony et al., 2016)

The effect of big data announcements on the market value of companies in China was investigated (Zhang, Wang & Pauleen, 2017). The sample consisted of 178 announcements from 2012 to 2016 using an event study methodology over an event window period of three days. The first hypothesis tested whether stock markets reacted positively to big data announcements. The second hypothesis queried whether the market responds positively to announcements made by knowledge-intensive firms.

The findings indicated significant statistical movement on cumulative abnormal returns on the announcement date. This supported the first hypothesis that investors believe that the value of the firm will increase in the future. The cumulative abnormal returns for knowledge-intensive firms were found to be statistically insignificant, therefore the second hypothesis is not supported as cumulative abnormal returns for non-knowledge-intensive firms were found to be statistically significant (Zhang, Wang & Pauleen, 2017).

2.5.3 *Events studies on the impact of cloud investments*

Parameswaran, Venkatesan, Gupta, Sharman, and Rao (2011) investigated the effect of cloud computing announcements on the value of a business using event study methodology. The study assessed 383 announcements from 2006 to 2010 analysing a day minus 4, day 0, plus 4 days window period.

The researchers tested 3 hypotheses. Firstly, to assess whether cloud-computing announcements positively affected the market valuation of all companies sampled. Secondly, to assess whether cloud-computing announcements positively affected the market valuation of adopters. The third looked at whether cloud-computing announcements positively affected the market valuation of

vendors. The positive impact was assessed through average abnormal returns (Parameswaran et al.,2011).

The findings indicated that the first hypothesis could not be rejected. There were significant average abnormal returns on the day of the announcement. The second outcome indicated that adopters benefited from announcements yielding positive mean abnormal returns. The same was true for the third hypothesis, which confirmed that vendors benefited from cloud-related announcements as indicated by positive mean abnormal returns. For the second and third hypothesis, the highest average abnormal returns were observed 2 days after the announcement date (Parameswaran et al., 2011)

In a related quest, Huntgeburth, Förderer, Ebertin, and Veit (2013) investigated whether the market recognised the value of investments in cloud computing. The study followed an event study methodology and examined share price control factors such as firm size; industry sector; innovation; timing of investment and strategic intent of the adopting firm. The study assessed 65 announcements from January 2017 to June 2012 with an event window of the day minus 3, day 0, and day plus 3.

The study found that all 65 announcements resulted in average cumulative returns that were positive and significant. When the data was assessed by firm size as measured by the value of the assets, large firms had positive abnormal returns and were statistically significant. At an industry analysis level, services were compared to manufacturing and the latter was found to provide positive average cumulative abnormal returns and were significant. The financial, health care, and information sectors provided positive average cumulative abnormal returns and were statistically significant. For strategic intent companies whose focus was on automation and information, positive cumulative abnormal returns were recorded which were statistically significant. Finally, innovative companies provided better results compared to non-innovative companies (Huntgeburth et al., 2013).

Employing an event study methodology, Mahmood et al. (2014) studied the effect of cloud computing announcements on market value. The study was based on

26 publicly traded American companies that adopted cloud technology. These firms were compared with 26 others who did not -adopt the technology. In addition, the study investigated whether cloud adopters were exposed to higher market risk (beta) when compared to non- adopters.

The findings indicated positive average cumulative abnormal returns over a 3-day window period, which were statistically significant at 10% for cloud adopting companies. Non-adopting firms indicated - negative average cumulative abnormal returns over the same period. The risk (beta) for adopters of cloud computing companies increased after adopting cloud technology however, it was not statistically significant. For the non-adopters, the increase in risk was less and not statistically significant.

Another study examined the market perception of cloud computing on the valuation of firms using an event study method with the extended resource-based view as an underlying theory (Son, Lee, Lee, Chang, 2014). The analysis was based on 212 announcements from 2006 to 2011. The study used ordinary least squares regression with cumulative abnormal returns as the dependent factor. The independent factors were market value, firms' size, prior experience, vendor reputation, service type, integration, and strategic benefits.

The findings were that investors had a positive perception of cloud investments increasing the market value of the business. For firm size, the findings indicated that smaller firms fared better than larger organisations. The market preferred software as a service (SaaS) rather than infrastructure solutions. Integration of the cloud technology into the firm’s systems appeared to be important and significant in influencing the market value. The firm’s prior experience in implementing cloud technology and vendor reputation were not important factors for investor sentiment that improved market value. Investors leaned towards operational benefits of the technology instead of strategic benefits (Son, Lee, Lee, Chang, 2014).

Table 2: Summary of event studies on 4IR technology investment effects

Author	Technology	Findings
Burnickas (2019)	Artificial Intelligence	• Cumulative abnormal returns were found to be statistically significant on the day of the announcement.
Rubin, Rubin (2013)	Business Intelligence and Data Analytics	• Stock return volatility was found to lower upon the announcement for the deployment of BI.
Tony et al. (2016)	Business Intelligence and Data Sciences	• Cumulative abnormal returns were not statistically significant for both big data adopting and non-adopting companies.
Zhang, Wang, & Pauleen (2017)	Business Intelligence and Data Analytics	• Cumulative abnormal returns found to be statistically significant on the day of the announcement
Parameswaran, Venkatesan, Gupta, Sharman & Rao (2011)	Cloud computing	• There were significant average abnormal returns on the day of the announcement
(Huntgeburth et al., 2013)	Cloud computing	• Cumulative abnormal returns were positive and significant.
(Mahmood, Arslan, Dandu & Udo (2014)	Cloud computing	• Cumulative abnormal returns were statistically significant for cloud adopting companies. • Non-adopting companies indicated a negative average cumulative abnormal return
Son, Lee, Lee, Chang (2014)	Cloud computing	• Investors had a positive perception of cloud investments to increase the market value of the business.

2.6 Conclusion on Literature Review

This literature review chapter has explained the context behind the interest in examining the performance effect of 4IR investments on shareholder sentiment as expressed through share price valuation. Investors as per the news or announcements they release judge business value-enhancing activities of listed firms daily. The global trend towards 4IR technologies has been advancing rapidly however; South African firms are in the early stages of embracing relevant competencies.

This study pursues advancement in the understanding of South African investor sentiment towards 4IR adoption by JSE listed firms. Share price movements are positioned as the signal indicator for responses. The literature review detailed how event studies have been employed by scholars to examine investment in fourth industrial revolution technology on the performance of firm share valuation. Although there have been multiple studies performed on IT investment effects, few studies exist on the effect of 4IR technology on share price value movements in South Africa.

The next chapter presents a detailed account of and rationale for the methodological choices made and how these guided explorations and testing of variables.

CHAPTER 3. RESEARCH METHODOLOGY

The previous chapter has outlined relevant literature demonstrating precedence in the employ of events study methodology through calculating abnormal profits.

This chapter will describe the methodology applied to address the research objective. The chapter commences with the research approach, and then discusses the research design and instrument that will be applied to the data collected to accurately define, analyse and interpret the data according to the research objectives.

3.1 Research approach

Saunders, Lewis, & Thornhill (2009) define a philosophical paradigm as the underlying belief system, which guides an academic investigation. This is a mind-set strategy; the researcher adopts to design the methodological structure of a research challenge to reach credible conclusions. The relevant paradigm for this study is positivism.

3.1.1 *Positivism*

Positivism comes from natural sciences and relates to theory inferred from observing empirical evidence. This phenomenon has been adopted within business and management research where empirical data is used to prove theoretical assertions through the development of a hypothesis (Saunders et al., 2009). The underlying assumption of positivism is objectivity meaning that data should be objectively collated and findings deduced through scientific methodologies (Maree, 2009). Positivism guides the study to be quantitative rather than qualitative (Creswell, 2014).

In this study, the researcher sought to prove hypotheses founded on the efficient market theory concerning the fourth industrial revolution by gathering empirical evidence on JSE listed companies. This guides to ensure that the research is

descriptive and explanatory in nature as consistent with quantitative methodology.

3.1.2 *Descriptive and Explanatory research*

Hypothesis testing seeks to clarify worldviews by providing empirical evidence those tests and validates the theory. This is achieved by understanding the descriptive nature of data and exploring relationships using independent variables (Saunders et al., 2009).

Descriptive research lays a foundation for explanatory enquiry that assists in revealing and explaining relationships between variables (Saunders et al., 2009). Descriptive research details characteristics of data sets whereas explanatory research employ mathematical models to explain the relationships within data.

3.2 Research design

This study is quantitative in nature and used the events study methodology by applying relevant mathematical tools. Scholars define event studies as the empirical investigation of the determinants of share price based on economic events (Bodie, Kane & Marcus, 2011; MacKinlay, 1997; Thompson, 1985).

In this study, the determinants of the share price movements identified as the variable of interest are fourth industrial revolution digital technologies. The economic event is the investment and the announcement thereof by the purchasing company of the aforementioned technologies in the targeted company.

Delattre (2007) used eight stages for event study, this approach has similarly been embraced and adjusted by other scholars (Chong, Liu & Tan, 2006; Zhou, 2018). A seven steps process (Zhou, 2018) was implemented as discussed below.

Stage 1 Identify the events

Announcements for the purchasing of a target company by the purchasing company relating to fourth industrial revolution technologies were identified from the SENS database. The search was designed to embrace information over the 12 months from January 2018 to December 2019 as calendar years.

Stage 2 Identify the announcement date

The date of the public announcement was determined. This is the date that the announcement was accessible to the public through the Stock Exchange News (SENS).

Stage 3 Data cleaning and selecting the final sample

The announcement was confirmed to reflect the application of the fourth industrial revolution technologies. For example, the purchase of a Fintech start-up would mean that there were underlying fourth industrial digital technologies involved as consistent with Fintech start-up operations. The researcher, a seasoned industry professional, used informed discretion supported by literature to link relevant technologies to applications. For example, an announcement for Fintech has linked to Business Intelligent and data analytics.

Stage 4 choosing an event window

The event window chosen for this study is three days before the announcement date, day zero being the announcement date, and three days after the announcement date. The three days option was selected as after that period, the strength of the estimation model is reduced (Lin, Jang & Chen, 2007; Jacobs, Singhal, & Subramania, 2010).

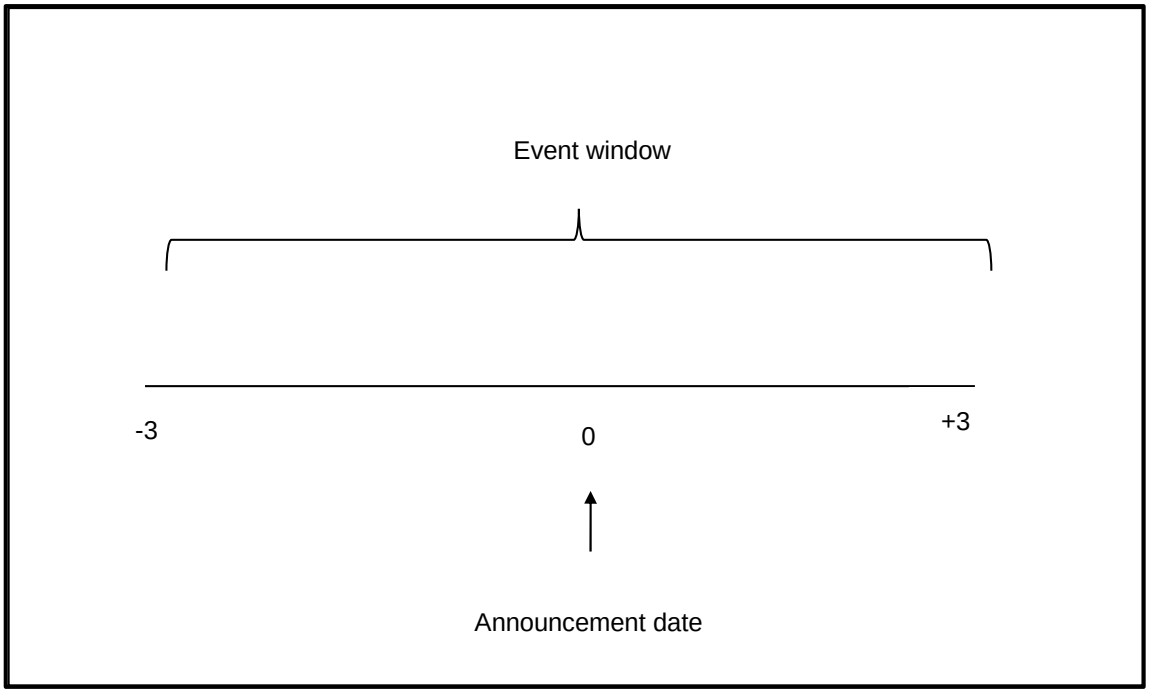

Figure 4: Event window applied

Source: Researcher

The day of the event, which is the announcement date on SENS and the closing share price three days before and after the announcement date, were the indicators were used for analyses.

Stage 5 choosing a model to determine the abnormal returns

Share price returns= Price (t)/Price (t-3) x Price (t+3) / Price (t)

Share index returns = Index (t)/ Index (t-3) x Index (t-3)/ Index (t)

Abnormal Returns= Share price returns- Index returns

Stage 6 assessing the impact of the event on the stock price

The share price three days after the announcement date was evaluated to check whether there is an increase or a decrease in the stock price after the announcement date. Thereafter abnormal returns were calculated as per the above formula and assessed to determine whether positive or negative.

Stage 7 evaluating the significance of the results

The output from stage 6 was then assessed using logistic regression to determine the statistical significance of the announcements on the market value of the company. The tests were assessed for statistical significance to determine whether the announcements of the fourth industrial revolution affected share price valuation and therefore on the performance of the firm.

3.3 Data collection methods

This study used secondary data obtained from JSE linked website (Share Data online) and the INET BFA database (IRESS). The data were collected in four steps.

The first step was to identify all JSE listed companies. This data was obtained from the JSE linked to the share data website. The companies listed on the website were compared to the official JSE website to ensure that the list from the share data online was complete.

The second step was to identify JSE listed companies that had announced the purchase of a target company to acquire fourth industrial revolution technologies. The announcements were obtained from the stock exchange news services (SENS), a JSE managed information network relied on by the public to inform on company news. The SENS data were also extracted from the Share Data online website.

The dates of announcements and the type of technology purchased were confined to the 2018 and 2019 calendar years. The companies that had made announcements were grouped per industry to compare within sectors and observe those that had not been announced. Industries that did not make announcements as per the investigation were excluded from the study to obtain the sample for the unit of study.

The third step was to capture the performance data of the sampled companies. The daily closing price for the three-day window period and the selected financial ratios were collected from the INET BFA database (IRESS). The IRESS database is trusted among South African professionals as a source of economic and financial data feeds. The daily closing price was obtained on the day of the announcement and three days after the announcement date. The financial ratios collected were the total debt to equity, current ratio, intangible assets to total assets ratio, and tangible assets to total assets ratio.

The final step was to identify industries to which the companies belong and collect industry index data. The daily index closing price for the three-day window period was collected from the INET BFA database (IRESS).

3.4 Population and sample

3.4.1 *Population*

Saunders et al. (2009) define a population as the full set of elements from which a sample can be selected. The study population consisted of all companies and securities listed on the JSE. The data was extracted from the share data online website and comprised 439 companies at the time of the study (Sharedataonline, 2020).

3.4.2 *Sample and sampling method*

The sampling method used in this study is nonprobability sampling. Etikan (2016) describes probability sampling as a method where all elements within a population have an equal chance of being selected. In contrast, in nonprobability sampling, the elements do not have an equal chance of being selected

This study used a purposive sampling method, which is also known as judgemental sampling because the researcher sets a criterion for selecting the sample. Within purposive sampling, the strategy used was maximum variation sampling or heterogeneous sampling defined as selecting elements across a broad spectrum (Saunders et al., 2009).

In support of the purposive sampling, the researcher used the following judgment.

First, the JSE listed company needed to have made announcements between the 2018 and 2019 calendar year for the purchase of a target company to purchase the following fourth industrial revolution technologies.

a) Additive manufacturing (3D Printing)
b) Artificial Intelligence and Robotics
c) Business Intelligence and Data Analytics
d) BlockChain
e) Cloud Computing
f) Internet of Things
g) Virtual and Augmented Reality

From the first judgment the researcher found that within the research scope period, 10 companies out of the 439 companies made 22 announcements on the purchase of a target company with fourth industrial revolution technologies. Two companies in the sample developed or organically developed digital technologies by investing resources within the group to start a new division or company. Meanwhile, another company announced the purchase of multiple technologies within the same notification period.

Table 3 indicates the companies, which made announcements, related to the purchase of a target company with fourth industrial revolution technologies.

Table 3: JSE listed companies announcing purchase of 4IR technologies

	Announcement Date	Full Name	Announcement key Words
1	15 Jan 2018	4Sight Holdings Ltd.	Cloud Computing, Business Intelligence, and Data Analytics Artificial Intelligence
2	19 Jan 2018	4Sight Holdings Ltd.	Cloud Computing Business Intelligence and Data Analytics Artificial Intelligence
3	01 Feb 2018	4Sight Holdings Ltd.	Cloud Computing Business Intelligence and Data Analytics Artificial Intelligence
4	28 Feb 2018	4Sight Holdings Ltd.	Cloud Computing Business Intelligence and Data Analytics Artificial Intelligence
5	16 Apr 2018	4Sight Holdings Ltd.	Internet of Things Cyber Security
6	25 Apr 2018	4Sight Holdings Ltd.	Cloud Computing Business Intelligence and Data Analytics
7	30 Apr 2018	4Sight Holdings Ltd.	Internet of Things Cyber Security
9	11 Jun 2018	Allied Electronics Corporation Ltd.	Cloud Computing Business Intelligence and Data Analytics
8	9 Dec 2019	Allied Electronics Corporation Ltd.	Cyber Security
10	08 Aug 2018	African Rainbow Capital Investments Ltd.	Fintech
11	02 Nov 2018	African Rainbow Capital Investments Ltd.	Fintech

	Announcement Date	Full Name	Announcement key Words
12	26 Oct 2018	Compagnie Financière Richemont South Africa	e-commerce
13	16 Feb 2018	Car track Holdings Ltd.	Business Intelligence and Data Analytics
14	27 Jun 2019	Discovery Ltd.	Fintech
15	08 Oct 2018	Datatec Ltd.	Cloud computing
16	03 Sept 2019	Datatec Ltd.	Cloud computing
17	14 Mar 2019	Huge Group Ltd.	Infrastructure as a Service
18	02 Mar 2018	Jasco Electronics Holdings Ltd.	Internet of Things Cyber Security Business Intelligence and Data Analytics
19	08 Feb 2018	Net 1 UEPS Technologies Inc.	Blockchain
20	21 Jun 2018	Net 1 UEPS Technologies Inc.	Easy Pay Solution
21	04 Oct 2018	Net 1 UEPS Technologies Inc.	Easy Pay Solution
22	08 Oct 2019	Net 1 UEPS Technologies Inc.	Business Intelligence and Data Analytics

Secondly, further organising of the companies, which had made announcements, the relevant industries were determined before a random sample of companies within the same industry was selected. This resulted in the identification of two universes of elements being firms who had announced the purchase of a target company to purchase 4IR technology versus those who had not (Announced=1, Not Announced=0). The sampled data from these companies represented our control variable. The researcher then selected announcements from the companies, which did not announce the purchase of a target investment related to 4IR technology (control variables). The announcements selected from these companies within the period 2018 to 2019 were related to the notification of major holdings; cautionary announcements; Broad-Based Black Economic Empowerment Act: Annual Compliance Report; dealings in own shares or securities; changes to the board of directors and renewal of cautionary announcements.

3.5 The research instrument

The research instrument used was a mathematical formula using logistic regression as the researcher sought to understand the effect of digital asset investment on the performance of the company. Such performance was identified as value movement in the share price. The question that the research sought to answer was whether there was an increase in the share price and abnormal returns as a result of announcements made by the purchasing company.

This study used binary data. Such data considered two possible states, the first being whether a JSE listed company has announced an investment in 4IR digital technologies. The second was that the company had not announced any such investment. Further, for the companies that had announced, the data was also binary in that it looked at whether there had been an increase in the share price or there had not been an increase in the share price. An increase in the share price was identified as 1, whereas a decrease in the share price was identified as 0. Finally, the binary data focused on whether the abnormal returns had increased or had not increased. An increase in abnormal returns was identified as 1, whereas a decrease in abnormal returns was identified as 0. Due to the nature of

the binary data, a logistic regression emerged as an appropriate statistical model to employ.

Regression models predict the magnitude of the relationship between two variables. Some regression models such as the simple linear and the multiple linear assume the relationship of the variable to be linear. Where there is uncertainty on whether the relationship between the dependent and independent variable is linear or non-linear, logistic regression is preferred especially where there are binary (yes or no) variables (Dutta, Bandopadhyay & Sengupta, 2012).

Logistic regression predicts the probability or the odds ratio that a certain event will occur based on the predictor or independent variable. The significance of the outcome is evaluated by the log-likelihood test (chi-square test) using a p-value of less than 0.05 to 0.10. Where the probability of an event lies between 0 and 1, linear regression modelling would be unrealistic as the independent variables in linear regression have to be greater or less than 1 (Dutta, Bandopadhyay & Sengupta, 2012).

The advantage of logistic regression is that it does not require the assumption that the affected variables have to be normally distributed and has the capacity to analyse a mixed type of predictors such as binary, continuous, discrete, and dichotomous (Dutta, Bandopadhyay & Sengupta, 2012). In this study, the independent variable was a mixture of discrete and continuous variables, which further justified the use of logistic regression.

Logistic regression is based on two assumptions, (1) the dependent variable has to be identifiable; not overlapping and binary, (2) it considers type I and II errors in predicting the outcome. Within these assumptions lie the disadvantages in that researchers overlook the cost of Type I and II errors in the predicted outcome (Dutta, Bandopadhyay & Sengupta, 2012).

3.5.1 *Technology Mapping*

Due to the small sample size and the 4IR data limitations as indicated in the literature review, the announcements were grouped into three categories, Artificial intelligence, Business Intelligence, and Data sciences, and Cloud computing. Table 5 maps the 4IR technologies as well their applications to the category grouping used in the final model.

Table 4: 4IR Technology Mapping and Grouping

Primary Technology	**Application**	**Final Grouping**
Artificial Intelligence	Internet of Things	AI_ based
Business Intelligence and Data Science	Fintech, Easy pay solution Cryptocurrency	BI_ based
Cloud	Cybersecurity Data infrastructure	Cloud-based

3.5.2 *Non-4IR Technology announcements and Financial ratios*

The literature review detailed work from numerous scholars (Burnickas, 2019; Huntgeburth et al., 2013; Mahmood et al., 2014; Parameswaran, et al., 2011; Tony et al., 2016; Zhang et al., 2017) which compared announcements between adopters and non-adopters of relevant 4IR technology. In this study, we obtained a sample of 92 announcements that were not related to 4IR Technologies to compare whether there was an increase in share price and abnormal returns.

Announcements relating to notifications of major holdings; BBBEE notifications; changes to the board of directors; dealing in own shares, cautionary and renewal of cautionary announcements were selected.

Further, based on guidance from literature, other factors identified such as firm size, innovation, strategic intent (Huntgeburth et al., 2013) and knowledge intensiveness (Zhang et al., 2017) had an impact. It was also decided to use the ratio of intangible assets to total non-current and tangible assets as the importance of non-disclosed intangibles in technology-intensive organisations was highlighted by scholars (Brynjolfsson & Hitt, 2000; Hsu et al., 2012).

This study includes capital structure ratios measured by debt to equity ratio and working capital management measured by the current ratio. The capital structure and working capital are key in determining the value of the organisation (Brynjolfsson & Hitt, 2000; Damodaran, 2009).

3.5.3 *Summary of independent variables*

A summary of all the independent variables is presented in Table 6.

Table 5: Summary of independent variables

Independent Variables	Description
Announcements	
Artificial Intelligence	Announcement of AI and IoT technologies with related applications
Business Intelligence and Data Analytics	Announcement of BI and blockchain technologies with related applications
Cloud Computing	Announcement of cloud technology and related applications
Cautionary Announcements	Cautionary and renewal of cautionary announcements
Securities	Announcements of the company dealing in own shares or securities
Notifications	Announcements for notification of major holdings, BBBEEE, change to the board of directors
Financial Data	
Debt/Equity Ratio	Total Long-term and short-term debt divided by Equity as obtained on the IRESS database, for the financial year in which the announcement was made.

	Information, where the financial year-end results were not published, was disregarded.
Intangible Assets/ Total Non-current Assets	Total Intangible Assets divided by total non-current recalculated from input data obtained from the IRESS database, for the financial year in which the announcement was made. Information, where the financial year-end results were not published, was disregarded.
Tangible/ Total Non-current assets	Total tangible assets divided by total non-current recalculated from input data obtained from the IRESS database, for the financial year in which the announcement was made. Information, where the financial year-end results were not published, was disregarded.
Current Ratio	Current Assets divided by Current liabilities. The ratio was obtained on the IRESS database, for the financial year in which the announcement was made. Information, where the financial year-end results were not published, was disregarded.
Abnormal Returns	Recalculated based on the closing price obtained on the IRESS database as per formula in section 3.2

3.5.4 *Hypotheses*

Hypothesis 1: *Increase in the share price on the day of the announcement*

H0: There is no significant increase in the share price for the purchaser on the day of the announcement for the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in the share price for the purchaser on the day of the announcement for the purchase of digital assets used in the fourth industrial revolution in the target company.

Hypothesis 2: *Increase in share price three days after the announcement date*

H0: There is no significant increase in the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company

Hypothesis 3: *Increase in abnormal returns on the day of the announcement*

H0: There is no significant increase in abnormal returns on the share price for the purchaser on the day of the announcement for the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in abnormal returns on the share price for the purchaser on the day of the announcement for the purchase of digital assets used in the fourth industrial revolution in the target company.

Hypothesis 4: Increase in abnormal returns three days after the announcement date

H0: There is no significant increase in abnormal returns on the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company.

H1: There is a significant increase in abnormal returns on the share price for the purchaser three days after the announcement date for the purchase of digital assets used in the fourth industrial revolution in the target company.

3.6 Data analysis and interpretation

In order to prove the hypotheses through empirical data, the SPSS tool was used for analysis. As mentioned in section 3.5 logistic regression was used to describe and explain data. The results of a logistic regression are interpreted through two variables; probability and the odds value.

Probability explores the number of chances that an event can occur considering all possible outcomes of a population. The odds value is defined as the probability of an event occurring divided by the probability of an event not occurring (Kaufman & Schervish, 1987). The regression analysis predicts whether an independent variable would be significant in the model by using a chi-square test analysed through the probability (p-value).

Three models were run. The first was to investigate the effect on the share price from 4IR digital technology announcements. The second model investigated the effect of the share price for announcements without 4IR digital technologies. For example, cautionary announcements, trading in securities, and notifications such as BBBEE status. The third model combined the first two models to understand holistic movement on the share price.

3.7 Limitations of the study

The fourth industrial revolution is at its initial stages in South Africa, companies rarely disclose investments in digital technology. Therefore, information on this subject is limited. It is also selectively shared. Although there may be companies on the JSE that are actively investing in 4IR digital technologies this information is not publicly available.

The performance of the share price is influenced by many other factors; this research did not include all possible variables that can influence the share price.

3.8 Ethical considerations

The subject of this study is based on publicly available data. Care was taken to ensure that there was no risk of any derogatory exposure to any firms, professional bodies, or government institutions.

This study was carried out under the auspices of academic study; therefore university protocol on ethical considerations for research work was observed and approved by the ethics committee.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

In the previous chapter, we discussed the methodology of this study. In this chapter, the focus will be on the results of the analysis. The hypotheses explained in Chapter 3, were tested using a panel logistic regression model. The dependent variable in the model uses panel data, with 1 presenting an increase in the share price or abnormal returns, whilst 0 represents where there is no increase in the share price and abnormal returns. The hypotheses investigated whether there is an increase in the share price or any abnormal returns on the share price of a listed company after the announcement of investment into digital assets.

The chapter presents the results on three models. The first tests the effect of announcements on the investment of digital technology by the purchaser of the target company. The second model tests whether announcements other than digital technology purchases affect the share price. The final model combines the first and second model to understand the holistic effect of any movements in the share price.

4.1 First Model: Announcements in 4IR digital technology

This section presents the results for 4IR announcements comprising of artificial intelligence, business intelligence, and cloud computing. The results for the four hypotheses are summarised in Table 6. The financial ratios selected are also included in the model. Models 1 and 2 display results of effects of the independent variables on the share price on the day of event announcement and after 3 days of the announcement, respectively. Whereas, models 3 and 4 display results of effects of the independent variables on the abnormal returns on the day of event announcement and after 3 days of the announcement, respectively.

Table 6: Results for 4IR technology announcements that affect the share price

Independent Variables	**Logistic Regression Models**			
	Share Price		**Abnormal Returns**	
Models/Hypothesis	**1** **On the day of Announcement**	**2** **After 3 days of Announcement**	**3** **On the day of Announcement**	**4** **After 3 days of Announcement**
Constant	1.40	0.07	0.62	-2.30
AI _ based	-3.44**(0.023)	0.79(0.611)	-0.60(0.674)	0.77(0.566)
BI _Data Science_ based	-0.78(0.550)	0.38(0.765)	0.07(0.959)	1.13(0.340)
Cloud _based	-3.23*(0,088)	-4.13**(0.025)	-0.85(0.580)	-0.66(0.674)
Capital _ Adequacy _ Ratio	0.003(0.578)	-0.0002(0.972)	0.004(0.360)	0.005(0.237)
Intangible _ Non-Current_ Assets	3.58(0.309)	3.48(0.302)	-1.59(0.557)	1.08(0.697)
Count	21	21	21	21
AIC	31.6	33.1	35.0	37.3
R-Sq.	32.6%	24.5%	17.5%	9.4%
Chi-Square	9.46* (0,092)	6.82(0.234)	4.88(0.431)	2.61(0.760)
Somers' D	0.71	0.61	0.61	0.40
Goodman-Kruskal Gamma	0.74	0.64	0.64	0.43

Table 6 summarises the results of the four hypotheses tested in this study. ***, **, * indicate significant levels at 1%, 5%, and 10% respectively, while standard errors are in parenthesis.

Hypothesis 1: Share price on the day of the announcement

In Table 6, hypothesis 1 investigates the increase in the share price for 4IR digital technology announcements on the day of the announcement. In hypothesis 1, the results indicate AI-based and cloud-based variables are significant on the day of announcement at 5% and 10% significant level, respectively. AI-based, BI-Data Science-based, and cloud-based negatively affect the share price increase on the day of the announcement. There is less probability of the share price increasing due to the announcement of AI-based and cloud computing. However, capital adequacy and intangible noncurrent assets positively affect the share price increase on the day of the announcement. Based on R-square, the variables can explain only 32.6% of share price increment on the day of the announcement and 66.4% is unknown. The model is significantly based on a Chi-square statistic of 9.46 at a 10% significant level. In addition, the

model can separate 71% between share price increase and non-share price increase based on Somer's D statistic.

Hypothesis 2: Share price after 3 days of the announcement

Hypothesis 2 investigates the increase in share price for 4IR digital technology announcements after three days of the announcement date. The results indicate that the Cloud-based variable is significant after 3 days of the announcement at a 5% significant level. AI-based and BI_Data Science-based affect positively while cloud-based negatively affect the share price increase after 3 days of announcement. Capital adequacy affects positively while intangible noncurrent assets negatively affect the share price increase after 3 days of announcement. Based on R-square, the variables can explain only 24.5% of share price increment after 3 days of announcement and 75.5% is unknown. The model is not statistically significant based on the Chi-square statistic of 6.82 at a 10% significant level. In addition, the model can separate 61% between share price increase and non-share price increase after 3 days of announcement based on Somer's D statistic.

Hypothesis 3: Abnormal return on the day of the announcement

This assertion investigates an increase in abnormal returns on the day of the announcement as a result of 4IR digital technology announcements. None of the variables are significant at the 10% level. However, AI-based, cloud-based and intangible noncurrent assets negatively affect the abnormal return on the day of the announcement. Capital adequacy and BI_Data Science-based affects positively the abnormal return on the day of the announcement. Based on R-square, the variables can explain only 17.5% of abnormal return on the day of the announcement and 82.5% is unknown. The model is not statistically significant based on the Chi-square statistic of 4.88. In addition, the model can separate 61% between positive abnormal return and non-positive abnormal return on the day of announcement based on Somer's D statistic. 1.

Hypothesis 4: Abnormal return after 3 days of the announcement

Hypothesis 4 investigates an increase in abnormal returns 3 days after the announcement date as a result of 4IR digital technology announcements. The results indicate that none of the variables are significant at the 10% level. However, AI-based, BI _Data Science-based, capital adequacy, and intangible noncurrent assets positively affect the abnormal return after 3 days of announcement. Cloud-based affects negatively the abnormal return after 3 days of announcement. Based on R-square, the variables can explain only 9.4% of abnormal return after 3 days of announcement and 90.6% is unknown. The model is not statistically significant based on the Chi-square statistic of 2.61 at a 10% significant level. In addition, the model can separate 40% between positive abnormal return and non-positive abnormal return after 3 days of announcement based on Somer's D statistic 1.

4.2 Second Model: Announcements other than 4IR Digital Technologies

This section presents the results of the second model which investigated the effect of non 4IR technologies-related announcements on the share price. These have been grouped into cautionary announcements, notifications, and securities as illustrated in Table 8. The current ratio, which measures the company's liquidity strength calculated by taking current assets over current liabilities was added as a control variable

Table 7: Results for non-4IR related variables

Independent Variables	**Logistic Regression Models**			
	Share Price		**Abnormal Returns**	
Models/Hypothesis	**1 On the day of Announcement**	**2 After 3 days of Announcement**	**3 On the day of Announcement**	**4 After 3 days of Announcement**
Constant	0.437	0.517	0.505	-0.803

Notifications BBBEE Annual Compliance Reports	-0.914*(0.088)	0.463(0.402)	-0.876(0.132)	0.319(0.569)
Securities	1.052(0.104)	-0.591(0.276)	0.334(0.610)	0.577(0.306)
Current	0.128(0.228)	-0.145(0.143)	-0.795***(0.001)	-0.071(0.501)
Count	86	86	86	86
AIC	107.77	119.68	105.87	117.90
R-Sq.	11.3%	5.4%	11.0%	1.2%
Chi-Square	12.67*** (0,000)	6.37*(0.095)	12.07***(0.007)	1.34(0.720)
Somers' D	0.42	0.28	0.51	0.14
Goodman-Kruskal Gamma	0.44	0.30	0.53	0.15

Table 7 summarises the results of the four hypotheses tested in this study. ***, **, * indicate significant levels at 1%, 5%, and 10% respectively, while standard errors are in parenthesis.

Hypothesis 1: Share price on the day of the announcement

In Table 7, Hypothesis 1, the report is significant on the day of announcement at a 10% significant level and negatively affects the share price increase on the day of the announcement. However, securities and current ratio positively affect the share price increase on the day of the announcement. Based on R-square, the variables can explain only 11.3% of share price increment on the day of the announcement and 88.6% is unknown. The model is significant based on the Chi-square statistic of 1267 at 1% significant level. In addition, the model can separate 42% between share price increase and non-share price increase based on Somer's D statistic.

Hypothesis 2: Share price after 3 days of the announcement

In Table 7 hypothesis 2, the results indicate that none of the variables are significant 3 days after the announcement. Securities and current ratio are affected negatively while reports positively affect the share price after 3 days of announcement. Based on R-square, the variables can explain only 5.4% of share price increment 3 days post announcement and 94.6% is unknown. The model is statistically significant based on a Chi-square statistic of 6.37 at a 10% significant level. In addition, the model can separate 28% between share price increase and non-share price based on Somers' D-statistic.

Hypothesis 3: Abnormal returns on the day of the announcement

The results in hypothesis 3 indicate that none of the variables are significant. However, notifications of BBBEE annual compliance reports and current ratio negatively affect the abnormal return on the day of the announcement, meanwhile, securities positively affect abnormal returns. Based on R-square, the variables can explain only 11.0% of abnormal return on the day of the announcement and 89% is unknown. The model is statistically significant based on the Chi-square statistic of 12.07 at 1% significant level. In addition, the model can separate 51% between positive abnormal return and non-positive abnormal return based on Somers' D-statistic.

Hypothesis 4: Abnormal return 3 days after the announcement

In hypothesis 4, the results indicate that none of the variables are significant. However, notifications of BBBEE annual compliance reports and securities positively affect the abnormal returns 3 days after the announcement. The current ratio negatively affects the abnormal return 3 days after the announcement. Based on R-square, the variables can explain only 1.2% of abnormal returns 3 days after the announcement and 98.8% is unknown. The model is not statistically significant based on a Chi-square statistic of 1.3. In addition, the model can separate 14% between positive abnormal return and non-positive abnormal return based on Somers' D-statistic.

4.3 Third Model: Combination of Announcement of 4IR and non-4IR digital technologies

This section presents the results of the third model, which investigated the effect of both 4IR digital technology announcements and those of the chosen non-4IR announcements as well as financial ratios. . The financial ratios included in the model are the current ratio and the debt ratio. The debt ratio represents the level of debt the organisation has compared to equity.

Table 8: Results of the Combined Model

Independent Variables	Logistic Regression Models			
Models/Hypothesis	Share Price		Abnormal Returns	
	1 On the day of Announcement	2 After 3 days of Announcement	3 On the day of Announcement	4 After 3 days of Announcement
Constant	0.155	1.330	-1.138	-0.953
AI _based	-1.549*(0.099)	1.65(0.142)	-0.14(0.893)	0.788(0.392)
BI _Data Science _based	0.824(0.303)	0.259(0.755)	1.519*(0.060)	0.550(0.466)
Cloud _based	-0.794(0.394)	-2.66***(0.009)	-0.79(0.425)	-0.370(0.689)
Notifications BBBEE Annual Compliance Reports	-0.892(0.116)	0.129(0.830)	-0.425(0.522)	0.418(0.464)
Securities	1.080(0.107)	-0.973*(0.093)	0.634(0.332)	0.674(0.253)
Current	0.202(0.135)	-0.261*(0.052)	-0.273(0.271)	-0.054(0.612)
Debt	0.0612(0.355)	-0.113*(0.091)	0.204***(0.006)	0.010(0.883)
Count	108	108	108	108
AIC	134.14	147.71	134.05	153.84
R-Sq.	14.8%	10.9%	15.7%	1.6%
Chi-Square	21.3***(0,003)	16.19**(0.023)	22.04***(0.002)	2.25(0.945)
Somers' D	0.50	0.39	0.49	0.14
Goodman-Kruskal Gamma	0.52	0.41	0.50	0.15

Table 8 summarises the results of the four hypotheses tested in this study. ***, **, * indicate significant levels at 1%, 5%, and 10% respectively, while standard errors are in parenthesis.

Hypothesis 1: Share price on the day of the announcement

In Table 8, hypothesis 1, the results indicate that only the AI-based announcements at a P value of 0.099 significantly influence movements in the share price on the day of news. However, the share price effect was negative. It was noted that announcements on cloud technologies and notifications of BBBEE compliance also negatively affect share price on the day of the announcement. BI-data science-based, debt ratio, and current ratio securities positively affect the share price on the day of announcement but are not significant. Based on R-square, the variables can explain only 14.8% of share price increment on the day of the announcement and 85.2% is unknown. The model is significant based on a Chi-square statistic of 21.3 at 1% significant level. In addition, the model can separate 50% between share price increase and non-share price increase based on Somers' D-statistic.

Hypothesis 2: Share price after 3 days of the announcement

In hypothesis 2, cloud technology related announcements significantly affect movements in share price at a P-value of 0.009. However, they negatively affect the increase in share price after three days of the announcement date. The debt ratio, current ratio, and securities are significant at a P value of 0.091, 0.052, and 0.093 respectively. AI and BI-data science record a positive effect while cloud technologies related debt ratio, current ratio, and securities negatively affect share price increase 3 days after the announcement. Based on R-square, the variables can only explain 10.9% of share price increment with 89.1% unknown. The model is statistically significant based on a Chi-square statistic of 16.19 at 5% significant level. In addition, the model can separate 39% between share price increase and non-share price increase based on Somers' D-statistic.

Hypothesis 3: Abnormal return on the day of the announcement

Hypothesis 3 the results indicate that BI _Data Science-based announcements are significant in explaining movements in the abnormal returns at a P-value of 0.060 and positively affect the increase in abnormal returns on the announcement date. The debt ratio variables are also significant in explaining movements in abnormal returns at a P-value of 0.060 and positively affect increases in abnormal returns on the day of the announcement. However, AI and cloud technologies related current ratio and notifications of BBBEE compliance reports are not significant and negatively affect the abnormal return on the day of the announcement. Announcements of the company trading in own securities are not significant in explaining increases in abnormal returns on announcement date but positively affect the abnormal return on the day of the announcement. Based on R-square, the variables can explain only 15.7% of abnormal return on the day of the announcement and 84.3% is unknown. The model is statistically significant based on a Chi-square statistic of 22.04 at 1% significant level. In addition, the model can separate 49% between positive abnormal return and non-positive abnormal return on the day of announcement based on Somers' D-statistic.

Hypothesis 4: Abnormal return after 3 days of the announcement

The results for hypothesis 4 indicate that none of the variables are significant in explaining movements in abnormal returns three days after the announcement date. However, AI-based, BI-Data Science-based, debt ratio, securities, and reports positively affect the abnormal return after 3 days of announcement. Cloud technologies related current ratios negatively affect abnormal return 3 days post news. Based on R-square, the variables can explain only 1.6% of abnormal returns after 3 days of announcement and 98.4% is unknown. The model is not statistically significant based on a Chi-square statistic of 2.25. . In addition, the model can separate 14% between positive abnormal return and non-positive abnormal return after 3 days of announcement based on Somers' D-statistic.

4.4 Chapter Summary

This chapter presented the results generated from the three different models carried out in this study, along with the four hypotheses that ran in each model. The three models included 41IR announcements, Non-4IR Announcements, and finally a combination of 4IR and Non-4IR announcements.

The first mode results presented in Table 6 proved that for 4IR announcements AI and cloud, based announcements were significant but negatively affected the probability of the share price increasing on the day of the announcement and three days post announcement. None of the other variables was statistically significant in proving the hypothesis.

The second model presented in Table 7, proved that announcements relating to company notifications were significant but negatively affected the probability of the share price increasing on the day of the announcement. The current ratio was significant in predicting abnormal returns on the day of announcement but negatively affected the probability of abnormal returns increasing on the day of the announcement.

The final model presented in Table 8, proved that BI_ Data science-based announcements significantly explain movements in abnormal returns on the day of the announcement and positively affect the probability of abnormal returns increasing. Table 9 below provides a summary of the results.

Table 9: Summary of Results

Hypotheses/ Model	**Model 1** ***Table 6***	**Model 2** ***Table 7***	**Model 3** ***Table 8***
Hypothesis 1 **Share price increase on the day of the announcement**	AI and cloud-based announcements were statistically significant but negatively affect the probability of the share price increasing on the day of the announcement	Announcements on company notifications on BEE compliance were statistically significant but negatively affect the probability of the share price increasing on the day of the announcement	None of the variables were statistically significant
Hypothesis 2 **Share price increase on three days post-announcement**	Cloud-based announcements were statistically significant but negatively affect the probability of the share price increasing three days post-announcement	None of the variables were statistically significant	Cloud-based, securities announcements as well as current and debt ratios were statistically significant but negatively affect the probability of the share price increasing three days post-announcement
Hypothesis 3 **Abnormal returns increase on the day of the announcement**	None of the variables were statistically significant	The current ratio was statistically significant but negatively affect the probability of abnormal returns increasing on the day of the announcement	BI_Data science based announcements were statistically significant and positively affect the probability of abnormal returns increasing on the day of the announcement

Hypothesis 4 **Abnormal returns increase on three days post-announcement**	None of the variables were statistically significant	None of the variables were statistically significant	None of the variables were statistically significant

These hypotheses there is no association between the variables of interest and the market value of the organisation. This may be due to the sample size selected and that of applicable announcements available on the SENS market database. The next chapter discusses the results in detail and links the findings to the literature.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

This chapter discusses the results for each hypothesis. The previous chapter presented the results with the conclusion that the null hypothesis for hypothesis 3 is accepted whereas the empirical evidence supported no other hypotheses. In this chapter, the results presented in chapter 4 are linked to the literature insights in a bid to explain the outcomes.

5.2 First Model: Announcements in 4IR digital technology

The empirical evidence failed to support all four hypotheses. Although AI investments and cloud technology announcements were significant in predicting movements in the share price, the variables negatively affected the probability of the share price increasing on the day of the announcement and three days post. Further, none of the variables had a significant effect on abnormal returns on the day of the announcement and three days after the announcement. One can infer that based on the empirical evidence, announcements of 4IR digital technologies currently do not affect the value of the organisation.

AI related announcements

In this study, the results from AI-related announcements negatively affected the probability of the share price increasing on the day of the announcement. The results were not significant in providing an increase in abnormal returns. This study results are contrary to Burnickas, 2019 who found significant abnormal returns on the day of announcements for companies who adopted AI technology. The contradiction is concerning hypothesis 3, which investigated the existence of abnormal returns on the announcement date. The results herein indicated that none of the factors was significant in predicting an increase in abnormal returns. As a further contrast, Burnickas (2019) noted a drop in the share price a day or two after the announcement date for both AI adopting companies and those that did not. This study found evidence contrary to the literature, as share price

movements on the day of the announcement were significant in response to AI-related news, although the effect on share price was negative. Whereas, on the third day after announcement AI related announcements were not significant but positively affected the probability of a share price increase.

One can infer that shareholders do not perceive AI investments as adding value to their investments. However, the insignificance of the results may be because of the fact that in this case, such news emerged from only one firm being Sight holdings. Given this, the inference of the results to all shareholders inhibited by the lack of companies announcing investments in AI technologies in the SENS database.

Cloud-based announcements

The results of cloud-based announcement indicated a significant relationship between cloud technology announcements and an increase in share price on the day of the announcement and three days after. However, such news had a probability of reducing the probability of an increase in share price on the day of the announcement and three days post. However, cloud technology investment announcements were not significant in predicting abnormal returns across the periods tracked.

These results are contrary to some scholars' findings (Huntgeburth et al., 2013; Mahmood et al, 2014; Parameswaran,et. al, 2011; Son et.al, 2014). The authors found a significant effect on abnormal returns on the announcement of cloud-based computing. The announcements were collected from the Lexis-Nexis database and studied stock exchanges across the world. The result, therefore, implies that shareholders have a positive perception of investments into cloud-based technologies on the market value of a firm. However, this study yielded a different picture. South African shareholders were found to have a negative perception of investments into cloud-based technologies. Notably, the insignificance of this outcome may stem from the small sample sizes as cloud technology announcements represented 8 observations from the study sample.

5.3 Second Model: Announcements, other than 4IR Digital Technologies

The results in the second indicate that announcements for notification of BBBEE compliance reports are significant on the day of announcement but have a negative effect on the probability of share price increase. Whereas the current ratio is significant in predicting abnormal returns on the announcement date, but negatively affected the probability of the abnormal returns increasing on the day of the announcement.

Lower and or negative abnormal returns were recorded from analysis of AI non-adopting companies (Burnickas, 2019) and when investing in non-adopting cloud technology companies (Mahmood et al, 2014). The results of this are consistent with the literature. The current ratio was the only variable that could predict an increase in abnormal returns, however, it indicated a negative effect in predicting an increase on the day of announcements and three days post announcement. However, notifications on BBBEE annual compliance were significant in predicting share price movements on the day of the announcement, but such prediction does not favour share price increase.

One can infer that South African shareholders also do not perceive announcements other than 4IR digital technologies to significantly impact the market value of a company. However, the results indicate that the market reacts more on the day of announcement when compared to three days after the announcement.

5.4 Third Model: Combination of Announcement of 4IR and non 4IR digital technologies

The third model depicts that AI investment and announcements significantly affected a negative movement in the share price on the announcement date. Further, cloud technologies also significantly predict negative movements in the share price only three days after the announcement date. As discussed in section 5.2, the findings are contrary to the literature review and infer that shareholders do not hold a positive perception of the announcement of AI and cloud-based technologies.

BI-data science related announcement significantly predicts a positive effect on an increase in abnormal returns on the announcement date. The findings are aligned to those of Zhang, et al. (2017) who found significant abnormal returns on the announcement of BI and data- science related news on the date of release. Similarly, Rubin & Rubin (2013) revealed low share price volatility upon the announcements of big data investments. However, the findings of Zhang, et al. (2017) and Rubin & Rubin (2013) were contradicted by another analysis that found no significant abnormal return on the announcements of big data investments (Tony et al., 2016). Zhang, et al. (2017) and Rubin & Rubin (2013) inferred that the insignificant results were due to the lack of shareholder knowledge on the benefits of big data on organisations.

The findings of this study however concur with a study by Microsoft (2019) that stipulated that South African companies although still at infancy stages in investing in sophisticated 4IR technologies, understand that the foundational technology is BI and big data. Therefore, shareholders realize the value of investing in BI as illustrated by the increase in abnormal returns on the day of the announcement. However, the market reaction appears to self-adjust three days after the announcement day, as BI-related announcements do not significantly predict increases in abnormal returns though the effect remains positive.

5.5 Conclusion

In this study, four hypotheses were tested in three different models. The first hypothesis tested an increase in share price on the announcement date. The second hypothesis tested the increase in share price three days after the announcement. The third hypothesis examined whether there was an increase in abnormal returns on the day of the announcement, while the fourth hypothesis tested the increase in abnormal returns three days after the announcement date. The three different models were used to test all four hypotheses, the first model exclusively focused on 4IR technologies announcements, the second model focused on announcements other than 4IR technologies and the third model holistically looked at both 4IR technologies and non-4IR strategy announcements.

From the first model, in the first hypothesis, AI and cloud technology announcements significantly predicted movements in the share price. The variables had an inverse relationship, which did not adequately explain the increase in the share price on the announcement date, rather decreases in the share price. Therefore, based on the first model the hypothesis is not supported.

The second model predicted that notifications for BBBEE compliance significantly predicted movements in the share price; however, the relationship is also negative. The model did not assist in explaining and supporting hypothesis 1. The third model provided evidence that AI is significant in predicting the share price on the announcement date but had an inverse relationship. Therefore, hypothesis 1 was not supported by empirical evidence in this model. It can be inferred that shareholders do not perceive investments in the 4IR technologies to positively increase the share value on the announcement date. The findings in this study were contrary to Burnickas (2019), who focused on USA companies. The contrary findings between this study and Burnickas (2019) as USA economy is more advanced than the South African economy and shareholders in the USA are more aware of the benefits that 4IR technologies can provide.

The second hypothesis was not supported by the empirical evidence as the first model provided AI-based announcements to significantly impact movements in

the share price 3 days post announcement. However, AI-based announcements negatively affected the probability of an increase in share price 3 days post announcement. . In the second model, none of the variables were significant and in the third model, cloud technology announcements, as well as the non-4IR announcements and financial ratios (current ratio and the debt ratio), could significantly explain the movements in the share price. However, there was an inverse relationship between all the variables and the share price.

The third hypothesis was supported in the third model. BI-data science related announcements significantly predicted an increase in abnormal returns as well as the debt ratio. It could be inferred that shareholders perceived positive prospects for companies that invest in BI- data science related announcements as well as those who had higher debt to equity ratio. None of the variables in the first model could explain the movements in abnormal returns. The second model predicted the current ratio to significantly explain movements in abnormal returns on the announcement date, however, it but negatively affected the probability of the abnormal returns increasing on the day of the announcement.

The fourth hypothesis failed to be accepted by any of the models as none of the variables could significantly predict the movement in abnormal returns three days after the announcement date. However, among the 4IR technologies investigated, shareholders on the JSE perceive announcements for BI_data science to significantly predict abnormal returns on the day of the announcement.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

In this chapter, the research findings are linked to the research objectives to help answer the research questions.

Recall, the objective of the study is to evaluate the effect of investment into digital assets within the 4IR on the value of firms. Performance effect was evaluated through changes in the share price and whether there were significant abnormal returns because of announcements made by the purchasing company.

6.2 Conclusions regarding research question 1

The first research question queried the effect of investments into 4IR digital assets on the share price of a purchasing firm.

Based on the study, AI and cloud technology announcements could significantly predict movements in the share price for the purchaser; however, negatively affected the probability of the share price increasing on the day of the announcement and 3 days post announcement.

Though the findings of this research are contrary to the findings of (Burnickas, 2019; Mahmood et al., 2014; Son, Lee, Lee & Chang, 2014), who have applied event study methodology in analysing the effect of investments in 4IR technology on share price, there is still room for further investigation using a different sample size, or focusing on a different stock market.

The non-4IR announcement BBBEE compliance is statistically significant in predicting share price movement, but negatively affected the probability of share price increasing on the day of the announcement.

The practical implications of the findings infer that investments in 4IR digital technology do not increase shareholders' wealth. It could be inferred that since the technology is new and shareholders do not understand the benefit of 4IR technologies and their association to creating shareholder wealth.

6.3 Conclusions regarding research question 2

The second research question was based on which of the 4IR technologies had more effect on changes to share price. None of the 4IR technologies provided a higher effect on the increase in the share price. Although AI and cloud technology announcements could significantly predict movements in the share price at the announcement date and three days post-announcement, but the movement is in a negative direction. Therefore, none of the of 4IR technology announcements had a favourable effect on the share price.

The practical implication may be that although investors are aware of investments in AI and cloud-based technologies, they may not understand the impact of these technologies in increasing shareholders' wealth. These advancements are still in their initial phases and have not been proven to be successfully applied by South African corporates, to unlock business benefits. It could be inferred that investors are of the view that the technology on its own, without the relevant intangible complementary assets, cannot unlock a competitive advantage that will result in positive future returns.

6.4 Conclusions regarding research question 3

The final research question explored the likelihood of abnormal returns because of the announcements for investments in fourth industrial revolution technology. Hypotheses 3 and 4 tested the effect of 4IR technology investment on abnormal returns. BI data science-based announcements were significant and positively related to increases in abnormal returns on the announcement date. Therefore, hypothesis 3 was supported. On the contrary, none of the variables (AI and cloud-based announcements) could significantly predict an increase in abnormal returns three days post.

These BI-related findings are consistent with that of previous scholars who found significance in the existence of abnormal returns and reduced share price volatility (Rubin & Rubin, 2013; Zhang, et al., 2017).

For non-4IR technologies, the debt ratio is significant in predicting an increase in abnormal returns.

The practical implication is that South African corporates have realised the benefit of BI data sciences on shareholder value. South African corporates have started the foundational work of implementing sophisticated 4IR technologies by ensuring that data can be extracted, processed, and interpreted through business intelligence technology. This result could be evidence of Microsoft (2019) recommends, that companies should invest in adequate business intelligence technologies as it forms the foundation for investing in other more sophisticated technologies.

6.5 Recommendations

Research into investments in 4IR digital technology on the performance of the company is still limited. According to the literature, studies in this field in the South African context remain scarce. This is exacerbated by challenges in accessing sufficient data to inform reliable scholarly investigations.

Common to the methodology of events studies, there may be multiple factors that affect the stock market which has not been considered in this research. This study sets out to capture evidence to support assertions that announcements for investments in 4IR digital technologies affected organisational performance. Except for BI-data science competency announcements, the results of the study indicated that investments into 4IR technology do not improve the performance of South African firms as measured by the market value, and therefore abnormal profits.

The recommendations for JSE listed executives include: Firstly, to provide information to investors on the objective of the investment and the expected benefits from such investments. The information provided by executives on SENS report provides the strategic objective of the acquisition and the financial performance of the acquired company. However, the news does not elaborate on how the technology will be integrated with current capabilities to realise benefits.

The 4IR technologies are still at the initial phases of advancement in South Africa. Although the maturity for the use of the technology differs between companies, customers already experience the use of the technology such as AI in chatbots. However, for the ordinary customer, the link between the application of the technologies and the services received is still a mystery.

Secondly, the executives need to inform investors on the application of the technologies through integrated reporting and educate them on the benefits that have already been realised by the organisation because of the use of the technologies. In searching for data, there was little information available on the investments of 4IR technologies in South African corporates. Executives may view the disclosure for these investments as revealing strategies for gaining competitive advantage. However, the protection of strategic assets may be depriving firms of opportunities for abnormal earnings through increased stock valuation.

Finally, there should be a balance in the communication of information to investors. This will help in an increase in share price whilst still complying with regulations to avoid insider trading.

6.7 Suggestions for further research

This research was carried out for two years and at a time when 4IR technology adoption was still at initial stages in South Africa. A longitudinal study in the future may prove more relevant as companies would have adopted and proven the benefit of such technology over time.

The source of the data played a role in limiting the scope. Although companies may have announced investments in 4IR technology through other channels, the study focused on SENS announcements as this database is directly linked to the JSE. The use of SENS announcements thus had a direct impact in limiting sample size. Future studies can be conducted using other databases such as Lexis-Nexis to obtain a global view of announcements as well as other stock exchanges.

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APPENDIX A: Logistic Regression Models

1. Announcements in 4IR Digital Technologies

a. Share Price Increase on the Day of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_on}}{1-\hat{Y}_{share\_up\_on}}\right) = \alpha_{share\_up\_on} + \beta_1\, AI_{based} + \beta_2\, Cloud_{based} + \beta_3\, BI\_DataScience_{based} + \beta_4\, Debt_{Equity} + \beta_5\, Tangible_{NonCurrentAssets} + \beta_6\, Intangible_{NonCurrentAssets} + \beta_7\, Current_{Ratio} + \beta_8\, Capital_{AdequacyRatio} + \varepsilon_{share\_up\_on}$$

Where $\alpha_{share\_up\_on}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{share\_up\_on}$ = error term

$\hat{Y}_{share\_up\_on}$ = predicted probability of the event which is coded with 1 (share price increase)

b. Share Price Increase after 3 Days of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_aft}}{1-\hat{Y}_{share\_up\_aft}}\right) = \alpha_{share\_up\_aft} + \beta_1 AI_{based} + \beta_2 Cloud_{based} + \beta_3 BI\_DataScience_{based} + \beta_4 Debt_{Equity} + \beta_5 Tangible_{NonCurrentAssets} + \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio} + \varepsilon_{share\_up\_aft}$$

Where $\alpha_{share\_up\_aft}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{share\_up\_aft}$ = error term

$\hat{Y}_{share\_up\_aft}$ = predicted probability of the event which is coded with 1 (share price increase)

c. Abnormal Returns on the Day of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{abnormalReturns\_ann}}{1-\hat{Y}_{abnormalReturns\_ann}}\right) = \alpha_{abnormalReturns\_ann} + \beta_1 AI_{based} + \beta_2 Cloud_{based} + \beta_3 BI\_DataScience_{based} + \beta_4 Tangible_{NonCurrentAssets} + \beta_5 Debt_{Equity} + \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio} + \varepsilon_{abnormalReturns\_ann}$$

Where $\alpha_{abnormalReturns\_ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_ann}$ = error term

$\hat{Y}_{abnormalReturns\_ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns on the day of announcement)

d. Abnormal Returns after 3 days of announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{abnormalReturns\_3ann}}{1-\hat{Y}_{abnormalReturns\_3ann}}\right) = \alpha_{abnormalReturns\_ann} + \beta_1 AI_{based} + \beta_2 Cloud_{based} + \beta_3 BI\_DataScience_{based} + \beta_4 Debt_{Equity} + \beta_5 Tangible_{NonCurrentAssets} + \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio} + \varepsilon_{abnormalReturns\_3ann}$$

Where $\alpha_{abnormalReturns\_3ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_3ann}$ = error term

$\hat{Y}_{abnormalReturns\_3ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns after three days of announcement)

2. Announcements other than 4IR Digital Technologies

a. Share Price Increase on the Day of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_on}}{1-\hat{Y}_{share\_up\_on}}\right) = \alpha_{share\_up\_on} + \beta_1 Reports_{Cautionary} + \beta_2 Securities_{Shares} + \beta_3 Notifications + \beta_4 Debt_{Equity} + \beta_5 Tangibe_{NonCurrentAssets} + \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio} + \varepsilon_{share\_up\_on}$$

Where $\alpha_{share\_up\_on}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{share\_up\_on}$ = error term

$\hat{Y}_{share\_up\_on}$ = predicted probability of the event which is coded with 1 (share price increase)

b. Share Price Increase after 3 Days of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_aft}}{1-\hat{Y}_{share\_up\_aft}}\right) = \alpha_{share\_up\_aft} + \beta_1 Reports_{Cautionary} + \beta_2 Securities_{Shares}$$

$$+ \beta_3 Notifications + \beta_4 Debt_{Equity}$$

$$+ \beta_5 Tangible_{NonCurrentAssets}$$

$$+ \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio}$$

$$+ \beta_8 Capital_{AdequacyRatio} + \varepsilon_{share\_up\_aft}$$

Where $\alpha_{share\_up\_aft}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{share\_up\_aft}$ = error term

$\hat{Y}_{share\_up\_aft}$ = predicted probability of the event which is coded with 1 (share price increase)

c. Abnormal Returns on the day of announcement Logistic Regression

$$\text{In}\left(\frac{\hat{Y}_{abnormalReturns_{ann}}}{1-\hat{Y}_{abnormalReturns_{ann}}}\right) = \alpha_{abnormalReturns_{ann}} + \beta_1 Reports_{Cautionary}$$

$$+ \beta_2 Securities_{Shares} +$$

$\beta_3 Notifications + \beta_4 Debt_{Equity}$

$$\beta_5 Tangible_{NonCurrentAssets} +$$

$\beta_6 Intangible_{NonCurrentAssets}$

$$+ \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio}$$

$$+ \varepsilon_{abnormalReturns\_ann}$$

Where $\alpha_{abnormalReturns\_ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_ann}$ = error term

$\hat{Y}_{abnormalReturns\_ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns on the day of announcement)

d. Abnormal Returns after 3 days of announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{abnormalReturns\_3ann}}{1-\hat{Y}_{abnormalReturns\_3ann}}\right) = \alpha_{abnormalReturns\_ann} + \beta_1 Reports_{Cautionary} + \beta_2 Securities_{Shares} + \beta_3 Notifications + \beta_4 Debt_{Equity} + \beta_5 Tangible_{NonCurrentAssets} + \beta_6 Intangible_{NonCurrentAssets} + \beta_7 Current_{Ratio} + \beta_8 Capital_{AdequacyRatio} + \varepsilon_{abnormalReturns\_3ann}$$

Where $\alpha_{abnormalReturns\_3ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_8$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_3ann}$ = error term

$\hat{Y}_{abnormalReturns\_3ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns after three days of announcement)

3. Combined Model

a. Share Price Increase on the Day of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_on}}{1-\hat{Y}_{share\_up\_on}}\right) = \alpha_{share\_up\_on} + \beta_1\, AI_{based} + \beta_2\, Cloud_{based} + \beta_3\, BI\_DataScience_{based} + \beta_4\, Reports_{Cautionary} + \beta_5\, Securities_{Shares} + \beta_6\, Notifications + \beta_7\, Debt_{Equity} + \beta_8\, Tangible_{NonCurrentAssets} + \beta_9\, Intangible_{NonCurrentAssets} + \beta_{10}\, Current_{Ratio} + \beta_{11}\, Capital_{AdequacyRatio} + \varepsilon_{share\_up\_on}$$

Where $\alpha_{share\_up\_on}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_{11}$ = Coefficients of independent variables

$\varepsilon_{share\_up\_on}$ = error term

$\hat{Y}_{share\_up\_on}$ = predicted probability of the event which is coded with 1 (share price increase)

b. Share Price Increase after 3 Days of Announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{share\_up\_aft}}{1-\hat{Y}_{share\_up\_aft}}\right) = \alpha_{share\_up\_aft} + \beta_1\, AI_{based} + \beta_2\, Cloud_{based} + \beta_3\, BI\_DataScience_{based} + \beta_4\, Reports_{Cautionary} + \beta_5\, Securities_{Shares} + \beta_6\, Notifications + \beta_7\, Debt_{Equity} + \beta_8\, Tangible_{NonCurrentAssets} + \beta_9\, Intangible_{NonCurrentAssets} + \beta_{10}\, Current_{Ratio} + \beta_{11}\, Capital_{AdequacyRatio} + \varepsilon_{share\_up\_aft}$$

Where $\alpha_{share\_up\_aft}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_{11}$ = Coefficients of independent variables

$\varepsilon_{share\_up\_aft}$ = error term

$\hat{Y}_{share\_up\_aft}$ = predicted probability of the event which is coded with 1 (share price increase)

c. Abnormal Returns on the day of announcement Logistic Regression

$$\text{In}\left(\frac{\hat{Y}_{abnormalReturns\_ann}}{1-\hat{Y}_{abnormalReturns\_ann}}\right) = \alpha_{abnormalReturns\_ann} + \beta_1 AI_{based} + \beta_2 Cloud_{based}$$

$$+ \beta_3 BI\_DataScience_{based} + \beta_4 Reports_{Cautionary} + \beta_5 Securities_{Shares}$$

$$+ \beta_6 Notifications \beta_7 Debt_{Equity} +$$

$$\beta_8 Tangible_{NonCurrentAssets} + \beta_9 Intangible_{NonCurrentAssets}$$

$$+ \beta_{10} Current_{Ratio} + \beta_{11} Capital_{AdequacyRatio} + \varepsilon_{abnormalReturns\_ann}$$

Where $\alpha_{abnormalReturns\_ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_{11}$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_ann}$ = error term

$\hat{Y}_{abnormalReturns\_ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns on the day of announcement)

d. Abnormal Returns after 3 days of announcement Logistic Regression

$$\ln\left(\frac{\hat{Y}_{abnormalReturns\_3ann}}{1-\hat{Y}_{abnormalReturns\_3ann}}\right) = \alpha_{abnormalReturns\_ann} + \beta_1\, AI_{based} + \beta_2\, Cloud_{based}$$

$$+ \beta_3\, BI\_DataScience_{based} + \beta_4\, Reports_{Cautionary} + \beta_5\, Securities_{Shares}$$

$$+ \beta_6\, Notifications \beta_7\, Debt_{Equity} +$$

$$\beta_8\, Tangible_{NonCurrentAssets} + \beta_9\, Intangible_{NonCurrentAssets}$$

$$+ \beta_{10}\, Current_{Ratio} + \beta_{11}\, Capital_{AdequacyRatio} + \varepsilon_{abnormalReturns\_3ann}$$

Where $\alpha_{abnormalReturns\_3ann}$ = constant value

$\beta_1, \beta_2, \ldots, \beta_{11}$ = Coefficients of independent variables

$\varepsilon_{abnormalReturns\_3ann}$ = error term

$\hat{Y}_{abnormalReturns\_3ann}$ = predicted probability of the event which is coded with 1 (positive abnormal returns after three days of announcement)