AUTOMATION INVESTMENT APPRAISALS

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I hereby declare that I have read and understood the regulations governing the submission of Master of Commerce dissertations, including those relating to length and plagiarism, as contained in the rules of the University, and that this dissertation conforms to those regulations.

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(JANUARY 2022)

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ABSTRACT

Intelligent automation software technology is key to remaining competitive in the current growing digital landscape. Appropriate techniques should be used to appraise such investments and make correct automation investment decisions. After a comprehensive literature review, three limitations on automation investment decision-making were found in the extant literature: (1) time value of money not considered, (2) interpretative and definitional issues related to the popular Return on Investment (ROI) technique, and (3) the widely recommended Net Present Value (NPV) technique appeared not to have been used. This study aims to identify which automation investment appraisal and valuation techniques are used in South Africa in practice and the relevant metrics applied, to assess these for potential gaps in their application and to ascertain the quality of automation investment decision-making. An online survey questionnaire was distributed to organisations that have invested in automation technology in South Africa to gather data from automation consumers and automation consultants. Payback period, ROI, and budget availability were the most common appraisal techniques used by respondents, followed by popular Discounted Cash Flow (DCF) capital budgeting techniques, NPV and Internal Rate of Return (IRR). The results further point toward deficiencies in the application of appraisal techniques compared to finance literature, which indicates suboptimal quality automation investment decision-making. Important unquantified qualitative factors influencing the decision-making process were also identified. These qualitative factors were considered by respondents more often in their decision-making process than quantitative factors. Future research in this area should include quantifying qualitative factors to improve the quality of automation investment decision-making.

Key words: Automation, intelligent automation, investment, appraisal technique, discounted cash flow, capital budgeting, valuation, technology.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS ii

ABSTRACT iii

TABLE OF CONTENTS iv

LIST OF TABLES vii

LIST OF FIGURES viii

LIST OF ACRONYMS ix

CHAPTER 1: INTRODUCTION 1

1.1 RELEVANCE OF AUTOMATION 1

1.2 RATIONALE FOR THIS STUDY 2

1.3 MAIN FINDINGS OF PREVIOUS STUDIES 3

1.4 RESEARCH PROBLEM 4

1.4.1 Background 4

1.4.2 Hypothesis 5

1.4.3 Research aim, questions, and objectives 5

1.4.4 Thesis Statement 6

1.5 RESEARCH APPROACH 6

1.6 MAIN RESEARCH FINDINGS 6

1.7 DISSERTATION STRUCTURE 7

CHAPTER 2: LITERATURE REVIEW 9

2.1 THEORETICAL FRAMEWORK 9

2.2.1 AUTOMATION TECHNOLOGY 11

2.2 CAPITAL BUDGETING TECHNIQUES 21

2.3 AUTOMATION INVESTMENT FRAMEWORK 25

CHAPTER 3: METHOD 28
3.1 RESEARCH METHODOLOGY OVERVIEW 28
3.1.1 Research Data 28
3.1.2 Questionnaire Design 29
3.1.3 Population and Sample Selection 30
3.1.4 Validity of instrument 32
3.1.5 Scope Limitations 32
3.2 DATA COLLECTION 32
3.2.1 Sample 32
3.2.2 Profile of respondents 32
CHAPTER 4: RESULTS AND DISCUSSION 37
4.1 TECHNOLOGY 37
4.2 APPRAISAL TECHNIQUES 38
4.2.1 Period of assessment 42
4.2.2 Discount rates applied 43
4.2.3 Appraisal technique inputs 44
4.3 COSTS AND BENEFIT METRICS 47
4.3.1 Quantified expenditure and cost savings 47
4.3.2 Automation Benefits 48
4.4 STRATEGIC AND OPERATIONAL FACTORS 49
4.5 INVESTMENT REVIEW 50
4.5.1 Investment outcomes 51
4.5.2 Difficulties experienced 51
4.5.3 Basis for decision 52
4.6 DISCUSSION SUMMARY 53
CHAPTER 5: CONCLUSION 55

4.2 RESEARCH OBJECTIVE ONE 56

4.3 RESEARCH OBJECTIVE TWO 56

4.4 RESEARCH OBJECTIVE THREE 57

4.5 RESEARCH OBJECTIVE FOUR 58

4.6 RESEARCH CONTRIBUTION 58

REFERENCES 60

APPENDIX A 69

SURVEY INSTRUMENT 69

LIST OF TABLES

Table 1: Software automation technologies 13

Table 2: Automation benefits 16

Table 3: Key automation success factors 18

Table 4: Operational factors to be considered 20

Table 5: Profile of respondents 33

Table 6: Organisational revenue 35

Table 7: Technology vendors by respondent organisation type 36

Table 8: Appraisal techniques applied 41

Table 9: Discount rates applied by organisations 44

Table 10: Other considerations 46

Table 11: Quantified expenditure and cost savings 47

Table 12: Automation benefits considered 49

Table 13: Automation success and operational factors considered 50

Table 14: Investment outcomes compared to initial assessment 51

Table 15: Appraisal difficulties experienced 52

Table 16: Basis for making automation investment decisions 53

Table 17: Research Questions Summary 54

LIST OF FIGURES

Figure 1: Drivers for investments in assets 11

Figure 2: Top three automation benefits survey results 15

Figure 3: Automation investment assessment framework 26

Figure 4: Organisational Industries 35

Figure 5: Intelligent automation technologies applied 37

Figure 6: Project appraisal periods 43

Figure 7: Finance metrics as inputs into appraisal techniques 45

LIST OF ACRONYMS

Acronym	Explanation
AI	Artificial Intelligence
ARR	Accounting Rate of Return
DCF	Discounted Cash Flow
FTE	Full-Time Equivalent
ICB	Industry Classification Benchmark
IRR	Internal Rate of Return
IT	Information Technology
JSE	Johannesburg Stock Exchange
NPV	Net Present Value
OCR	Optical Character Recognition
ROI	Return on Investment
RPA	Robotics Process Automation
SMEs	Small and medium-sized enterprises
VBA	Visual Basic for Applications
WACC	Weighted Average Cost of Capital

CHAPTER 1: INTRODUCTION

1.1 RELEVANCE OF AUTOMATION

Investing in intelligent automation software has become an inevitable part of the decision-making agenda of organisations that want to survive and thrive in the current digital age. Making a correct or incorrect automation investment decision can have significant consequences for an organisation. It is estimated that 47% of total US employment will be automatable over the next decade or two (Frey & Osborne, 2017), while the McKinsey Global Institute predicts that a midpoint scenario for automation of activities could substitute around 15% of current time worked globally by 2030 (Bughin et al., 2018). These are potential world-transforming predictions that will change the way humans work and live (Bornet et al., 2020). In 2019 Deloitte surveyed 523 executives in various industries across 26 countries, with combined organisational revenue of $2.7 trillion, on their automation strategies and related workforce impact (Watson et al., 2019). Selected key findings from this survey by Deloitte indicated the following:

a) 58% of executives had already started on their automation journey, with 8% scaling to more than 50 automations, double the number of scaled automations in 2018.
b) On average, the executives expect automation to increase their workforce capacity by 27% over the next three years, totalling an additional 2.4 million full-time employees.

According to McKinsey & Company (2021), the COVID-19 pandemic has fundamentally changed the business environment favouring companies with superior technological capabilities. The decision for organisations to invest in internal automation projects have therefore become topical and even critical, as automation is becoming increasingly pervasive in our environment and key to remaining competitive and relevant within the current growing digital landscape (Berruti et al., 2017; Bornet et al., 2020; Bughin et al., 2018; Kedziora & Kiviranta, 2018; Ng et al., 2021; Siderska, 2020; Syed et al., 2020; Watson et al., 2019; Wright et al., 2017).

The integration of Robotics Process Automation (RPA) and Artificial Intelligence (AI) is called Intelligent Automation, which is a combination of technologies that replicates human capabilities such as language, vision, execution skills, thinking and learning to create an automated software-based digital workforce, having the potential to mirror human decision-making (Bornet et al., 2020; Coombs et al., 2020; Watson et al., 2019). Intelligent Automation, also referred to as Hyperautomation, is included in the Gartner Top Strategic Technology Trends for 2021 and 2022 (Gartner & Burke, 2020; Gartner & Groombridge, 2021), confirming its relevance within the technological landscape. For purposes of this paper, the term *automation* will refer in general to Intelligent Automation, as described above.

1.2 RATIONALE FOR THIS STUDY

Automation is still a relatively new concept, with limited research conducted in this field up to now. It is, however, a field on the rise and will continue to become more relevant each passing year (Bornet et al., 2020; Bughin et al., 2018; Coombs et al., 2020; Frey & Osborne, 2017). Automation investment decisions are essential to remaining competitive and relevant within the current growing digital landscape (Berruti et al., 2017; Bornet et al., 2020; Kedziora & Kiviranta, 2018; Ng et al., 2021; Siderska, 2020; Syed et al., 2020; Watson et al., 2019; Wright et al., 2017). An issue that has routinely frustrated executives in many organisations is how to get to grips with the actual value that information technology adds to the business it serves (Kauffman et al., 2015). McKinsey has found that leading organisations approaching automation in the right way can generate three to four times higher returns on their investments than their competitors (Baroudy et al., 2021). However, no mention is made of how these returns are measured, for example, whether any capital budgeting techniques were used or whether the impacts of risk, taxation or inflation were considered. The absence of information related to calculating the returns makes it difficult to assess the quality of decision-making and understand whether the methods were appropriately used. For this reason, this study aimed to identify and evaluate the automation investment decision-making practices of organisations in South Africa.

The Agency Cost of Free Cash Flow Theory highlights the agency costs of over-investment, which argues that managers are incentivised to potentially waste excess cash on unprofitable projects (Jensen, 1986). Therefore, empirical methods that accurately measure an automation investment return are essential in preventing agency costs. It will further be assessed whether inputs into the appraisal techniques include unavoidable and resource-dependent costs such as license renewals and system maintenance and staff training or layoff costs related to people investments.

Syed et al. (2020) indicated that research is needed to define and measure RPA benefits, particularly on value creation for the firm, instead of having a cost reduction only focus. Therefore, by conducting this research, a case may potentially be made for concrete changes in how automation investments should be appraised. The scope of this research is not to propose an optimal investment appraisal technique for automation investments but rather to critically assess current techniques used against relevant literature and identify potential gaps in how the techniques are being applied. Consequently, this could lead to additional research being conducted to enhance the methods and metrics used to appraise automation investments, including considering the time value of money, appropriate risk considerations, and complete measurement of all relevant benefits and costs.

1.3 MAIN FINDINGS OF PREVIOUS STUDIES

Coombs et al. (2020, pg.11) identified several future Intelligent Automation research agendas, including: ‘what is the return on investment from investments in Intelligent Automation, how should such returns be measured, and over what timescale should such investments be evaluated?’. Therefore, Coombs et al. (2020) introduced a research gap regarding the investment return nature, measurement, and timescale of evaluation, which is impacted by the time value of money. The absence of considering the time value of money was also observed during an extensive literature review.

Only two capital budgeting techniques are presently identified in the literature for purposes of making automation investment decisions, those being the ROI – also known as Accounting Rate of Return (ARR) – and payback period methods, neither of which consider the time value of money (Baroudy et al., 2021; Lacity & Willcocks, 2016; Santos et al., 2019; Watson et al., 2019; Wright et al., 2017). Apart from identifying the techniques as ROI and payback period, no other information was identified in literature on how the techniques were applied. Therefore, it is unclear whether these techniques were applied as defined, given that Correia (2012) and Hall and Millard (2011) indicated there are potential interpretative and definitional issues related to the ROI method.

The use of DCF methods for automation investment appraisals was not observed in literature at all, even though DCF methods, such as NPV and IRR, are the most widely used capital budgeting techniques in practice generally (Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Myers, 1984; Pintarič & Kravanja, 2017; Ruiz Campo & Zuniga-Jara, 2018; Shrieves & Wachowicz, 2001; Siziba & Hall, 2019).

1.4 RESEARCH PROBLEM

1.4.1 Background

Extant literature identifies the most widely used capital budgeting techniques as follows: NPV, IRR, Payback Period, Discounted Payback Period, Profitability Index, and ARR (alternatively ROI) (Ballantine & Stray, 1998; Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Myers, 1984; Pintarič & Kravanja, 2017; Ruiz Campo & Zuniga-Jara, 2018; Shrieves & Wachowicz, 2001; Siziba & Hall, 2019). While multiple capital budgeting and valuation techniques are being used in practice, there is no consensus in the literature regarding techniques used to appraise automation investments (Baroudy et al., 2021; Correia, 2012; Correia & Cramer, 2008; Lacity & Willcocks, 2016; Osinski et al., 2017; Pastor et al., 2017; Santos et al., 2019; Watson et al., 2019; Wright et al., 2017). Given the growing trend of investing in automation, there is also limited research indicating which techniques would be most appropriate to appraise automation investments (Baroudy et al., 2021; Coombs et al., 2020; Correia, 2012; Hall & Millard, 2011; Lacity & Willcocks, 2016; Osinski et al., 2017; Pastor et al., 2017; Santos et al., 2019; Siziba & Hall, 2019; Syed et al., 2020; Watson et al., 2019; Wright et al., 2017). In addition, given the complexity of some of these capital budgeting and valuation techniques, literature has not sufficiently addressed the usability of the techniques by management of organisations (Osinski et al., 2017; Pastor et al., 2017; Siziba & Hall, 2019). Despite being widely used in practice as general investment appraisal techniques, the complete and apparent absence of DCF techniques, according to literature, when assessing automation investments highlights the possibility of incorrect decisions being made by organisations. The growing relevance of automation, as well as the potential impact of incorrect investment decisions being made, emphasises that the methods used to appraise automation investments are, indeed, worthy of further study (Bornet et al., 2020; Coombs et al., 2020; Frey & Osborne, 2017; Syed et al., 2020).

This gap in the literature was addressed by conducting an online questionnaire survey on selected organisations to discern the automation investment appraisal techniques used and why. Additionally, the organisations' techniques were compared against relevant literature to identify potential gaps in their application.

1.4.2 Hypothesis

This research hypothesised that organisations are making suboptimal automation investment decisions due to their failure to correctly adopt appropriate valuation techniques, in line with relevant finance theory.

1.4.3 Research aim, questions, and objectives

The research aim of this study is to examine the techniques employed to appraise automation investments. To satisfy this aim, the following research question is posed: What are the determinants of automation investment appraisals?

The following research objectives and sub-questions are relevant to satisfy the research aim and question:

1. To identify the current automation technologies commonly invested in and the valuation techniques used to appraise such automation investments (Research Objective 1):

   1.1 Which automation technologies are commonly invested in by organisations? (Research Question 1).

   1.2 Which valuation techniques are used to appraise automation investment decisions? (Research Question 2).

2. To identify potential gaps and make recommendations in using and applying automation investment appraisal techniques and related metrics (Research Objective 2):

   2.1 Are automation investment decisions made according to relevant theory by correctly utilising appropriate recognised valuation techniques? (Research Question 3).

3. To examine the metrics used for automation investment decision-making and design an investment decision-making framework (Research Objective 3):

3.1 What metrics are included in the techniques used to appraise automation investment decisions? (Research Question 4).

4. To assess the quality of automation investment decision-making in practice (Research Objective 4):

   4.1 What is the quality of automation investment decision-making in practice? (Research Question 5).

1.4.4 Thesis Statement

Managers should use a combination of correctly applied DCF and non-DCF valuation techniques to appraise automation capital investments of organisations, ensuring they consider the time value of money, appropriate project risks, inflation, taxation, and expansion of metrics beyond just cost savings by including other relevant automation benefits as metrics.

1.5 RESEARCH APPROACH

This study used a mixed method to achieve its research objectives, using an online survey questionnaire to gather data. Primary data were gathered directly from organisations that have invested in automation (consumers) and organisations that provide automation implementation professional services and technology to other organisations (consultants). The data collected included both qualitative and quantitative data. The target population for this research consisted of organisations in South Africa that have invested in automation technology. The sample was selected through non-probability sampling, where purposive sampling was employed to choose participants due to the nature of the questionnaire being aimed at persons possessing both decision-making authority related to automation investments and superior financial knowledge.

1.6 MAIN RESEARCH FINDINGS

The results indicate that the most used techniques to make automation investment decisions are the payback period, followed by ROI and budget availability. DCF techniques are used but only account for 34.4% of responses. NPV and IRR are the most popular DCF techniques used, while DCF technique usage is more prevalent in larger organisations. Compared to finance theory, gaps were also identified in the treatment of items such as risk adjustment, taxation, inflation, financing, and sunk costs.

A key finding in this study was that respondents – particularly automation consultants – appear to be making fundamental mistakes in applying finance theory to investment appraisal techniques. The incorrect application of finance theory when using investment appraisal techniques could result in incorrect decision-making, which appears to be the case with automation investments. Both costs and benefits appear to be understated, as inputs into the appraisal techniques, with certain essential costs and benefits either not considered or not quantified as part of the investment appraisal. This study also highlights those qualitative factors that play an essential role in automation investment decision-making in practice and proposes a framework for making automation investment decisions. It is recommended that further research is required to quantify qualitative automation considerations, such as potentially adjusting for project risk. In addition, the study adds to literature by exposing spreadsheets as prevalent automation technology and revealing budget availability as a popular automation investment appraisal technique.

While there have been many studies on capital budgeting techniques globally, based on an intensive literature review, there is no known published study to date which focuses on automation investment decision-making. This is a novel study on automation investment appraisal techniques, with the data and findings contributing to literature as part of a highly topical and growing research field. The evidence points towards deficiencies in automation investment decision-making in practice and highlights the need and focus areas for future research to improve the quality of automation investment decision-making going forward.

1.7 DISSERTATION STRUCTURE

This dissertation is organised into five chapters, including the Introduction (Chapter 1). The following section is a literature review covering fundamental theories, automation technology, and capital budgeting and valuation techniques (Chapter 2). The subsequent section describes the research method, including data types, sources, collection methods, sample selection, analysis methods, and scope limitations (Chapter 3). This is followed by the results and discussion section, which presents the sample, and detailed survey responses received, including a discussion of findings from the survey results (Chapter 4). The discussion highlights automation investment appraisal techniques, the relevant metrics applied, and identified gaps in applying the appraisal techniques. Lastly, the paper concludes with a summary of the key findings that answered the research questions, highlighting the contribution of this paper to literature and areas for future research (Chapter 5).

CHAPTER 2: LITERATURE REVIEW

In this chapter, the literature relevant to this study is discussed. Firstly, the theoretical drivers for investment in automation assets are considered, being the Agency Cost of Free Cash Flow Theory, Resource Dependency Theory, and the Theory of Technology Dominance. This is followed by a review of the extant literature related to technologies underpinning automation assets, as well as capital budgeting techniques.

2.1 THEORETICAL FRAMEWORK

The decision to invest in income-generating assets is due to the need for shareholder value maximisation. However, the Agency Cost of Free Cash Flow Theory suggests a conflict of interest between shareholders and management on the application of free cash flow, as shareholders prefer all cash in excess of maintaining assets and funding positive NPV projects to be distributed to them, whereas non-distribution creates the potential for management to squander the funds (Jensen, 1986; Richardson, 2006; Warue et al., 2018). Free cash flow is the cash in excess of what is required to fund positive NPV projects at the company's relevant cost of capital (Jensen, 1986; Richardson, 2006; Warue et al., 2018). Based on the Agency Cost of Free Cash Flow Theory, management might invest free cash flow in projects, such as automation, thereby increasing the potential for managerial opportunism and over-investment. Managerial opportunism occurs when company information is used for personal gains, such as avoiding payouts to shareholders by financing projects internally, which reduces the need to incur monitoring of capital markets when new capital is raised (Jensen, 1986). Over-investment is an investment beyond what is required to maintain assets and finance positive NPV projects (Richardson, 2006). Therefore, management should invest in automation projects with the objective of value creation, making the techniques to measure such value creation relevant for research.

The Resource Dependency Theory recognises the importance and influence of external dependent contingencies on an organisation and dictates that organisations maintain control over their core assets (Andreassen et al., 2018; Hillman et al., 2009). Based on the high level of future estimated automation of current jobs (Frey & Osborne, 2017), reducing the dependence on human resources could positively impact organisations as technology can work around the clock without resting (Syed et al., 2020). However, automation can in and of itself become an external dependency as companies might need to modify their operations to remain competitive and do business in a largely automated economy (Berruti et al., 2017; Frey & Osborne, 2017). Therefore, the Resource Dependence Theory could impact the return on automation investments, as organisations become dependent on automation infrastructure service providers, which comes at an unavoidable cost such as automation software license renewals and maintenance cost of systems. It is, therefore, essential to consider such costs in the process of making automation investment decisions.

The Theory of Technology Dominance was first introduced by Arnold and Sutton (1998) to identify prerequisites for the successful implementation of intelligent decision aids. Intelligent decision aids are systems that support intelligent decision-making (Triki & Weisner, 2014). A critical factor in the Theory of Technology Dominance is the level of reliance by a user on an intelligent decision aid (Hampton, 2005; Triki & Weisner, 2014). Technology dominance potentially exists if a user relies on a decision aid to an unwarranted degree, thereby entrusting a decision to a decision aid (Triki & Weisner, 2014). Arnold and Sutton (1998) further identify specific long-term effects of technology dominance on users and decision aids, such as deskilling experts and slow-down of knowledge expansion (Triki & Weisner, 2014). The Theory of Technology Dominance is relevant to automation investment decision-making, as some form of reliance on automation technology is necessary to achieve desired returns, such as increased efficiency and accuracy (Coombs et al., 2020; Ng et al., 2021; Syed et al., 2020). The level of reliance will determine whether technology dominance exists; however, the presence of some form of reliance could result in automation assets becoming critical investments for organisations in the current digital age. Technology dominance could further result in organisations losing control over automation investments, becoming more resource-dependent on automation technology and service providers, increasing the risk related to such investments, and impacting returns generated from automation assets.

Theoretically, the drivers for investments in automation assets are presented below.

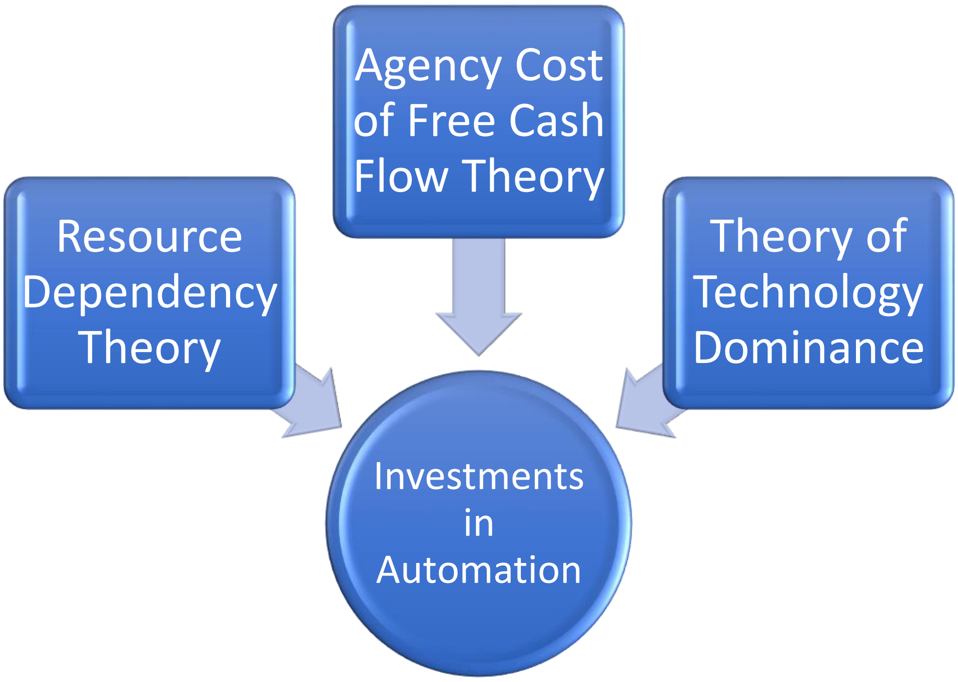

Figure 1: Drivers for investments in assets

2.2.1 AUTOMATION TECHNOLOGY

Over the past 30 years, spreadsheets have been some of the most widely used software tools for data manipulation, storage, and modelling. Some of the most popular current spreadsheet products are Microsoft Excel and Google Sheets (Birch et al., 2017; Rahman et al., 2021). With its built-in programming language, Visual Basic for Applications (VBA), Excel enables users to automate repetitive tasks via macros and data connections, utilising Excel as the user interface and VBA as the programming language (Birch et al., 2017; Microsoft, 2021). Spreadsheet technology has similar attributes to RPA, using user interfaces, data connections, recorders, and underlying programming logic and languages to automate complex, repetitive and routine processes (Birch et al., 2017). According to Wewerka and Reichert (2021), desktop automation is human attended and acts by utilising technological infrastructure operated by a human user. Based on the criteria identified by Wewerka and Reichert (2021), the use of spreadsheets for automation can also be defined as a type of desktop automation, as users act through Excel infrastructure and typically attend the relevant automation while it runs on their desktops. No spreadsheet technology category or type was identified in automation related literature, and it appears as if literature overlooks a potentially common automation technology type, being spreadsheets (Birch et al., 2017; Rahman et al., 2021). While spreadsheets have certain limitations compared to more advanced technologies, such as limited scaling options (Birch et al., 2017), it does not make it irrelevant for automation. To supplement the first research question about which automation technologies are commonly invested in by organisations, it will be assessed whether spreadsheets are used as automation technology in practice. The use of spreadsheet technology for automation will confirm the existence of a gap in the literature, which does not currently include spreadsheet technology as a type of automation technology.

Described as the gateway technology to AI, RPA is a rules-based software that can automate repetitive business processes by mimicking routine manual tasks and workflow processes usually performed by humans (Ng et al., 2021; Siderska, 2020). Although RPA is powerful, it has weaknesses such as being limited to highly rule-based, structured and repetitive decision-making logic, as well as being constrained by the quality, or lack thereof, of the actual predefined business processes which it seeks to automate (Hofmann et al., 2020; Ng et al., 2021). RPA does not function effectively in a frequently changing environment, therefore, organisations are now seeking more intelligence and cognitive abilities from their digital workforce in the form of AI technologies such as machine learning, big data management and smart workflow (Borges et al., 2021; Di Vaio et al., 2020; Ng et al., 2021; Syed et al., 2020). RPA is one type of technology, while AI refers to a wide range of technologies (Bornet et al., 2020; Coombs et al., 2020; Ng et al., 2021). The drive for a digital workforce impacts the human capital theory, where economic benefits are derived from investing in people (Sweetland, 1996). With automation potentially resulting in a reduction of human labour, it could have the impact of substituting investments in people with investments in automation (Frey & Osborne, 2017). AI refers to software algorithms that find patterns in data to act intelligently by making predictions, taking corrective actions, and displaying human cognitive behaviour such as emotional and social intelligence (Di Vaio et al., 2020; Raj & Seamans, 2019). The integration of RPA and AI is also referred to as Intelligent Automation (Bornet et al., 2020; Coombs et al., 2020; Watson et al., 2019).

From a broader Industry 4.0 perspective, 111 technology types have previously been identified (Klingenberg et al., 2021), all of which are not necessarily related to automation. Based on an extensive literature review, a more precise landscape of the software automation technologies relevant to this paper and commonly found in practice, is presented below in Table 1. In terms of categorising the landscape, there are four main human-like capabilities within which software automation technology can lie, namely: language, vision, execution, thinking & learning (Bornet et al., 2020). These four capabilities are used as categories to differentiate between the relevant technologies.

Table 1: Software automation technologies

Category	Technology	Description	Source
Vision	Optical Character Recognition (OCR)	Identify alphabetical and numeric data contained in images and turn it into digital data.	(Beerbaum, 2020; Bornet et al., 2020; Coombs et al., 2020; Siderska, 2020; Watson et al., 2019)
	Intelligent Character Recognition	Recognition techniques need less data than traditional ML models to detect patterns and deliver faster and more accurate results than existing OCR technologies.	(Beerbaum, 2020; Bornet et al., 2020; Ray et al., 2020)
	Image and Video Analysis	Extraction of meaningful data from digital images and video.	(Bornet et al., 2020; Quellec et al., 2017)
	Biometrics	Analysis of human beings' unique physical and behavioural characteristics, such as fingerprints and irises.	(Bornet et al., 2020; Li et al., 2018)
Execution	Smart Workflow	Automated integration of tasks within an end-to-end process.	(Berruti et al., 2017; Bornet et al., 2020)
	Spreadsheets	Automate repetitive tasks via tools like macros and data connections as a type of desktop automation.	(Birch et al., 2017; Rahman et al., 2021)
	Robotics Process automation	Automation of business processes, using software robots that interact with systems through their user interface, improving efficiency and reducing costs.	(Beerbaum, 2020; Berruti et al., 2017; Bornet et al., 2020; Coombs et al., 2020; Enriquez et al., 2020; Hofmann et al., 2020; Kedziora & Kiviranta, 2018; Leshob et al., 2018; Ng et al., 2021; Ratia et al., 2018; Santos et al., 2019; Siderska, 2020; Syed et al., 2020; Van der Aalst et

			al., 2018; Wewerka & Reichert, 2021)
Language	Cognitive agents	Technology that leverages machine learning and natural language processing to build virtual agents, such as chatbots or virtual assistants	(Berruti et al., 2017; Bornet et al., 2020; Ng et al., 2021; Siderska, 2020; Syed et al., 2020)
	Natural language processing	Translation of data observations into prose	(Beerbaum, 2020; Berruti et al., 2017; Coombs et al., 2020; Ng et al., 2021; Siderska, 2020; Syed et al., 2020)
	Sentiment analysis	Test mining that can identify and extract emotion and sentiment	(Bornet et al., 2020; Ng et al., 2021)
	Speech analytics	Transcription of discussions into text which turn it into structured data that can be analysed	(Bornet et al., 2020; Watson et al., 2019)
Thinking & Learning	Big Data Management and Analytics	Acquiring, storing and analysing large and frequently changing sets of data	(Borges et al., 2021; Bornet et al., 2020; Di Vaio et al., 2020; Ng et al., 2021)
	Machine Learning	Algorithms that identify patterns in data from which it applies learning to subsequent decisions	(Beerbaum, 2020; Berruti et al., 2017; Borges et al., 2021; Bornet et al., 2020; Coombs et al., 2020; Di Vaio et al., 2020; Frey & Osborne, 2017; Ng et al., 2021; Quellec et al., 2017; Raj & Seamans, 2019; Siderska, 2020; Syed et al., 2020; Van der Aalst et al., 2018)

Source: Compiled by author

Automation's reported benefits include boosting efficiency and productivity, with savings easy to calculate (Beerbaum, 2020). According to a Deloitte survey, increased productivity is the top benefit expected from automation (Watson et al., 2019) – refer to Figure 2 for the survey results. Increased productivity should be assessed from two angles. Firstly, automation technology is available 24/7 without needing to rest or take a break, and secondly, it can free employees from time-consuming tasks to participate in more value-adding activities (Syed et al., 2020). While cost reduction is ranked second in the Deloitte survey, it is ranked top of the list according to a systematic literature review performed by Syed et al. (2020).

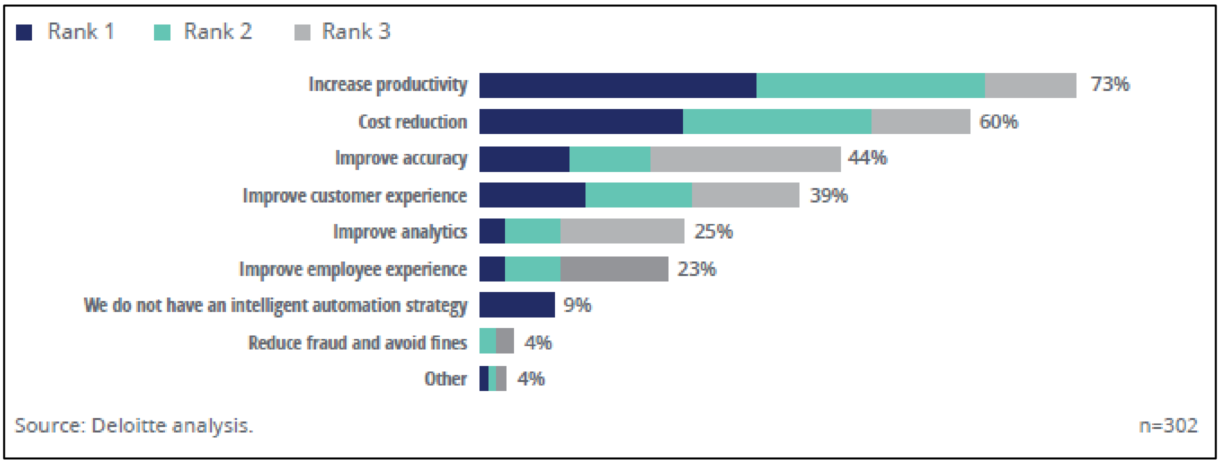

Figure 2: Top three automation benefits survey results

Source: Watson et al. (2019)

Ultimately, the main goal of automation is automating business processes to increase value creation for shareholders, offer labour cost savings solutions, and extend automation technology to more cognitive processes that are labour intensive or manual (Ng et al., 2021). Enriquez et al. (2020) claim the benefit in cost savings are significant and that an RPA software license may cost between one-fifth and one-third of the price of a full-time employee. According to Syed et al. (2020), RPA has cut staff-related costs by 20% to 50% and reduced transaction processing by 30% to 50%. Telefonica, one of the world's first scaled RPA implementations back in 2015, reported a payback period of 12 months and an ROI of 650% to 800% over three years – mainly based on Full-Time Equivalent (FTE) savings (Lacity & Willcocks, 2016). Based on the literature above, there appears to be a definite cost-saving focus when assessing automation benefits, necessitating future expansion to other metrics as identified by Syed et al. (2020).

Value should be considered from holistic value creation and a value capture perspective (Sjödin et al., 2020). Value creation is the process of increasing value generation, while value capturing is securing profits from value creation (Sjödin et al., 2020). If efficiencies are created which reduce the time it takes staff to perform their duties, and those staff do not use the time to add other profit-generating value and are still being paid their total remuneration, value was created through efficiencies, but not captured by securing profits from it (Ng et al., 2021). In some automation projects, no significant job losses have been observed, which would eliminate the claimed benefits if there was no other value added by the impacted staff (Asatiani & Penttinen, 2016). According to Watson et al.

(2019), between 50% and 78% of executives claim to have a clear understanding of how they will capture value from their automation projects, yet only 35% to 54% go on to estimate a payback period, while the difference in revenue increase between those who claim to understand value capturing and those who do not is only 2%. Based on the findings by Watson et al. (2019), it does not appear as if claimed understanding of automation value is appropriately translated into measurement and value capturing.

Value can be considered in quantitative monetary terms, such as the impact on revenue and costs, including qualitative considerations such as reputation, market position and social impact (Ratia et al., 2018). Value creation should also be considered from a stakeholder perspective due to the impact different stakeholders of a business can have on its value capturing (Freudenreich et al., 2020). These stakeholders include customers (which is commonly regarded as the most critical), business partners, employees, societal and financial stakeholders (Freudenreich et al., 2020). From an automation perspective, it is also essential to consider the impact of automation on these stakeholders to ensure value capturing occurs. A key example is the potential value-adding impact of automation on employees. According to (Morgan, 2017), companies that prioritise and drive employee experience have more than four times the average profit and more than two times the average revenue than those that do not.

The following Table summarises critical automation benefits according to current literature, which can impact the returns on automation investments:

Table 2: Automation benefits

Benefit	Expected value	Source
Efficiency	Productivity increase, Cost reduction, More innovation	(Beerbaum, 2020; Bornet et al., 2020; Coombs et al., 2020; Kedziora & Kiviranta, 2018; Lacity & Willcocks, 2016; Leshob et al., 2018; Ng et al., 2021; Ratia et al., 2018; Santos et al., 2019; Siderska, 2020; Syed et al., 2020; Watson et al., 2019)
Processing speed	Cost reduction, increased output speed	(Coombs et al., 2020; Lacity & Willcocks, 2016; Ng et al., 2021; Ratia et al., 2018; Santos et al., 2019; Siderska, 2020)
Accuracy	Increased quality, reduction in quantity and cost of errors,	(Leshob et al., 2018; Ng et al., 2021; Ratia et al., 2018; Santos et al., 2019; Siderska, 2020; Syed et al., 2020; Watson et al., 2019)

Customer satisfaction	Increased customer retention and acquisition, customer growth, revenue growth	(Ratia et al., 2018; Watson et al., 2019)
Compliance and risk management	Reduction in penalties, fines and fraud, reputational benefits	(Bornet et al., 2020; Coombs et al., 2020; Leshob et al., 2018; Ratia et al., 2018; Syed et al., 2020)
Visibility and transparency	Improved strategic decision-making by management	(Ng et al., 2021; Syed et al., 2020; Watson et al., 2019)
Employee satisfaction and engagement	Reduced employee attrition and related costs, increased employee satisfaction leading to improved employee retention and customer retention and growth	(Berruti et al., 2017; Bornet et al., 2020; Hofmann et al., 2020; Morgan, 2017; Ng et al., 2021; Santos et al., 2019; Wright et al., 2017)

Source: Compiled by author

According to Bell (2020, pg.12), 62% of organisations surveyed report that ‘something stops them from investing in technologies that automate routine tasks and processes’. A Deloitte RPA survey, which attracted over 400 responses worldwide, indicate that participants reported an average payback period of fewer than 15 months, with an average of 20% of FTE capacity provided by robots (Wright et al., 2017). Upon face value, such a payback period provides compelling evidence of value. However, the same survey found that only 3% of organisations have scaled their digital workforce (Wright et al., 2017). If automation payback periods are less than 15 months, why have only 3% scaled? KPMG (2019) has identified uncertainty about the financial investment needed in automation as the second biggest inhibitor to automation success. RPA is sometimes seen as a way to quickly achieve a high return on investment, with savings that are easily calculated, however, in practice it is not always as simple as that (Beerbaum, 2020; Bornet et al., 2020; Van der Aalst et al., 2018). For example, process complexity is one key variable that can easily be underestimated and result in diminishing returns in an automation project (Syed et al., 2020). Qualitative considerations are also sometimes overlooked, which can have negative consequences, and are often difficult to quantify, such as lower staff morale and poor governance (Bornet et al., 2020; Coombs et al., 2020). The cost of maintaining RPA would also need to be considered in any business case, as these costs are not immaterial and cannot be ignored (Enriquez et al., 2020). One main driving factor behind RPA maintenance is the potential onerous extent of exception handling and management (IEEE Corporate Advisory Group, 2017; Ng et al., 2021). Other challenges such as system failures, runtime errors, and exception cases due to data or location changes are inevitable in everyday business operations (Ng et al., 2021).

Many organisations have implemented RPA without proper governance and program management, which negatively impacted the business (Bornet et al., 2020). Benefits realisation of automation is dependent on several key success factors, which can differ given various business contexts (Syed et al., 2020). If the success of an automation project hinges on these factors, it should be considered when measuring and making automation investment decisions. Considering these qualitative factors during the automation investment decision-making process can increase automation returns (Watson et al., 2019). Due to its potential impact on automation success, returns, and decision-making, the relevant success factors according to extant literature need to be identified and assessed as part of this study. Table 3 indicates the key success factors for automation investments, according to literature, and a description of their impact. This study will assess whether these success factors are considered in practice when automation investment decisions are being made, which will be an indicator of decision-making quality.

Table 3: Key automation success factors

Success Factor	Description	Source
Enterprise strategy for Intelligent Automation	Companies with an enterprise-wide strategy driven by top management with proper governance and program management – as opposed to silo business unit strategy – report higher returns on workforce capacity, cost reduction and increased revenue.	(Bornet et al., 2020; Ng et al., 2021; Syed et al., 2020; Watson et al., 2019)
Combining RPA with AI	RPA and AI combined – resulting in Intelligent Automation – appears to be the most powerful factor to increase revenue through automation.	(Bornet et al., 2020; Watson et al., 2019)
Technology and IT infrastructure	A supportive IT function with the required technology and infrastructure is more effective at reducing costs.	(Bornet et al., 2020; Lacity & Willcocks, 2016; Ng et al., 2021; Syed et al., 2020; Watson et al., 2019)

Mature processes	Once automated, mature and defined processes increase workforce capacity gains. Therefore, processes should be redesigned if they are outdated or not fit-for-purpose.	(Bornet et al., 2020; Syed et al., 2020; Watson et al., 2019)
Clear understanding of Intelligent Automation strategy and value capturing	Top management with a clearer understanding of automation strategy and value capturing increases cost savings. Uncertainty on the financial investment required can be an inhibitor to automation.	(KPMG, 2019; Ng et al., 2021; Watson et al., 2019)
Human capital	Intelligent Automation projects should be implemented and maintained only by resources who are appropriately skilled and accepting of the automation implementation. Talent should be appropriately managed.	(Bornet et al., 2020; Bughin et al., 2018; Coombs et al., 2020; Syed et al., 2020)

Source: Compiled by author

The most critical part of any automation project is the upfront design, as getting it right from the start will realise more benefits later (Watson et al., 2019; Wewerka & Reichert, 2021). The nature and presence of certain operational factors related to automation suitability, complexity and ease of implementation can impact the potential return on automation investments and need to be considered when assessing an automation investment business case (Berruti et al., 2017; Bornet et al., 2020; Hofmann et al., 2020; Lacity & Willcocks, 2016; Leshob et al., 2018; Syed et al., 2020; Wewerka & Reichert, 2021; Wright et al., 2017). Processes with high automation potential do not necessarily guarantee high returns. Therefore, these processes need to be assessed within the relevant business model and organisational context where they exist. In Table 4, variables impacting automation have been extracted from literature, and its potential impact is highlighted to illustrate the importance of considering these variables as part of making automation investment decisions. These variables will be considered as indicators of automation investment decision-making quality. This study will assess whether these variables are considered in practice to evaluate the impact on automation investment decision-making.

Table 4: Operational factors to be considered

VARIABLE	POTENTIAL IMPACT	SOURCE
Process complexity	Higher complexity increases automation cost but also potential return.	(Berruti et al., 2017; Bornet et al., 2020; Hofmann et al., 2020; Lacity & Willcocks, 2016; Leshob et al., 2018; Syed et al., 2020; Wewerka & Reichert, 2021; Wright et al., 2017)
High volume of data	Increased return potential if high volumes can be automated due to potential time-saving.	
Highly rule-based processes	Increased automation potential as rules-based processes are easily automated instead of unstructured environments.	
Large number of FTE	Increased return and automation potential, as there will be inherent inefficiencies where large numbers of FTE work in an unautomated environment.	
Mature and stable processes	Increased return and automation potential as the likelihood of process changes after automation implementation are less.	
Digitised data input	Increased automation potential as ingesting digital data is easier than manual data.	
Structured data input	Increased automation potential as structured data can more easily be converted into rules and development logic.	
Highly manual processes	Increased return potential as manual processes are time-consuming to execute.	
Highly transactional processes	Increased return and automation potential as transactional processes are typically well structured and tend to be time-consuming when done manually.	
Low levels of exception handling	Increased automation potential as low levels of exception handling increase straight-through processing success and can indicate lower complexity processes.	
Highly repetitive	Increased automation potential as highly repetitive tasks are easily replicated by software robots.	
Well documented processes and systems	Increased return potential as the implementation time can reduce if reliance can be placed on documentation by the automation team.	
High level of integration between systems	While it can have increased return and automation potential due to the ability of software robots to move data, it can also make it more complex, depending on the nature and volumes of the data.	

Source: Compiled by author

Automation generally promises to reduce costs, improve process performance, efficiency, scalability, audit trails, security, and compliance, while being easy to implement at relatively low costs (Enriquez et al., 2020; Hofmann et al., 2020; Santos et al., 2019). However, Bornet et al. (2020) state that some proponents and technology vendors within the automation industry erroneously claim it is a universal solution, and they further exaggerate its cost-effectiveness and ease of implementation. According to Ng et al. (2021, pg.2), ‘the description and functionalities of Intelligent Automation in commercial products are sometimes exaggerated’. Many technology investments actually fail to deliver promised benefits, and some even cause significant losses (Kauffman et al., 2015). In several instances, actual comprehensive measuring of investment returns is lacking entirely or omits specific key metrics (Syed et al., 2020; Watson et al., 2019). According to Watson et al. (2019), 54% of surveyed organisations in the pilot phase of an automation project had not estimated a payback period at all, while 35% of organisations already implementing and scaling solutions had not done so either. In the case of organisations that calculate payback periods, it is uncertain which cost and benefit metrics are being used to calculate these returns (Watson et al., 2019). While there is the element of uncertainty with new technologies, the apparent lack of applying investment appraisal techniques in most organisations during the pilot phase of an automation project indicates a potential misunderstanding of the value drivers, relevant metrics, and appropriate techniques to sufficiently assess automation investments.

2.2 CAPITAL BUDGETING TECHNIQUES

Over the last five decades, numerous surveys of capital budgeting practices have been carried out, both internationally and in South Africa (Correia, 2012; Hall & Millard, 2011; Kengatharan, 2016; Ryan & Ryan, 2002; Shaban et al., 2017; Siziba & Hall, 2019). A capital budgeting project invests cash outflows to receive future cash inflows; therefore, an appropriate appraisal is essential due to relatively large amounts of money being committed for extended periods of time (Hall & Millard, 2011). In the case of automation, there are high upfront implementation costs. At the same time, software licenses are typically contractually acquired for several years, which makes capital budgeting techniques – and time value of money – relevant for making correct automation investment decisions. Capital budgeting techniques can generally be classified into sophisticated and naive techniques, with the difference being that sophisticated techniques consider the time value of money, future cash flows and project risk, while naive techniques do not (Correia, 2012; Hall & Millard, 2011; Kengatharan, 2016; Siziba & Hall, 2019). According to Correia (2012), it is generally accepted that DCF techniques, which are sophisticated, should be employed for capital budgeting purposes. Myers (1984) states that capital investment decisions are usually based on the DCF theory, representing the present value of future cash flows. Literature indicates the main DCF capital budgeting techniques generally used are the NPV, IRR, Discounted Payback Period, and Profitability Index, while the main non-DCF techniques are the Payback Period and ARR (ROI) (Ballantine & Stray, 1998; Correia, 2012; Hall & Millard, 2011; Lima et al., 2017; Pintarič & Kravanja, 2017; Ruiz Campo & Zuniga-Jara, 2018; Shvetsova et al., 2018; Siziba & Hall, 2019). However, there are certain limitations to these capital budgeting techniques, such as qualitative and other intangible costs and benefits are not accounted for, and uncertainties over subjective assumptions used for cash flows and discount rates (Ballantine & Stray, 1998; Shvetsova et al., 2018). Other approaches to capital budgeting have also been introduced, such as the Modified Internal Rate of Return (MIRR), Economic Value Added (EVA™), which compares net operating profit after tax to the cost of capital, the Capital Asset Pricing Model, and Real Option Valuation such as Monte Carlo simulations and decision trees (Correia, 2012; Ryan & Ryan, 2002; Shrieves & Wachowicz, 2001; Siziba & Hall, 2019). However, these alternative methods are unpopular mainly due to their complexity (Siziba & Hall, 2019).

While there have been various global historical capital budgeting trends, it does appear as if the top two most-used capital budgeting techniques are the NPV and IRR methods, both of which are DCF methods that have increased in popularity over time (Correia, 2012; Hall & Millard, 2011; Myers, 1984; Pintarič & Kravanja, 2017; Ruiz Campo & Zuniga-Jara, 2018; Shaban et al., 2017; Shrieves & Wachowicz, 2001; Siziba & Hall, 2019). Some studies have observed that DCF methods are more prevalent in larger firms and companies where employees have graduate qualifications (Brijlal & Quesada, 2009; Correia, 2012). According to Correia (2012), NPV is theoretically the correct method to use as it indicates the project with the greatest NPV of future cash flows. A weakness of the IRR method is that it implies a single reinvestment discount rate of the IRR itself, whereas NPV can make use of risk-adjusted discount rates, such as adjusting the Weighted Average Cost of Capital (WACC) (Correia, 2012; Ruiz Campo & Zuniga-Jara, 2018; Shvetsova et al., 2018). The MIRR has been proposed to deal with this weakness of the IRR, however, its use in practice has remained relatively low (Brincks et al., 2020; Correia, 2012; Ryan & Ryan, 2002). The NPV method is also preferred in scenarios where project cash flows experience changes of sign between positive and negative over the project life, resulting in multiple IRR's (Correia, 2012; Pintarič & Kravanja, 2017). A downside to the NPV method is the difficulties in estimating a discount rate, such as the WACC and the influence that this rate can have on the outcome for a specific project (Ruiz Campo & Zuniga-Jara, 2018). Since the different methods have different advantages and drawbacks, it is beneficial to use more than one method when comparing and assessing investments (Shvetsova et al., 2018). It has been observed in the literature that companies use, on average, between two and three methods per project and tend to combine DCF and non-DCF methods when making capital investment decisions (Correia, 2012; Siziba & Hall, 2019). Even though DCF methods appear to be preferred, non-DCF methods are still widely used (Correia, 2012; Siziba & Hall, 2019). Since automation investments have high levels of uncertainty, and therefore risk, capital budgeting techniques need to be assessed and adjusted to reflect the appropriate level of project risk for decision-making purposes (Correia, 2012; Hall & Millard, 2011; Kauffman et al., 2015).

A risk assessment technique is applied to the capital budgeting process by adjusting for risk, such as adjusting the WACC, adjusting cash flows, or adjusting payback periods (Correia, 2012). Various risk assessment techniques exist, such as sensitivity analysis, scenario analysis, probability analysis, decision trees, and real options analysis (Correia, 2012; Hall & Millard, 2011; Kengatharan, 2016). Based on literature, it appears that the less sophisticated sensitivity and scenario analyses are the most widely-used risk assessment techniques (Correia, 2012; Hall & Millard, 2011).

Proper use of capital budgeting techniques is key to achieving the desired outcome of making correct capital investment decisions, whereas incorrect application of techniques can lead to inappropriate decisions (Correia, 2012). The incorrect applications of capital budgeting techniques may lead to severe consequences such as revenue losses due to adverse selection of projects. Common pitfalls were highlighted in various surveys carried out on capital budgeting practices which were misapplied in practice (Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Ryan & Ryan, 2002), the findings of which were:

1. The selection of an incorrect technique, such as IRR, when assessing mutually exclusive projects or projects with changes in cash flow signs over the course of the project.

2. Project risk was not adjusted in the discount rate, cash flows, or payback period, depending on the technique applied. For example, the DCF method should be risk-adjusted in either the discount rate or future cash flows, and not both.
3. Future cash flows were not adjusted for inflation, which must be done if a nominal discount rate, such as the WACC, is applied. Alternatively, inflation does not have to be considered if a real discount rate is applied.
4. Future cash flows did not account for the impact of taxation. Considering taxation is essential as it can significantly impact cash flows, affecting investment decisions. Certain discount rates, such as WACC, are post-tax rates that must be aligned to post-tax cash flows.

Investments in capital projects are long-term, and incorrect decision-making cannot be easily reversed due to commitment to capital, finance, and human resources. Prior studies have highlighted the critical need for knowledgeable personnel preparing these analyses since the poor application of capital budgeting techniques may lead to severe losses and increased risk (Correia, 2012; Hall & Millard, 2011).

In addition to considering risk, it is essential to consider the time it takes to generate returns after investment in assets. Kauffman et al. (2015) stated that both time and risk are vital since IT-related investments have high potential benefits but also high uncertainty on when returns may be realised. Understanding the length of time between an automation investment and its return has been identified as a gap by Coombs et al. (2020). DCF methods that correctly incorporate project risk appear to have the potential to address that gap as it introduces the time value of money concept (Correia, 2012; Pintarič & Kravanja, 2017).

Since automation technology within the scope of this paper is software related, it will be relevant to assess whether the valuation techniques for intangibles will be appropriate methods to measure and appraise automation technology investments (Bornet et al., 2020). The valuation of intangibles appears to be relatively complex due to the diversity and number of valuation methods and possible variables (Osinski et al., 2017; Pastor et al., 2017). Up to 44 different valuation methods for intangibles have been identified in literature (Osinski et al., 2017; Pastor et al., 2017). Some methods are quantitative, such as the Black-Scholes formula and the Monte-Carlo simulation, while qualitative methods incorporate integrated frameworks and indicators (Pastor et al., 2017). However, general DCF techniques are also proposed as acceptable methods to value intangibles, which aligns with the most widely used capital budgeting techniques, and therefore appears to be appropriate for appraising intangible automation investments (Correia, 2012; Pastor et al., 2017).

2.3 AUTOMATION INVESTMENT FRAMEWORK

The main objective of a business model is to create, deliver and capture value (Andreassen et al., 2018; Freudenreich et al., 2020). According to a McKinsey Global Institute analysis, there appears to be a two-way relationship between AI adoption and profit, with early AI adopters experiencing an additional 15% to 20% uplift in profit (Berruti et al., 2017). While there seems to be a positive correlation between automation and profit generation – if done correctly – a comprehensive assessment of value and subsequent profit increase over time, which considers both quantitative and qualitative factors, seems to be required to assess the returns on automation investments holistically.

However, according to Ng et al. (2021), there is currently no generic Intelligent Automation framework due to problem dependencies and the unpredictability of variables that will impact the design of an automation solution and business case. Many automation projects have not even calculated an ROI or equivalent, and the lack of defined metrics and benefits for calculating a return is notable in current literature (Syed et al., 2020; Watson et al., 2019). In addition, no evidence was found in the literature indicating DCF methods were being considered or used to appraise automation investment decisions. Based on the literature reviewed, the gaps identified by Coombs et al. (2020) and Syed et al. (2020), being the lack of automation return and benefit metrics, appear to be valid and relevant. To address these gaps in making automation investment decisions and ensure a holistic and comprehensive investment assessment is performed prior to investing, the author proposes the following framework:

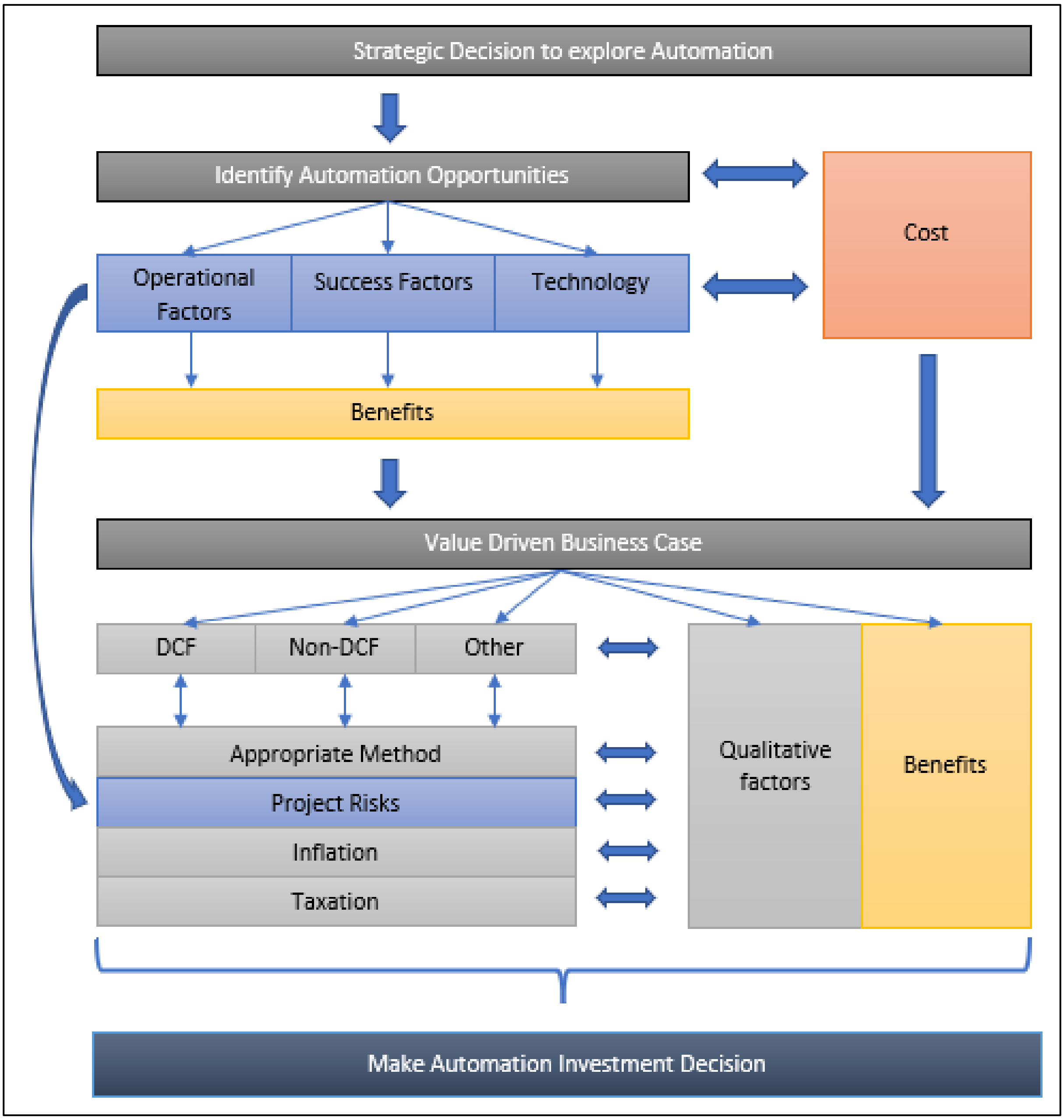

Figure 3: Automation investment assessment framework

Source: Compiled by author

According to Figure 3, during the process of identifying automation investment opportunities, the following factors need to be considered:

a) Technology (Table 1) – choosing and combining the correct combination of technologies is critical in achieving the desired and optimal result.

b) Success factors (Table 3) – the presence of success factors will potentially decrease risk, while the absence thereof will increase risk, which needs to be mitigated to maximise the returns on an automation project.

c) Operational factors (Table 4) – these are factors that need to be considered to make automation investment decisions, which will impact the risk and potential benefits.

When identifying automation opportunities, costs are incurred while benefits are also identified, and both benefits and costs need to be measured to put together a business case for automation (Coombs et al., 2020; Syed et al., 2020). For measurement purposes, the following techniques can be applied, as identified in the literature:

a) DCF methods such as NPV, IRR, Profitability Index, or discounted payback period.
b) Non-DCF methods such as ARR (ROI) or payback period.
c) Other methods such as EVA™, Capital Asset Pricing Model, and Real Option Valuation which include the Monte Carlo simulation and decision trees.

The techniques need to be applied correctly by avoiding common pitfalls and ensuring the correct techniques are applied according to the circumstances, adjusted for project risks, inflation, and taxation, while considering the impact of qualitative factors and benefits (Correia, 2012). Qualitative factors can potentially be quantified by adjusting cash flows or the discount rate as a risk adjustment (Correia, 2012; Hall & Millard, 2011).

CHAPTER 3: METHOD

This chapter addresses the data types and sources, collection methods, time of collection, sample selection, and a description of the analysis methods to be used. In addition, scope limitations are also highlighted.

3.1 RESEARCH METHODOLOGY OVERVIEW

3.1.1 Research Data

Primary data were gathered directly from organisations that have invested in automation (consumers) and from organisations that provide professional automation services to other organisations (consultants). There have been 13 published studies on capital budgeting techniques in South Africa since 1976, which used surveys to gather primary data for their research (Correia, 2012; Siziba & Hall, 2019). While this study does not focus solely on capital budgeting techniques, it is similar in nature to these prior published studies, and using surveys as a data-gathering method appears to be well-grounded in literature. Therefore, field research was conducted by sending out an online survey questionnaire to collect data. Distributing surveys through online channels provides flexibility and efficiency when researching as it can be conducted through various online channels, such as via e-mail or social media, and it also reduces the distribution and data collection time (Evans & Mathur, 2005). Online surveys can provide potential global reach and access to large samples based on many global internet users at a low cost of administration (Evans & Mathur, 2005). According to Correia and Cramer (2008), surveys can be used to identify differences between actual practices and financial theory, which aligns with the objectives of this study. The online questionnaire survey sent to participants consisted of open and closed questions related to the techniques used and metrics applied by organisations for automation investment appraisals to test the hypothesis. Qualitative and quantitative data were collected and used to perform a mixed study, although the study is mainly qualitative. The purpose was to identify characteristics and patterns in the data to test the hypothesis, answer the research questions and achieve the research objectives. This research represents a cross-sectional study as information was gathered at a point in time. The data were descriptive, as it did not include the controlling of any variables. It is deductive research as it aimed to test the application of capital budgeting and valuations techniques. However, it is also exploratory research as it explored aspects that have not yet been extensively researched, being automation investment appraisal techniques and decision-making in South Africa. This study employed a descriptive analysis approach to describe the collected data in a meaningful way. The results were compiled using a combination of Qualtrics and Excel.

3.1.2 Questionnaire Design

The questionnaire was compiled in English, and participants were not required to identify themselves or their organisations. LinkedIn, e-mail, and WhatsApp were the primary distribution channels, and the questionnaire was mobile device friendly, as it could be completed on a smartphone. Weekly reminders were sent via the distribution channels for one month to increase the response rate, after which the survey was ended. Please refer to Appendix A for the survey instrument.

Literature was used to construct the questionnaire, with data being gathered about the relevant factors impacting automation investment decisions – as indicated in the automation investment-decision making framework (Figure 3). The questionnaire was divided into seven sections to obtain sufficient and relevant evidence to answer the research questions and satisfy the research objectives. The first and second sections focused on the profiles of respondents and their organisations. These sections provide context and relevance for the automation investment appraisal and decision-making processes applied by respondents and partially determine the confidence which can be placed in the results from the selected sample. Information on the respondent and organisational profiles have been used in previous surveys about capital budgeting techniques to place the relevant results of those studies into perspective (Hall & Millard, 2011; Maroyi & Van der Poll, 2012). The third section consisted of questions about automation technologies implemented to answer research question one regarding automation technologies commonly invested in by organisations. Technologies prevalent according to extant literature – as identified in Table 1 – were used as the basis for this section’s questions. The fourth section examined relevant automation investment appraisal techniques used and their application according to finance theory. This information was used to answer research questions two and three about the valuation techniques employed and the application of finance theory in the appraisal process. The survey questions for section four were derived from identifying recognised valuation and capital budgeting techniques according to literature, and the common pitfalls and essential factors to consider when applying these techniques. Essential factors include the selection of the appropriate appraisal technique, project risk adjustments, inflation adjustments, taxation considerations, applicable discount rates, and period of assessment in order to make optimal investment decisions (Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Ryan & Ryan, 2002). The fifth and sixth sections were about quantitative and qualitative metrics used in the automation investment appraisal process, which were used to answer research question four regarding metrics applied to appraise automation investments. The questions for sections five and six were obtained through examination of literature and identifying relevant automation benefits (Table 2), strategic (Table 3), and operational (Table 4) factors impacting automation investment decisions. The seventh section focused on automation investment outcomes and reasons for such to assess the quality of decision-making and identify areas for future research. Sections four to seven also contributed to answering research question five about the quality of automation investment decision making.

3.1.3 Population and Sample Selection

The target population for this research consisted of organisations that have invested in automation technology in South Africa. Many organisations use consultants and technology vendors to implement automation projects and develop business cases. The questionnaire was also sent to automation consultants to expand the survey's reach.

The non-probability sampling method was used to select a sample. There was a level of subjectivity in selecting the sample due to the population of organisations that have invested in automation in South Africa being unknown. Purposive samples are most common as a form of non-probability sampling, with sample size guided by the extant literature. All participants selected were familiar with the issues central to automation and investment decision-making, which were considered specialist fields. For this reason, the following sampling criteria were applied to uphold the integrity of the data collection:

1. Participants must have implemented at least one business process automation using automation technology, being RPA or AI, either within their organisation or as a consultant in a client’s organisation.

2. To perform a robust interrogation of the automation investment decision-making techniques and obtain a holistic view of the different factors influencing automation investment decisions in South Africa, respondents should be represented by:
    a. Various levels of management and roles within the automation investment decision-making process, from middle management to top management to cover the entire decision-making inputs and process.
    b. Various tenure lengths and qualifications – matric, graduate, and postgraduate – were used as a proxy for relevant experience and expertise to make automation investment decisions.
    c. Organisations in South Africa of various revenue levels and from various Johannesburg Stock Exchange (JSE) industry sectors. This ensured sufficient automation landscape coverage irrespective of entity size or industry. The organisations did not need to be listed on the JSE for sample inclusion, which would have reduced the coverage considerably.
3. RPA is described as the gateway to Intelligent Automation (Siderska, 2020). Therefore, implementations from ‘leading’ RPA technology vendors, according to the Gartner Magic Quadrant for RPA, were used as a proxy indicator for the sample. These ‘leading’ vendors are UI Path, Automation Anywhere, Blue Prism, and Microsoft (Ray et al., 2021). A sample that includes extensive use of these RPA vendors can be expected to provide a high degree of confidence related to automation research and should ensure sufficient automation industry coverage. However, the sample was not limited to organisations implementing technology from these four vendors only.

Maroyi and Van der Poll (2012) conducted a similar study on capital budgeting techniques used by companies in South Africa, which had a total sample size of 20 companies but only obtained 13 responses. Since this study is focused on automation investments, which is only a subset of capital budgeting related investments, a similar sample size is deemed reasonable and sufficient to provide confidence in the results. The sampling method of this study consisted of purposive sampling of organisations that fit the sampling criteria.

3.1.4 Validity of instrument

Leedy and Ormrod (2015) stated that pilot testing on a questionnaire is essential to ensure it is a reliable information collection tool. Therefore, a pilot test was carried out on four individuals: an established researcher, two capital budgeting lecturers, and an automation consultant. The questionnaire was subsequently modified to account for feedback such as:

1. The design of the questionnaire was streamlined to counteract the risk of participant fatigue.
2. Themes were consolidated to simplify the various technology offerings, metrics, and appraisal techniques extracted from literature to make it easier for the participant to understand.
3. The data collection was completed using Qualtrics, a recognised online survey application.

3.1.5 Scope Limitations

Scope limitations related to this study include the population and sample methods, as not all organisations that invested in automation in South Africa could be surveyed. There will, therefore, be some level of subjectivity in such a sample selection which will result in a non-probability sample.

3.2 DATA COLLECTION

3.2.1 Sample

This study had a response rate of 61.7%, with 37 responses received from 60 surveys distributed. Qualtrics was used as the online survey tool for constructing the survey and collating responses. After eliminating incomplete surveys, the study had a total of 22 completed survey responses, being 36.7% of the sample. Based on the Maroyi and Van der Poll (2012) study, the number of responses received appears sufficient to draw conclusions on automation investment appraisal techniques and decision-making in South Africa and identify areas for future research in this growing topic.

3.2.2 Profile of respondents

The profile of respondents and organisations they represent provides context and relevance for the respondents' automation investment appraisal and decision-making processes. Refer to Table 5 for a summary of the individual respondent profiles. The questions gathering information about the individual profile of respondents were designed to indicate the education and experience of respondents completing the questionnaire and evaluate the level of expertise applied. 81.8% of respondents were at senior manager level and above, with 59.1% being in their roles for more than ten years, and 68.2% had post-graduate qualifications. The three roles in the automation investment decision-making process that attracted the most responses were that of decision-maker (59.1%), followed by the reviewer (45.5%), and calculation performer (40.9%). Based on these results, it can be deduced that respondents had sufficient expertise, experience, and authority to influence and make automation investment decisions within their organisations.

Table 5: Profile of respondents

Characteristics	**Number**	**Percentage**
Role:		
CEO	4	18.2%
CFO	1	4.5%
Director	8	36.4%
Senior Manager	5	22.7%
Manager	3	13.6%
Academic researcher [1]	1	4.6%
	22	**100%**
Tenure:		
>20 years	4	18.2%
15-20 years	3	13.6%
10-15 years	6	27.3%
5-10 years	5	22.7%
0-5 years	4	18.2%
	22	**100%**
Highest Qualification:		
PhD	0	0.0%
Masters	7	31.8%
Honours	8	36.4%
Bachelors	2	9.1%

[1] Academic researcher in the field of automation, and therefore considered an expert in the field.

Diploma	3	13.6%
Matric	2	9.1%
	22	**100%**

From a responding organisational profile perspective, sampled organisations were classified into two categories: consumers of automation and consultants delivering automation solutions. Of the 22 respondents, seven (31.8%) were consultants delivering automation solutions and technology, which indicates a relatively high level of respondent specialisation in the sample. Consultants delivering automation are generally automation experts, and including them in the sample should provide added confidence in the results of this study. All responding organisations are based in South Africa, while some have cross border operations in the rest of Africa.

The Industry Classification Benchmark (ICB), used by the Johannesburg Stock Exchange, was used to identify the industries of responding organisations. Some respondents operate in multiple industries. Of the 11 ICB categories, eight are represented in the responses, with Technology (31.8%) and Consumer Staples (27.3%) representing the most responses – refer to Figure 4. Technology industry responses were mainly (85.7%) from automation consulting and technology organisations. Firstly, the general spread of industries from the 11 ICB categories provides a degree of confidence that the results from this study can be applied to automation as an entire field without being industry-specific. Secondly, the high level of Technology industry responses further emphasises the level of respondent specialisation knowledge included in the sample.

No responses were received from organisations within the Utilities, Energy, and Telecommunications industries. With Utilities being an industry in which State-Owned Enterprises and municipalities are very prevalent, it can be expected to receive a low response rate. Governmental organisations are expected to make decisions for the greater good, not necessarily organisational project profitability (Thomas, 2012). While there is insufficient evidence to draw clear conclusions on Energy and Telecommunications' non-responses, it might indicate a reduced focus on automation, as defined in this study, within these industries.

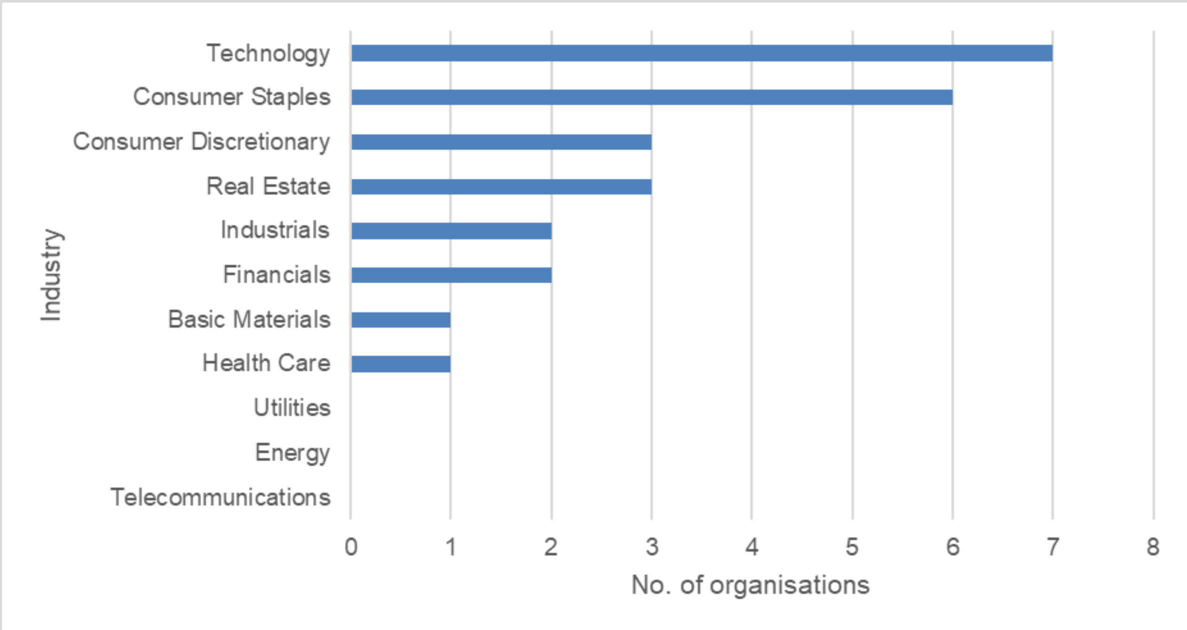

Figure 4: Organisational Industries

From an organisational size perspective, 54.5% of respondent organisations had over R50 million annual revenue, 31.8% over R1 billion, and 13.6% over R5 billion (Table 6). Of the organisations with annual revenue of less than R50 million, 30% are automation consulting service providers, indicating an acceptable level of specialism in the smaller respondent organisations. Therefore, the results of this study will provide insight into automation investment decision-making across organisations of different sizes.

Table 6: Organisational revenue

Characteristics	Number	Percentage
Revenue:		
< R50 million	10	45.5%
R50 million - R1 billion	5	22.7%
R1 billion - R5 billion	4	18.2%
> R5 billion	3	13.6%
	22	**100%**

Due to the difficulties of identifying the organisations that implemented automation in South Africa, implementations from 'leading' RPA technology vendors – according to Gartner (Ray et al., 2021) – were used as a proxy indicator for the sample (Table 7). With 90.9% of respondents having implemented technology from these leading RPA vendors, it provides a level of confidence about the relevance of the sample from an automation technology perspective. Only two (9.1%) respondents did not implement automation technology from the four leading RPA technology vendors. Microsoft was the technology most respondents implemented, an interesting observation based on Microsoft's recent entry into the RPA industry.

Table 7: Technology vendors by respondent organisation type

Vendor	Total	Consumer	Consultant
UI Path [2]	3	1	2
Automation Anywhere [2]	2	0	2
Blue Prism [2]	6	2	4
Microsoft [2]	20	14	6
Other vendors [3]	8	5	3
Total	**39**	**22**	**17**

[2] Part of the four 'leading' RPA technology vendors as defined by Gartner (Ray et al., 2021).
[3] Other vendors consist of: ServiceNow, Delta, Omni Accounting, Octo, Granite, M-Files, Chronoscan and custom developed software. Of these, only ServiceNow was mentioned in the Gartner report on RPA vendors, although it was not considered a leader (Ray et al., 2021).

CHAPTER 4: RESULTS AND DISCUSSION

Chapter four presents the results of this study and the discussion thereof to answer the research questions. Overall, the results indicate that suboptimal automation investment decisions appear to be made in practice due to deficiencies in applying finance theory related to investment appraisal techniques.

4.1 TECHNOLOGY

This research is based on the quality of decision-making related to automation technology investments. Consequently, the technology implemented by the respondents needs to fall within the field of automation, as highlighted in Table 1. This study found that of the 22 completed responses received, all indicated investment in automation technology as defined.

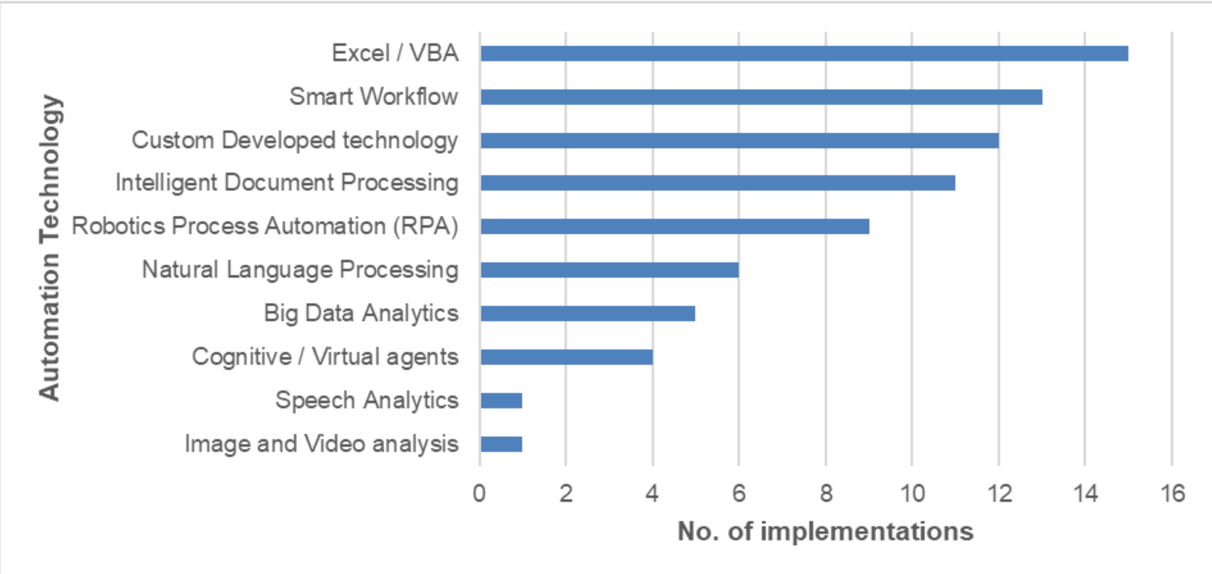

Figure 5: Intelligent automation technologies applied

In satisfying the first research question (which automation technologies are commonly invested in by organisations?), desktop automation through Excel and VBA appears to be the most frequently used automation technology, followed by smart workflow and custom-developed technologies. Although Excel and VBA are distinctly different technologies, they practically function in combination with each other, which provides normal Excel users with the ability to automate repetitive tasks via macros and data connections, utilising Excel as the user interface and VBA as the programming language (Birch et al., 2017; Microsoft, 2021). Interestingly, Excel and VBA were not identified in the literature as automation technologies, despite their popularity in practice. However, it must be noted that Excel and VBA is vendor-specific software from Microsoft and not a technology category, which might explain why it is not mentioned by name. However, no similar spreadsheet technology category or type was mentioned in the literature, which was identified as a gap in the literature review. Consequently, the gap has been confirmed by the results of this study as a valid finding, which is that spreadsheets are extensively used in practice for automation purposes and should be considered in automation related literature despite any limitations in comparison to some of the more advanced technologies.

It was further found that, despite the importance of RPA in automation related literature, the overall number of respondents implementing RPA appears to be unexpectedly low. RPA represents only 11.7% of technologies implemented, as extracted from Figure 5. RPA appears to be much more widely used in larger organisations than in smaller organisations, with 85.7% of respondent organisations with a turnover greater than R1 billion using RPA, while only 20% of organisations with turnover less than R1 billion use RPA. The limited current use of RPA in smaller organisations (revenues < R1 billion) could be due to budget constraints and the historically high pricing of RPA technology. Gartner states there are currently about 60 RPA vendors in the market, with varying capabilities at different price points, although prices are only now becoming more affordable for small and medium-sized enterprises (SMEs) (Ray et al., 2021). Another interesting observation from Figure 5 is that AI technologies, such as natural language processing, big data analytics, and cognitive agents, appear not yet to be extensively used in South Africa. The reasons behind this observation would require further research, but it does appear to indicate a current gap in the South African technology market.

4.2 APPRAISAL TECHNIQUES

The use of DCF methods for automation investment appraisals was not observed in literature at all, even though DCF methods, such as NPV and IRR, are the most widely used capital budgeting techniques in practice generally (Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Myers, 1984; Pintarič & Kravanja, 2017; Ruiz Campo & Zuniga-Jara, 2018; Shrieves & Wachowicz, 2001; Siziba & Hall, 2019). This research hypothesised that organisations are making suboptimal automation investment decisions due to their failure to adopt appropriate valuation techniques. According to the results depicted in Table 8, this hypothesis is supported since most techniques applied were non-DCF techniques. In satisfying the second research question (which valuation techniques are used to appraise automation investment decisions?), the three most used techniques employed for automation investment decision-making are the payback period (21.3%), ROI (16.4%), and budget availability (16.4%). These results corroborate the findings in the extant literature, confirming that the main techniques used for automation investment decision-making are non-DCF techniques. (Baroudy et al., 2021; Lacity & Willcocks, 2016; Santos et al., 2019; Watson et al., 2019; Wright et al., 2017). However, this study contributed to the extant literature by exposing budget availability as another popular automation investment appraisal technique. Budget availability is not a recognised appraisal technique in literature and therefore is an industry practice. This type of practice mainly focuses on costs in light of the available budget and does not sufficiently consider returns and benefits, which is not optimal for organisations since it would not lead to value maximising activities.

Table 8 further presents the most popular DCF techniques used for automation investment decision-making: NPV (14.8%) and IRR (14.8%). DCF techniques are only used by respondents 34.4% of the time, which is low when considering that DCF techniques are the most appropriate methods for making capital investment decisions, according to Correia (2012). Of the total sample, 31.8% indicated they do not use DCF techniques at all. However, in the literature, no DCF techniques were identified for making automation investment decisions, while this research does indicate the use of DCF techniques. The apparent silence about DCF techniques in automation investment-related literature and the low levels of DCF technique application in this study is potentially an indication of insufficient finance knowledge and application in the field of automation investment decision-making. It is also apparent that DCF techniques are used more frequently in larger organisations, being used up to 50% of the time in larger organisations with annual revenue greater than R5 billion, while it is used only 25% of the time in organisations with less than R50 million annual revenue. This finding highlights the potential of different results being produced dependent on the size of organisations included in the sample. The more frequent use of DCF techniques for capital budgeting purposes by larger companies was also highlighted by Correia (2012) and this finding, therefore, corresponds to literature.

Automation consumers use DCF techniques more frequently (42.1%) than automation consultants (21.7%). This finding is potentially indicative that automation consultants might not have sufficient financial background and training to use the appropriate investment decision-making techniques supported by finance theory. It might also explain why DCF techniques are not mentioned in automation related literature. The findings in this study, as per Table 8, also corroborate the results of similar studies on capital budgeting techniques, with the use of more complicated techniques such as Monte Carlo Simulations and MIRR seldomly used, mainly due to their complexity (Correia, 2012). The number of techniques used averages at 2.8 per organisation, which aligns with literature indicating the number of techniques used to evaluate capital budgeting decisions is between two and three (Correia, 2012; Siziba & Hall, 2019). Using more techniques potentially increases the quality of investment decision-making, based on the different advantages of each technique mitigating the disadvantages of other techniques.

Overall, this study has shown that there is still a risk of suboptimal automation investment decision-making due to the relatively low use of DCF techniques and the deficiencies of using budget availability as an appraisal technique.

Table 8: Appraisal techniques applied

#				Annual Revenue (ZAR) of organisation				Organisation type	
			Total	< R50 million	R50 million - R1 billion	R1 billion - R5 billion	> R5 billion	Consumer	Consultant
	Sample Count		22	10	5	4	3	15	7
#	**Investment appraisal technique:**	**%**	**n**	**n**	**n**	**n**	**n**	**n**	**n**
1	Payback Period	21.3%	13	4	3	3	3	7	6
2	Return on Investment	16.4%	10	5	3	2	0	4	6
2	Budget availability	16.4%	10	5	3	1	1	6	4
4	Net Present Value [4]	14.8%	9	2	3	2	2	6	3
4	Internal Rate of Return [4]	14.8%	9	3	1	3	2	7	2
6	Economic Value Added	9.8%	6	4	1	1	0	4	2
7	Profitability Index [4]	3.3%	2	1	0	1	0	2	0
8	Discounted Payback Period [4]	1.6%	1	0	0	1	0	1	0
8	Capital Asset Pricing Model	1.6%	1	0	0	1	0	1	0
10	Modified Internal Rate of Return [4]	0.0%	0	0	0	0	0	0	0
10	Real Option Valuation	0.0%	0	0	0	0	0	0	0
	Total	**100%**	**61**	**24**	**14**	**15**	**8**	**38**	**23**
	% DCF techniques applied		34.4%	25.0%	28.6%	46.7%	50.0%	42.1%	21.7%
	Average no. of techniques applied		2.8	2.4	2.8	3.8	2.7	2.5	3.3

[4] DCF appraisal techniques

For purposes of satisfying research questions three (are automation investment decisions made according to relevant theory by correctly utilising appropriate recognised valuation techniques?) and five (what is the quality of automation investment decision-making in practice?), the relevant theoretical factors to consider when applying investment appraisal techniques are further discussed in this subsection, being: the period of assessment, discount rates applied, and other appraisal technique inputs.

4.2.1 Period of assessment

With automation software mostly being multi-year contracts, with benefits to be realised and costs incurred over the life span of such a contract, it is essential to consider inputs into the investment appraisal technique over the entire period, not just the perceived costs and benefits at inception. Using appropriate assessment periods will also increase the quality of automation investment decisions. Literature indicates understanding automation investments' timescale as a potential research area (Coombs et al., 2020). The identified periods of assessment applied by participants appear to be appropriate in most of the survey responses. Most respondents indicated that data is considered over a two to three year period, as per Figure 6. This period appears reasonable based on the novelty of automation, as it could potentially become challenging to make assessments for periods longer than three years. The assessment period might also depend on the project's software license contract term, which can vary. No respondents indicated the use of forecast data beyond five years, which aligns with other forecasting practices, such as calculating the value in use according to IAS 36 (Impairment of Assets), which proposes that only forecast data up to five years should be used (Deloitte, 2021). 18.2% of organisations only considered data up to one year, which is not appropriate as it is likely that automation investments will have costs or benefits after one year (Coombs et al., 2020).

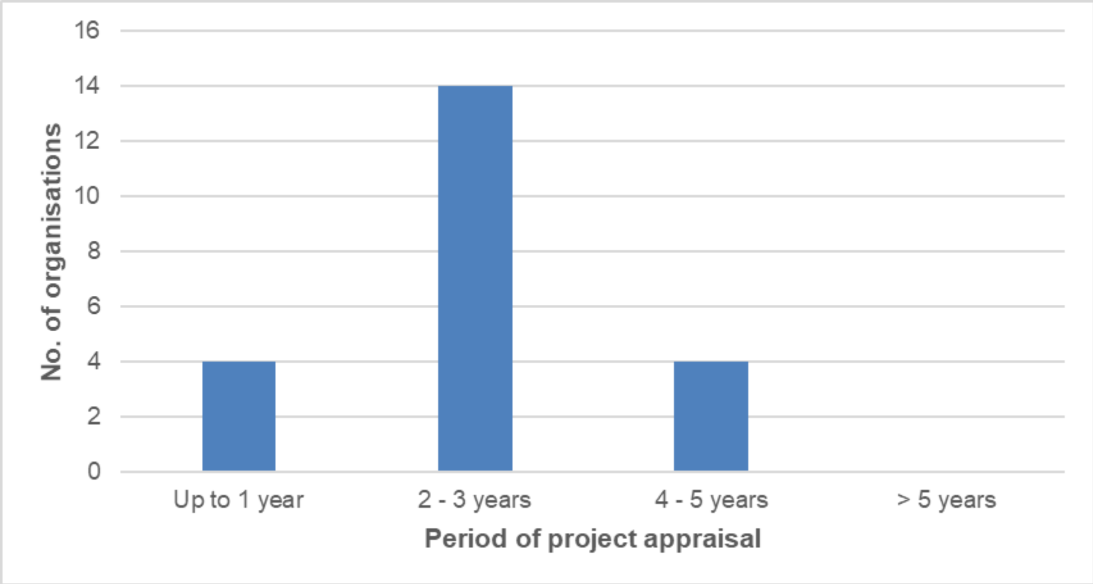

Figure 6: Project appraisal periods

4.2.2 Discount rates applied

According to finance theory, project cash flows should be discounted to present value by project-specific risk-adjusted discount rates, although this is not always very common in practice due to the difficulties sometimes being experienced with risk adjustments (Correia, 2012). The WACC of an organisation typically includes inflation – as it is a nominal rate – and the tax impact of interest deductibility (Correia & Cramer, 2008). If the WACC of the appropriate business unit within an organisation is then adjusted for project-specific risks, it appears to be the most technically correct rate to use for purposes of automation investment decisions (Correia & Cramer, 2008). However, obtaining an accurate WACC – adjusted for project risks – can be complicated, and therefore it is not surprising that there are various other rates also being used in practice. Despite the relative complexity of calculating an accurate WACC, it still appears to be the most popular discount rate used, albeit not always adjusted for project risk. As indicated in Table 9, WACC (combination of risk adjusted and unadjusted) is the discount rate most used by organisations (27.3%), followed by inflation (22.7%). The number of organisations that do not use discount rates and therefore do not apply DCF methods is high at 31.8%, which is potentially an indicator of incorrect automation investment decisions. Participants' low use of risk-adjusted discount rates aligns with previous research as literature indicates that many companies do not use appropriate risk-adjusted discount rates to appraise project investments (Correia, 2012).

Table 9: Discount rates applied by organisations

Discount rate	Number	Percentage
None (no DCF methods)	7	31.8%
Inflation	5	22.7%
WACC - adjusted for project risks	4	18.2%
WACC - unadjusted	2	9.1%
Prime interest rate	2	9.1%
Inflation + GDP growth	2	9.1%
	22	**100%**

4.2.3 Appraisal technique inputs

Incorporating specific metrics into the appraisal calculations is vital for achieving correct outcomes from a finance theory perspective when making investment decisions. According to literature, three such key metrics are risk, taxation, and inflation, which need to be appropriately considered to ensure accurate calculations as follows (Correia, 2012; Correia & Cramer, 2008; Hall & Millard, 2011; Ryan & Ryan, 2002):

a) Project risk should be adjusted in either cash flows or discount rate, and not both. The project period can also be adjusted to account for project risk.
b) Taxation should be adjusted in both cash flows and the discount rate. WACC typically takes this into account based on the after-tax cost of debt.
c) Inflation should be aligned between cash flows and discount rates. Cash flows should be adjusted with inflation if a nominal discount rate is used and not adjusted for inflation if a real discount rate is used.

All three metrics appear to be primarily considered by respondents as adjustments in cash flows, with minimal adjustment to discount rates, as shown in Figure 7. With discount rates expected to be after-tax rates and very often nominal rates, it is surprising that none of the metrics seem to be considered more often by adjusting the discount rate. Cash flows seem to be adjusted more frequently, while many respondents indicated non-consideration of the metrics. The low levels of discount rate adjustment and the high levels of non-consideration of all three metrics bring into question the financial basis and accuracy of automation investment decisions from a finance theory perspective. On average, 61.9% of automation consultants did not consider any of these metrics, as opposed to 35.6% of automation consumers, which is another potential indicator that automation consultants might not have sufficient financial knowledge or experience to make or recommend automation investment decisions. These findings of relatively low-level consideration of project risk, taxation, and inflation are also in line with the literature, as it was found that these metrics are not appropriately considered in many instances during capital budget decision-making in practice (Correia, 2012; Hall & Millard, 2011).

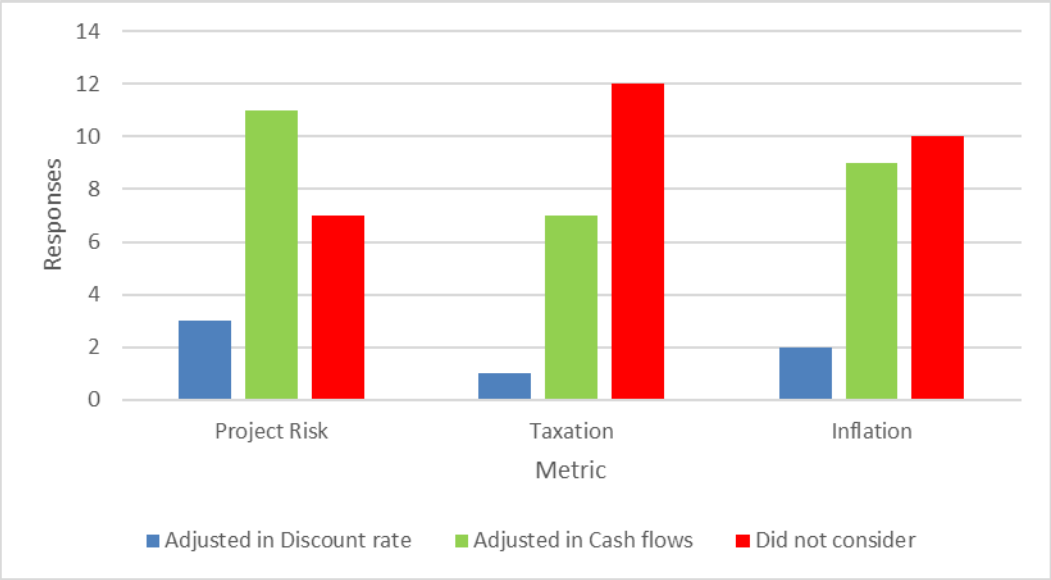

Figure 7: Finance metrics as inputs into appraisal techniques

When making project investment decisions, other essential factors include financing options, sunk costs, and opportunity costs of mutually exclusive projects. Incorrect treatment of these elements can result in incorrect decisions being made. Financing decisions should not impact project investment decisions as the cost of financing is already included in the WACC. However, there can be an interaction between these decisions, such as when specific financing options are dependent on an investment decision (Correia & Cramer, 2008). As per Table 10, 31.8% of respondents indicated that financing decisions impact automation investment decisions, which should not typically be the case. Of the respondents who indicated financing impacted the investment decision, 85.7% are in organisations with less than R1 billion annual revenue, and 57.1% are in automation consultants, which brings into question the financial theory application of these respondent categories. Sunk costs were removed by only 18.2% of respondents, while 13.6% indicated there were no sunk costs. Most respondents (68.2%) either did not consider or remove sunk costs from the appraisal, with 85.7% of automation consultants in the sample included in this category. Opportunity costs for mutually exclusive projects were considered by 45.1% of respondents, with 4.5% indicating there were no mutually exclusive projects. 50% of respondents did not include or consider such opportunity costs with a relatively even spread between organisations.

The considerations highlighted in Table 10 can significantly impact an investment decision if not treated correctly. It appears as if a portion of the sample treated these considerations incorrectly, especially in smaller organisations and by automation consultants. This further highlights the finance theory application deficiencies in smaller organisations and automation consultants, potentially impacting appropriate automation investment decision-making.

Table 10: Other considerations

Consideration	**Number**	**Percentage**
Did the investment financing method impact the automation investment decision?:		
Yes	7	31.8%
No	15	68.2%
	22	**100%**
How were sunk costs treated in the relevant calculations:		
Removed	4	18.2%
Not removed	9	40.9%
Did not consider	6	27.3%
No sunk costs	3	13.6%
	22	**100%**
For mutually exclusive projects, were opportunity costs of other projects considered:		
Yes	10	45.5%
No	5	22.7%
Did not consider	6	27.3%
No mutually exclusive project	1	4.5%
	22	**100%**

4.3 COSTS AND BENEFIT METRICS

Prior studies on automation found that automation metrics and benefits could be expanded from a cost reduction focus to a benefit increase focus and is worthy of further study (Coombs et al., 2020; Syed et al., 2020). This section focuses on survey responses related to quantitative and qualitative costs and benefits metrics, which impact automation investment decisions and satisfies research questions four (what metrics are included in the techniques used to appraise automation investment decisions?) and five (what is the quality of automation investment decision-making in practice?).

4.3.1 Quantified expenditure and cost savings

Table 11 indicates the relevant quantified investment outlay costs and employee cost savings considered in respondents' automation investment calculations and decision-making processes. Most respondents consider consulting fees, software costs, IT costs, and salary savings. Other costs and savings do not seem to be sufficiently considered, potentially impacting investment decisions. The impact on staff, and related training costs, has been identified in literature as a success factor for automation, per Table 3, and the consideration of such costs by respondents is lower than anticipated. It is also interesting to note that salary cost savings were considered by 90.9% of respondents, but not other employee-related costs, such as equipment and facility savings. It, therefore, appears as if the total cost of employment – inclusive of direct and indirect overheads – is not considered when savings are assessed for making automation investment decisions. This omission can potentially understate savings and project returns and incorrectly reject profitable automation investments.

Table 11: Quantified expenditure and cost savings

Expenditure/Saving Description	Number (sample = 22)	Percentage of sample
Investment outlay expenditure:		
External consulting fees	20	90.9%
Staff project participation costs	10	45.5%
Staff training costs	14	63.6%
Staff layoff costs	4	18.2%
Staff recruitment costs	8	36.4%
COE / Control Room running costs	10	45.5%

Software license purchase costs	21	95.5%
Software license renewal costs	20	90.9%
IT Infrastructure capital costs	20	90.9%
IT Infrastructure maintenance costs	18	81.8%
Working capital changes	3	13.6%
Foreign currency valuation differences	4	18.2%
Others	1	4.5%
Employee (FTE) savings:		
Salary	20	90.9%
Recruitment	6	27.3%
Training	11	50.0%
Facility usage	7	31.8%
Equipment	6	27.3%
IT	9	40.9%
None considered	1	4.5%

4.3.2 Automation Benefits

Syed et al. (2020) identify the definition and measurement of automation benefits as an area of future research. Table 12 summarises the key automation benefits according to literature and indicates whether respondents either quantified or qualitatively considered the benefits in their automation investment decision-making process. Cost savings is the benefit most considered and most quantified by respondents. This finding aligns with the literature that highlights the current over-emphasis on cost savings to make automation investment decisions, with insufficient correlating focus on benefits (Syed et al., 2020). An important observation from Table 12 is that all identified automation benefits have been quantified by at least one respondent. Therefore, while there might be difficulties quantifying certain benefits such as employee satisfaction, it appears to be attempted in practice. The importance of qualitative considerations is also highlighted in Table 12, with more benefits currently being considered qualitatively as opposed to being quantified. This finding aligns with the literature, which indicates that certain qualitative considerations are important, although sometimes overlooked, and are often difficult to quantify (Bornet et al., 2020; Coombs et al., 2020). While respondents appear to have extensively considered qualitative factors, the current lack of quantifying automation benefits can result in an understatement of automation investment returns, leading to incorrect decision-making. Based on the automation benefits considered in Table 12, the quality of automation investment decision-making is negatively impacted by incomplete benefits quantification. Additional research in this field is required, specifically related to an increased understanding of automation benefits, to quantify such returns for investment decision-making. This study can be used in future research as indicators of quantitative and qualitative benefits currently considered in practice.

Table 12: Automation benefits considered

		Considered and quantified		Considered qualitatively - Not quantified	
	Automation Benefit	**n**	**% of sample**	**n**	**% of sample**
1	Overhead / general cost savings	17	77.3%	5	22.7%
2	Increased accuracy through reduced error	10	45.5%	11	50.0%
3	Increased compliance and risk mitigation	6	27.3%	13	59.1%
4	Processing speed	9	40.9%	9	40.9%
5	Employee satisfaction / Net Promoter Score	1	4.5%	17	77.3%
6	Revenue increase	10	45.5%	7	31.8%
7	Transparency for improved decision-making	3	13.6%	12	54.5%
8	Operational agility	2	9.1%	12	54.5%
9	Client Net Promoter Score / CSAT	3	13.6%	10	45.5%
10	Other	0	0.0%	1	4.5%
	Total responses	**61**		**97**	

4.4 STRATEGIC AND OPERATIONAL FACTORS

To answer research questions four (what metrics are included in the techniques used to appraise automation investment decisions?) and five (what is the quality of automation investment decision-making in practice?), several key strategic success and operational factors, which can significantly impact an automation project's outcome, have been highlighted in Table 3. These are qualitative considerations, which can also influence metrics such as project risk and result in quantitative adjustments to appraisal technique inputs. However, the scope of this study does not include the quantitative impact these factors might have on automation appraisals. Instead, it focuses on whether these factors are considered qualitatively in making automation investment decisions to assess decision-making quality. Consideration of these factors would be indicative of better automation investment decision-making. The results in Table 13 indicate that, on average, strategic level automation success factors are considered by 67.3% of the sample, while the lower level operational factors are considered by 57.1% of the sample. On average, automation consultants (71.8%) consider both the strategic and operational factors more than automation consumers (57.7%), which highlights that consultants are subject matter experts in the field of automation. While there is currently no benchmark to compare these results to, most respondents considered these factors, which indicates it plays a substantial role in automation investment decision-making and should positively impact automation decision-making quality.

Table 13: Automation success and operational factors considered

Factor Description	**Number (sample = 22)**	**Percentage of sample**
<u>Strategic automation success factors:</u>		
Organisation automation strategy and/or internal synergies	14	63.6%
Combining different technologies to enhance automation capability	15	68.2%
Suitability of current IT infrastructure to automation technology	14	63.6%
Maturity of processes to be automated	15	68.2%
The impact of automation on staff	16	72.7%
Average		**67.3%**
<u>Operational factors:</u>		
Automation complexity	17	77.3%
Data volumes	14	63.6%
Number of FTE	7	31.8%
Digitised data	8	36.4%
Structured data	9	40.9%
Repetitive processes	18	81.8%
System integration	15	68.2%
Average		**57.1%**

4.5 INVESTMENT REVIEW

This section focuses on the survey results of actual investment outcomes compared to the initial assessment and identifies difficulties respondents experience in the automation investment decision-making process. These results will be used to further assess the automation investment decision-making quality in light of previous survey responses, thereby fulfilling research question five (what is the quality of automation investment decision-making in practice?) and identifying future research areas.

4.5.1 Investment outcomes

As per Table 14, only 4.5% of respondents indicate higher than expected returns, while 18.2% indicate returns align with the initial appraisal. A total of 77.3% either indicate lower (9.1%) or unknown (68.2%) returns on automation investments. These findings are surprising as organisations go through rigorous investment decision-making processes, such as using an overall average of 2.8 investment appraisal techniques (Table 8) but then do not subsequently assess whether there has been a return on the investment. However, these findings align with literature that indicates comprehensive measuring of automation investment returns, such as payback periods, is lacking (Syed et al., 2020; Watson et al., 2019). This further brings into question on what basis automation investment decisions are made if they are not assessed subsequently. Not assessing automation investments could indicate managerial opportunism and over-investment of free cash flow into automation projects, as identified as a shareholder and management conflict of interest by Jensen (1986). Shareholders might prefer to receive dividends instead of investing in projects that are not being assessed for profitability.

Table 14: Investment outcomes compared to initial assessment

Outcome	Number	Percentage
In line with the initial appraisal	4	18.2%
Higher returns	1	4.5%
Lower returns	2	9.1%
Too difficult to accurately quantify	7	31.8%
Post completion audits are not performed	8	36.4%
	22	**100%**

4.5.2 Difficulties experienced

Before concluding on the reasons for automation investment decisions, the difficulties experienced when making such decisions will first be considered. These difficulties might shed more light on why investment returns are not assessed in the same way investment decisions are. According to Table 15, the top two difficulties constitute 48.1% of the total number of responses received for this question. These results corroborate the results in Tables 12 and 13, which indicate that savings are not sufficiently considered during decision-making, and many automation benefits are not quantifiable. While non-consideration of cost savings is potentially an oversight, which can be corrected, quantifying automation benefits is not necessarily easily correctable. Syed et al. (2020) stated that there should be a shift in focus from automation cost savings to automation benefits; however, the actual identification and quantification of such benefits appear to be problematic in practice. While further research is required in this area, it also emphasises that suboptimal automation investment decisions appear to be made in practice.

Table 15: Appraisal difficulties experienced

	Difficulties	n	% of sample (22)
1	Identifying and quantifying automation benefits and savings	16	29.6%
2	Too many qualitative considerations not quantifiable	10	18.5%
3	Selecting appropriate capital investment appraisal techniques	6	11.1%
4	Insufficient understanding of investment appraisal techniques	6	11.1%
5	Identifying and quantifying the investment outlay	5	9.3%
6	Assessing the impact of project risk on financial data	5	9.3%
7	Calculating a relevant discount rate	2	3.7%
8	Poor data quality	2	3.7%
9	Others	1	1.9%
10	No difficulties experienced	1	1.9%

4.5.3 Basis for decision

Much effort goes into making automation investment decisions based on the number and types of appraisal techniques applied and metrics considered. However, with many organisations not appearing to understand the return on their investment, as per Table 14, the basis of their decisions are worthy of further exploration. As per Table 16, there are strategic and market force criteria, apart from quantifiable returns, which also drive automation investment decision-making and provide additional insight into the factors impacting automation investment decisions. Strategic intent and competitive advantage are important considerations for investment decisions.

Investment decisions should result in value creation; if no assessment of such value creation occurs for automation investments, there is a risk of managerial opportunism and over-investment. Other factors such as ‘fear of falling behind the market’ being a basis of decision-making for 36.4% of the respondents indicate potential incorrect decision-making as it is not an optimal investment decision-making basis. Only 54.5% of organisations base their decisions on quantifiable returns, highlighting the risk of suboptimal decision-making. It is surprising to see such a low response rate for quantifiable returns as a factor contributing to automation investment decision-making, especially considering the results in Table 8, which indicates that all respondents performed quantitative appraisals. Therefore, it is clear that qualitative considerations currently play a larger than expected role in automation investment decision-making which further highlights the need to perform additional research on understanding and quantifying automation returns.

Table 16: Basis for making automation investment decisions

	Factor	n	% of sample (22)
1	Quantifiable returns based on capital budgeting appraisal techniques	12	54.5%
2	Digitisation strategy	10	45.5%
3	Seeking competitive advantage	10	45.5%
4	Fear of falling behind the market	8	36.4%
5	Other qualitative considerations	6	27.3%
6	Others	1	4.5%

4.6 DISCUSSION SUMMARY

In order to test the hypothesis of this research study, several research questions were examined. Table 17 illustrates the high-level results and conclusions reached for each research question and includes cross-references to the relevant results discussion sections. Based on the results as depicted in Table 17, it appears as if the hypothesis of this study has been supported by this research, which is that suboptimal automation investment decisions are being made in South Africa at present.

Table 17: Research Questions Summary

No.	Research Question	High level result / conclusion	Cross reference
1	Which automation technologies are commonly invested in by organisations?	Spreadsheets are the most used automation technology, followed by smart workflow and customised technologies. Notably, RPA and AI type technologies are not yet extensively used in South Africa.	Paragraph 4.1 Figure 5 Table 7
2	Which valuation techniques are used to appraise automation investment decisions?	Literature indicated that DCF techniques are the most widely used and technically correct for investment appraisals. However, the top three techniques used for automation investment appraisals are payback period, ROI, and budget availability, none of which are DCF methods. Budget availability has been exposed as a popular automation investment appraisal technique, albeit suboptimal. Payback period and ROI have also been identified as popular methods, both in practice and literature. Relative low use of DCF methods supports the hypothesis of this study and is indicative of potential suboptimal automation investment decision making.	Paragraph 4.2 Table 8
3	Are automation investment decisions made according to relevant theory by correctly utilising appropriate recognised valuation techniques?	Periods of assessment were primarily appropriate for automation investments. Deficiencies were noted in applying discount rates, with few risk-adjusted rates being used and insufficient consideration of taxation and inflation impacts. Furthermore, many responses did not consider financing options, sunk costs, and the impact of mutually exclusive projects. Incorrect application of finance theory was more noticeable in smaller organisations and automation consultants.	Paragraph 4.2 Figure 6 Table 9 Figure 7 Table 10
4	What are the metrics included in the techniques used to appraise automation investment decisions?	Certain relevant indirect costs were not considered in automation appraisals. Most benefits considered were qualitative and not quantified, which aligns to literature about the need to quantify qualitative factors. This indicates possible understatement of certain costs and benefits in automation investment appraisals leading to suboptimal decisions. Other qualitative strategic and operational factors (not quantified) appeared to be extensively considered in automation decisions, especially by automation consultants.	Paragraph 4.3 Table 11 Table 12 Paragraph 4.4 Table 13
5	What is the quality of automation investment decision-making in practice?	Low levels of post-completion audits related to automation investment returns reduce the ability to assess decision-making quality. The many difficulties experienced by respondents in the appraisal process were highlighted, indicating potential deficiencies in decision-making. It appears that qualitative factors play a prominent role in automation investment decision making. Deficiencies noted in satisfying research questions two, three, and four are also indicative of suboptimal automation investment decisions currently being made in practice in South Africa, which supports the hypothesis of this study.	Paragraph 4.5 Table 14 Table 15 Table 16

CHAPTER 5: CONCLUSION

Despite the existence and practical application of multiple capital budgeting and valuation techniques to make investment decisions, there is a lack of consensus and limited research on the most appropriate techniques to appraise automation investments. According to the extant literature, DCF techniques are not used to make automation investment decisions, which is a potential indicator of incorrect decision-making. Automation is a topic worthy of research due to its growing relevance and the potential impact of incorrect investment decision-making. The objectives of this study were to:

1. Contribute to literature by identifying the current automation technologies commonly invested in and the valuation techniques used to appraise such automation investments.
2. Identify potential gaps and make recommendations in the use and application of automation investment appraisal techniques and related metrics used.
3. Assess the quality of automation investment decision-making in practice.
4. Examine the metrics used for automation investment decision-making and design an investment decision-making framework.

To ensure the objectives of this study were achieved, the sample needed to provide a sufficient degree of confidence in the results. To that extent, the profile of respondents and their organisations were relevant. Upon analysis, the profile of survey respondents appeared to indicate sufficient qualifications, experience, and expertise to make automation investment decisions within their organisations. The presence of automation consultants within the sample increased the level of expertise in the sample, albeit not from a finance perspective but rather from an automation design and implementation perspective. The revenue and headcount sizes of the organisations also range from SMEs to large multinationals, which increases confidence in the research findings being relevant across a wide range of organisations.

What follows are the relevant conclusions related to each research objective, as indicated by the results of this study.

4.2 RESEARCH OBJECTIVE ONE

A gap identified in the literature, supported by this study's findings, is that spreadsheet technology is being used extensively for automation purposes even though it is not mentioned in automation literature. Despite spreadsheet technology having been around for about 30 years, it remains relevant for modern-day automation and needs to be considered in automation related literature. In this study, spreadsheet technology was the leading technology type used for automation, emphasising its popularity and extent of use, followed by smart workflow and customised technologies. Notably, RPA and AI type technologies are not yet extensively used in South Africa.

All respondents applied some form of automation investment appraisal technique, with the payback period (21.3%), ROI (16.4%), and budget availability (16.4%) being the top three techniques applied. DCF techniques only account for 34.4% of the responses. DCF techniques were more frequently used by larger organisations and less frequently by smaller organisations and automation consultants. This finding might be due to larger organisations having better finance skills, while automation consultants are not necessarily trained in finance and investment decision-making. Although the use of payback period and ROI was also prevalent in literature on automation investment decision-making, it does not align with the more general capital budgeting trends of using NPV and IRR (DCF techniques) as primary appraisal techniques (Correia, 2012). Therefore, it does appear as if DCF techniques are not sufficiently utilised in appraising automation investments, which will negatively impact the quality of decision-making. The use of budget availability as an appraisal technique has been identified as a contribution to the extant literature. However, it does not lead to optimal decision-making due to its focus on costs, while it largely disregards quantifiable long term value creation and benefits.

4.3 RESEARCH OBJECTIVE TWO

Responses on the discount rates applied for discounting cash flows varied, although WACC and inflation were the most prevalent rates used. The number of organisations that did not discount cash flows was relatively high, indicating a high potential of suboptimal automation investment decision-making. Regarding adjusting for project risk, taxation, and inflation, respondents indicated adjustments for these metrics were mainly being done in cash flows or not considered at all, while very few adjustments were made in the discount rate. Most automation consultants did not consider any of these metrics, while many smaller organisations and automation consultants seem to have treated financing and sunk costs incorrectly in the appraisal calculations. These findings further emphasise the apparent lack of financial acumen and quality of decision-making amongst automation consultants and SMEs.

The results indicate that both costs and benefits might be understated when assessing automation investments. Benefits can be in the form of cost savings and other income-related increases. Notably, it does not appear as if the total cost of employment is considered for staff-related cost savings, with the focus on salary costs only. The majority of other benefits were considered as qualitative factors but were not quantified. Therefore, it appears as if there is a risk of both costs and benefits being understated in appraisal calculations, with most benefits not being quantified. If benefits are not quantified sufficiently, it could lead to incorrect rejections of profitable automation projects – from a purely quantitative perspective. Qualitative factors appear to play an important role in automation investment decision-making, which is indicated by the extensive consideration of qualitative benefits and strategic and operational factors. Qualitative factors can potentially be quantified by adjusting for project risk, such as amending the discount rate if a DCF technique is applied (Correia, 2012; Hall & Millard, 2011).

4.4 RESEARCH OBJECTIVE THREE

The basis for deciding to invest in automation is not only based on quantifiable returns but heavily impacted by qualitative factors, strategy, and the need to remain competitive and relevant within the current digital landscape. Most respondents did not review the original investment decisions and outcomes, making it difficult to assess the quality of the original investment decision quantitatively. Many respondents indicated they experienced difficulties when quantifying benefits and savings, with too many qualitative considerations that are not quantifiable.

While automation is undoubtedly relevant, pervasive, and here to stay, this research has highlighted particular challenges with making automation investment decisions. Gaps have been identified in applying capital budgeting techniques and related finance theory. In addition, there appears to be the potential understatement of costs and benefits and major difficulties in quantifying qualitative considerations when appraising automation investments. The evidence of this study points towards questionable and suboptimal current automation investment decision-making occurring in practice.

4.5 RESEARCH OBJECTIVE FOUR

Numerous quantitative and qualitative metrics were identified as being used in practice to make automation investment decisions. To reduce bias and subjectivity, further research is required on quantifying qualitative considerations, as they appear to be material factors in automation investment decision-making. The automation investment decision-making framework (Figure 3) was designed, as deduced from literature, which can also be used as a basis for future research on this topic.

4.6 RESEARCH CONTRIBUTION

This study has contributed to research and extant literature on automation investment appraisals in South Africa, as follows:

1. Exposed the following novel findings related to current automation technologies and the valuation techniques used to appraise such automation investments:
    a. Spreadsheet technology is extensively used as automation technology, although not recognised in automation literature.
    b. Budget availability is a popular automation investment appraisal technique, albeit flawed and potentially resulting in suboptimal decision-making.
2. Highlighted the qualitative factors being considered in practice, which are essential to automation investment decision making, and an important area for future research.
3. Proposed an automation investment decision-making framework (Figure 3) for making automation investment decisions, which can also be used as a basis for future research.
4. Identified that automation consultants need to be upskilled in finance or use finance experts to assist in recommending automation investments to their clients.
5. Concluded that current automation investment decision making in South Africa appears to be suboptimal. Stakeholders such as management, consultants, and investors need to be aware of the risks and pitfalls related to automation

investment decision making practices and the consequences of potential incorrect decisions.

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APPENDIX A

SURVEY INSTRUMENT

Personal Details

Your current role

- ◯ CEO
- ◯ CFO
- ◯ COO
- ◯ Director
- ◯ Senior Manager
- ◯ Manager
- ◯ Accountant
- ◯ Other

How long have you been in this role

- ◯ 0-5 years
- ◯ 5-10 years
- ◯ 10-15 years
- ◯ 15-20 years
- ◯ >20 years

Your highest qualification obtained

- ◯ PhD
- ◯ Masters
- ◯ Honours
- ◯ Bachelors
- ◯ Diploma
- ◯ Certificate
- ◯ Matric

Your role in the automation investment decision making process

Select all that apply

- [ ] Calculation performer
- [ ] Reviewer
- [ ] Decision maker
- [ ] Other

Employer's organisational details

Your employer's primary organisation type

- ( ) Consumer of automation technology and services
- ( ) Delivery of automation consulting and technology

Location of organisation

- ( ) South Africa
- ( ) Other

Industry of organisation

- [ ] Technology
- [ ] Telecommunications
- [ ] Health Care
- [ ] Financials
- [ ] Real Estate
- [ ] Consumer Discretionary
- [ ] Consumer Staples
- [ ] Industrials
- [ ] Basic Materials
- [ ] Energy
- [ ] Utilities

Annual Revenue (ZAR) of organisation

- ◯ < R50 million
- ◯ R50 million - R1 billion
- ◯ R1 billion - R5 billion
- ◯ > R5 billion

Total number of current staff employed by organisation

Automation Technology

Technology implemented by your organisation

Select all that apply

- ☐ Robotics Process Automation (RPA)
- ☐ Intelligent Document Processing (e.g. OCR)
- ☐ Smart Workflow
- ☐ Image and Video analysis
- ☐ Cognitive / Virtual agents (e.g. chatbots)
- ☐ Natural Language Processing
- ☐ Speech Analytics
- ☐ Big Data Analytics
- ☐ Excel / VBA
- ☐ Low code application platforms
- ☐ Custom Developed technology
- ☐ Cloud software integration
- ☐ Other 1
- ☐ Other 2
- ☐ Other 3

Which vendor's technology was implemented

Select all that apply

- [ ] UI Path
- [ ] Automation Anywhere
- [ ] Blue Prism
- [ ] Microsoft
- [ ] Other

Automation Investment Appraisal Techniques

Techniques used to appraise automation investment decisions

Select all that apply

- [ ] Net Present Value
- [ ] Internal Rate of Return
- [ ] Modified Internal Rate of Return
- [ ] Payback Period
- [ ] Discounted Payback Period
- [ ] Return on Investment (Accounting Rate of Return)
- [ ] Profitability Index
- [ ] Economic Value Added
- [ ] Capital Asset Pricing Model
- [ ] Monte Carlo Simulations
- [ ] Other
- [ ] Budget availability

Over what period is financial data appraised

- ( ) Up to 1 year
- ( ) 2 - 3 years
- ( ) 4 - 5 years
- ( ) > 5 years

Which discount rate is applied for DCF methods

- ◯ WACC - unadjusted
- ◯ WACC - adjusted for project specific risks
- ◯ Inflation
- ◯ Prime interest rate
- ◯ Inflation + GDP growth
- ◯ Other
- ◯ DCF methods weren't used

Which of the following were considered in the appraisal calculation

	Adjusted in Cash flows	Adjusted in Discount rate	Did not consider
Project Risk	☐	☐	☐
Taxation	☐	☐	☐
Inflation	☐	☐	☐

Did the investment financing method impact the automation investment decision

- ◯ Yes
- ◯ No

How were sunk costs treated in the relevant calculations

- ◯ Removed
- ◯ Not removed
- ◯ Did not consider
- ◯ No sunk costs

For mutually exclusive projects, were opportunity costs of other projects considered

- ◯ Yes
- ◯ No
- ◯ Did not consider
- ◯ No mutually exclusive project

Metrics considered in appraisal

Investment outlay costs quantified and included in the investment appraisal are:

Select all that apply

- [ ] External consulting fees,
- [ ] Staff project participation costs,
- [ ] Staff training costs,
- [ ] Staff layoff costs,
- [ ] Staff recruitment costs,
- [ ] Centre of Excellence / Control Room running costs,
- [ ] Software license purchase costs,
- [ ] Software license renewal costs,
- [ ] IT Infrastructure capital costs,
- [ ] IT Infrastructure maintenance costs,
- [ ] Working capital changes,
- [ ] Foreign currency valuation differences,
- [ ] Others
- [ ] None considered

Employee (FTE) cost savings quantified and included in the investment appraisal are:

Select all that apply

- [ ] Salary
- [ ] Recruitment
- [ ] Training
- [ ] Facility usage
- [ ] Equipment
- [ ] IT
- [ ] Others
- [ ] None considered

Automation benefits considered and/or quantified in the appraisal calculation are:

Select all that apply

	Considered and quantified	Considered qualitatively - Not quantifiable
Revenue increase,	☐	☐
Overhead / general cost savings,	☐	☐
Processing speed,	☐	☐
Increased accuracy through reduced error rate,	☐	☐
Increased compliance and risk mitigation,	☐	☐
Client Net Promoter Score / CSAT,	☐	☐
Employee satisfaction / Net Promoter Score,	☐	☐
Transparency for improved decision making,	☐	☐
Operational agility,	☐	☐
Other 1	☐	☐
Other 2	☐	☐
Other 3	☐	☐

Other qualitative factors

Strategic factors considered when making Automation investment decisions are:

Select all that apply

- ☐ Organisation automation strategy and/or internal synergies,
- ☐ Combining different technologies to enhance automation capability,
- ☐ Suitability of current IT infrastructure to automation technology,
- ☐ Maturity of processes to be automated,
- ☐ The impact of automation on staff,
- ☐ Others
- ☐ None considered

Operational factors considered when deciding on which processes to automate are:

Select all that apply

- [ ] Automation complexity
- [ ] Data volumes
- [ ] Number of FTE
- [ ] Digitised data
- [ ] Structured data
- [ ] Repetitive processes
- [ ] System integration
- [ ] Others
- [ ] None considered

Conclusion

How do actual investment outcomes compare to initial appraisals

- ○ In line with initial appraisal
- ○ Higher returns
- ○ Lower returns
- ○ Too difficult to accurately quantify
- ○ Post completion audits are not performed

Why were lower returns realised in comparison to initial appraisal

Select all that apply

- [ ] Incorrect modelling of investment appraisal
- [ ] Incorrect or incomplete input data used in appraisal calculation
- [ ] Other
- [ ] Unknown

Difficulties experienced when appraising automation investment decisions:

Select all that apply

- ☐ Selecting appropriate capital investment appraisal techniques,
- ☐ Insufficient understanding of capital investment appraisal techniques,
- ☐ Identifying and quantifying the investment outlay,
- ☐ Identifying and quantifying automation benefits and savings,
- ☐ Calculating a relevant discount rate,
- ☐ Assessing the impact of project risk on financial data,
- ☐ Too many qualitative considerations not quantifiable,
- ☐ Poor data quality
- ☐ Others
- ☐ No difficulties experienced

What are your automation investment decisions most based upon

Select all that apply

- ☐ Quantifiable returns based on capital budgeting appraisal techniques,
- ☐ Digitisation strategy,
- ☐ Seeking competitive advantage
- ☐ Fear of falling behind the market,
- ☐ Other qualitative considerations,
- ☐ Others
- ☐ Unknown
