The Importance of Robotic Process Automation (RPA) on Customer Experience in the South African Financial Sector

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ABSTRACT

Robotic process automation (RPA) is a technology that enables businesses to automate repetitive business functions that are considered mundane in order to boost productivity and reduce expenses. Digital transformation, more specifically RPA, has received increased attention in the financial sector because of its potential to improve user and customer satisfaction. This study investigates how RPA affects customer experience in the financial sector in South Africa.

A quantitative research approach was used in the study, which included an analysis of the data collected from 215 South African participants against a review of the current existing literature on the RPA subject matter. According to the results, the variables that drive RPA adoption can enhance the customer experience by increasing perceived usefulness, boosting reliability and availability, increasing perceived security, and enhancing perceived ease of use. However, RPA adoption is still in the early stages in the South African financial sector, and there are a number of obstacles to it, including concerns about data and job security. Additionally, to increase the adoption rates in order for financial services providers to fully gain the benefits of RPA, the businesses will need to confront the adoption barriers and make the necessary investments in infrastructure and resources.

This study adds to the understanding of how RPA can enhance the customer experience within the financial sector and offers insightful intelligence to any South African business already making use of or considering to use RPA.

Keywords: Robotic Process Automation (RPA), RPA adoption, Net Promoter Score (NPS), reliability and availability, perceived usefulness, security, customer experience

DECLARATION

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

Signature: TMndebele

Signed at: Paulshof, South Africa, on 24 February, 2023

DEDICATION

I dedicate this research to God the Almighty; He has been my way, my truth, and my life. I would also like to dedicate this research to my friends and family, more especially my mother, Cathrina Pelo and sister, Thembisile Mnisi, who have shown me unconditional love and support from the moment I took my first breath. For that, I am eternally grateful.

To my best friend and husband, Ndumiso Masala, who has been affected by every step of my journey, thank you for encouraging me to start and being by my side until I finished, love does not begin to describe how I feel about you and our family.

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1. INTRODUCTION

1.1 Research Purpose Statement

This research will primarily focus on investment platforms provided by South African Financial Services Providers (FSPs) like FNB, Investec, Nedbank, Allan Gray, and more of the same.

Digitisation has become a crucial element of remaining competitive in the financial industry, it has aggressively transformed business operations across various industries, and automation is a big part of this process (Research ICT Africa, 2022). Robotic Process Automation (RPA) is a complex and cutting-edge form of said automation and currently, there are various studies projecting that as RPA progresses further, many existing jobs today will be redefined and rewritten (Fernandez & Aman, 2018) (Mckinsey, 2017) (Eikebrokk & Olsen, 2020). As a result, organisations aiming for longevity and remaining competitive in their respective markets now need to prepare themselves for this disruption and prepare for the adoption of RPA, while carefully pondering how this adoption will impact their end-user, the customer.

1.2 Background and Context

Syed et al. (2020) define robotics as software that is coded to complete and function as human beings in system interactions. Related overall process automation refers to workflow management systems or systems that are process-aware. Robotic process automation is a relatively new technology that consists of robots or “bots” that imitate the manual processes completed by human beings by making use of a variety of computer programs to conduct these different business processes (Syed et al., 2020).

These robots often conduct well-structured, rule-based activities that are repetitive in nature. These repetitive activities mean that robots can follow the same process for every iteration. As a result, a human would no longer be required to complete these tasks, with the general sense that a robot would sufficiently complete them the same every single time without error. Robots can do tasks like automatic query processing, and data transfers, as well as tasks like payroll data aggregation from multiple sources, to name only a few (Bataev & Davydov, 2020).

1.2.1 The Revolution of Robotic Process Automation

Automation is a topic that countless South African businesses in the financial sector have been driving for many years now; this drive has resulted in digital banks like Bank Zero and Discovery Bank, as well as digital investment platforms like Easy Equities. The latter has even integrated into the South African banking industry with relative ease. As new businesses emerge, organisations that have operated in the financial industry for longer, legacy banks like FNB, Nedbank, Sanlam, and Investec have also started making use of RPA to become more efficient in their operations and to remain competitive in this evolving market (Tew, 2019).

According to Bank of America Merrill Lynch, (2015), the expectation is for robots to perform the function of 45% of manufacturing jobs by 2025, a significant 10% increase from the current state of the industry in 2023. The market for robotics and AI solutions would have been worth US$153 billion by 2020. Machine learning and interfaces like voice and facial recognition are set to revolutionise the banking and finance industries. These are the same industries that are looking to gain competitive advantage, reduce costs and consistently increase operating margins. RPA is rapidly becoming the mechanism of change across these four key areas: processes, operations, customer experience and business infrastructure (Bank of America Merrill Lynch, 2015).

Blue Prism, a software company conducted research in 2020 centred around the South African market and how business decision-makers or leaders and knowledge workers perceive RPA and its implementation. Figure 1 is an output of that study which shows the intended revolution of RPA through South African businesses, with the outcome of the study showing that 90% of business leaders believe that RPA is a significant driver of their digital transformation journeys.

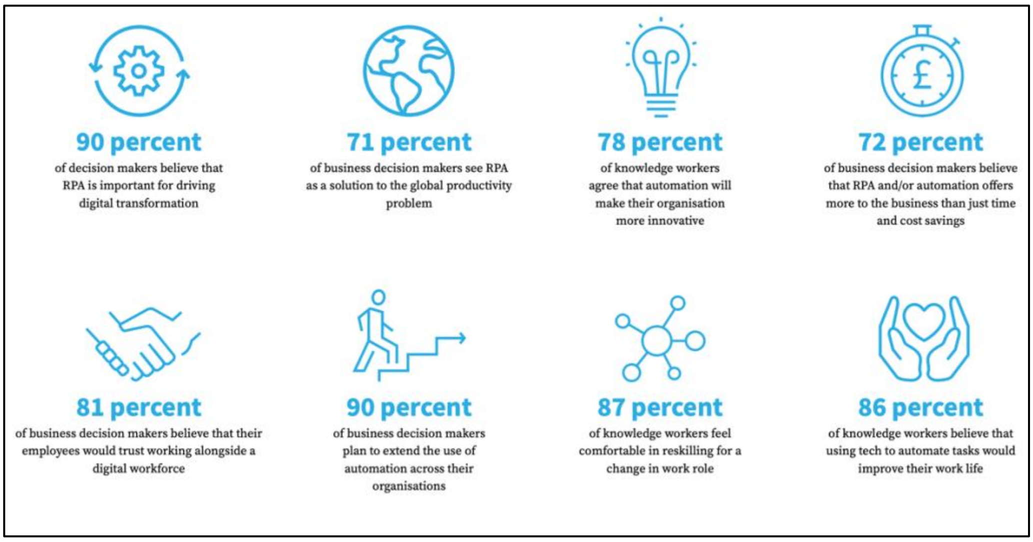

Figure 1: Results from Study on the Impact of a Digital Workforce on Agility and Survival (Blue Prism, 2020)

According to an article by an international banker (2021), RPA is a combination of robotic automation and artificial intelligence, which can also be referred to as "smart" or "intelligent" automation. It essentially provides organisations with a rule-based virtual workforce. The robotics allow these organisations to automate and construct automation platforms for their front and back offices, as well as for support functions. A survey conducted by Deloitte in 2022 of over a hundred leaders in Shared Services revealed that 74% of said leaders planned to investigate the RPA technology in the next year and 22% had already piloted or fully implemented RPA in their organisations (Deloitte, 2022).

1.2.2 The utilisation and Benefits of Robotic Process Automation

Some of the key advantages of delegating manual tasks to robotics include but are not limited to: cost savings, time savings (because RPA frees ups employees to take on more complex tasks), a reduction (and even total elimination) of human error, and scalability, because robots can perform tasks at a higher speed than any human. Scalability also implies that automated systems can manage quantities that are considerably bigger, also ensuring that tasks are still completed on time even at that level (Gartner, 2022). A classic example of this in the banking sector is account openings, a procedure that is often repetitive, laborious, and time-consuming for all involved. Tasks like these can be completed quicker and with better accuracy when they are automated, and this means that RPA can greatly enhance the integrity and quality of financial data in the long run.

Additionally, RPA has the ability to produce copious amounts of information based on data and the analysis thereof, which has also proven to deliver substantial benefits to the financial services industry (Gartner, 2022). As a result, banks, investment platforms and insurers are investing in RPA to remain competitive in a sector that is consistently evolving by making use of automated investing systems that utilise algorithms to organise individuals and group investment portfolios, for example. These digital investment solutions are powerful tools that can assist in reinforcing the link between credibility and service delivery, which would eventually positively impact the customer's experience (Mavlutova et al., 2022).

1.3 Research Problem Statement

In research conducted by Mckinsey (2017), the organisation presented the overall percentage of activities that can be automated in each part of the world. In the appendix of this research paper, Figure 1 shows Southern Africa being at the lower end with less than 45%, highlighting the potential of this region and certifying the ground of opportunity that can be explored through the adoption of automation. From the same research conducted by Mckinsey, the gap in automatic industrialization between the first world and the third is very evident, highlighting the rising global pressures of advancement (McKinsey, 2017). Organisations in the African region are going against global players who, through automation, are able to enter the market with more advanced products at an even quicker rate. As a result, most businesses have a greater need than ever to increase their profitability whilst decreasing their expenditure, and the best way to go about this is to automate (Bataev & Davydov, 2020). AI and RPA are currently at the forefront of this automation with more organisations opting to focus on building virtual workers to take care of repetitive tasks to reduce costs (Zaharia-Radulescu et al., 2017).

It is true that the South African financial sector is facing overwhelming pressure to automate by implementing RPA across their functions and departments, but there is also a need to determine if RPA is indeed the silver-bullet industries believe it to be, with a specific focus on the impact of adopting RPA will have on the end-user.

This is important given that many financial services providers are using RPA to automate their back-office processes, such as customer onboarding, transaction processing, and accounting, according to a McKinsey & Company report titled "Intelligent process automation in banking: A global perspective on trends, adoption, and emerging practices," which was released in May 2021. The report indicates that RPA can assist banks in streamlining their processes and lowering costs by automating routine, rule-based procedures.

It has been said that the business sectors stand to benefit greatly from automation technologies, benefits that include but are not limited to: cost savings, enhanced performance, and improved customer experience (Bataev & Davydov, 2020). Important to note, however, is that customer preparedness is a vital aspect of a new technology's successful adoption (Kumar et al., 2021).

In the following section, through the literature review, the new technologies that are being implemented in the retail financial services industry will be discussed. Organisations will have to adopt these new technologies to reap the benefits, which include cost savings, enhanced performance, and improved customer experience. The different industries and uses of automation will be highlighted like those in the healthcare, insurance, and telecommunications industries that are all making use of RPA (Mckinsey, 2017).

This research will look at the problem of improving the customer’s experience in the South African finance sector through the use of RPA. This will be done through an assessment of the net promoter score, reliability and availability, perceived usefulness, and security as independent variables.

1.4 Research Objectives

- Investigate the importance of RPA on customer experience in the South African financial sector by making use of the Net Promoter Score (NPS).
- To investigate the impact of the perceived usefulness of RPA in the financial services sector.
- To examine the influence of perceived reliability and availability of RPA in the financial sector and if these result in a better customer experience.

- Investigate the influence of perceived ease of use of RPA in the financial sector and if this results in increased customer experience
- To examine the influence of the security of RPA in the financial sector and if it results in better adoption and customer experience

1.5 Research Questions

- Does RPA result in high net promoter scores?
- Does the perceived usefulness of RPA positively influence the experience of customers in the financial sector?
- What is the relationship between the perceived reliability of RPA and the customer experience in the financial sector?
- What is the relationship between the perceived ease of use of RPA and the customer experience in the South African financial sector?
- How does security influence the adoption of RPA in the financial sector?

1.6 Delimitation and Limitations of the Research

This research will make use of a quantitative research methodology. The data will be collected from individuals that make use of investment platforms through various online platforms.

Additionally, the research will make use of data collection through an anonymous questionnaire with a 5-point Likert scale that measures customer experience on the basis of the study's reviewed literature. The questionnaire will be distributed through channels that include email, WhatsApp, and LinkedIn to get as many responses as possible. SPSS Statistics, an IBM software typically used for data analysis, will be utilised to test the hypothesis and analyse the data that is collected through the questionnaires. The use of Structural Equation Modelling is a delimitation for this study however can be used in future studies.

The timeframe for data collection is over a two to three-month period, once the questions are confirmed, this is one of the limitations of the study as a longer timeline would have been preferred to allow for a larger sample size that would account for more of the South African population.

1.7 Significance of the research

RPA has been described by Asatiani and Penttinen (2016), as a “cutting-edge” business process that is focused on automation technology, the use of which has proven to provide positive outcomes when automating back-office processes. With the popularity of RPA growing across the globe and across various industries, it has become increasingly important to research the RPA field and present more literature for all affected parties to consider. This research is set to add to the body of work that currently exists and investigate an important gap in the impact of RPA adoption on customer experience, with a specific focus on the financial services industry in South Africa.

This research augments studies like that done by Kumar and Balaramachandran (2018) on the impact of Robotic Process automation on customer experience in the banking industry and focused mainly on the Asia Pacific area. This research will also add to the work done by Lamberton et al., (2017), who focused on the implementation of RPA and AI in the insurance industry. Additionally, the research will also add value to a multitude of industries and sectors like the following:

- **Financial Service Organisations:** The research will highlight the impact of RPA on the business processes, which in recent years has become the focus of many financial service organisations - uncovering how this technology will impact the source of their income and their customers.
- **Employees in the Financial Service Industry**: The literature of this paper will highlight how the implementation of RPA will impact employees; an important consideration as such findings will change employees’ way of working in the long term. This information will assist employees in gaining more knowledge about their future of working, allowing them to prepare themselves for what is coming.
- **Customers of Investment Platforms**: The customers refer to the individuals who make use of investment platforms, through different formats like web and digital applications. This research will share findings linked to customer satisfaction and allow them to have the ability to identify which elements linked to RPA add the most value to their experience.

- **Financial Intelligence Centre (FIC) and other Policymakers**: The FIC, as one of the most important governing bodies in the financial services industry, as well as other policymakers, can gain value from the understanding of how RPA adoption will impact the interaction between customers and the organisations that they monitor. The data impact of implementing RPA and how it will affect customers will be of interest to these governing bodies.

2. LITERATURE REVIEW

2.1 The Definition of Robotic Process Automation

Technological advancements like artificial intelligence (AI), data science, and machine learning are proving to be important when it comes to the progression of various industries (Singh & Namekar, 2020), meaning that the question of what should be automated and what should remain a human task is becoming a popular question. Amongst these advances is Robotic Process Automation (RPA), which is a generic term used to describe tools that operate on a user interface with other computer systems in the same manner that human beings would (Doguc, 2020). This kind of technology replaces human intervention through 'outside-in' automation, which varies from the traditional 'inside-out' approach. What this means is that the core information system remains untouched and unchanged, and the RPA interacts with the "front-end" systems (van der Aalst et al., 2018).

In a definition provided by Gartner, written by Tornbohm (2017), RPA is said to be a tool that implements "If, Then, and Else" statements that can be found in structured data that utilises a variety of user interfaces and interactions or APIs to manage code, digital mainframes, or servers. RPA tools map a process using coding language they get from specific software and the robotic elements triggered with runtimes assigned to execute scripts can complete the process.

Ultimately, RPA enables its users to design bots that simulate interactions with other applications, these applications can then complete a multitude of processes like communicating with other digital systems, data manipulation, transactions, and triggered replies (Doguc, 2020). According to Boulton (2018), technology like RPA is expected to have an economic impact amounting to $6.7 trillion by 2025, making it the second-highest most valuable industry behind the telecommunication industry.

2.2 The usage and impact of RPA

In the works of Kumar et al. (2021), a breakdown of RPA tools is listed as the following:

- Excel – This is considered a basic automation tool
- Software robots – These can interact and connect with other systems

- Cognitive automation robots – These robots have the ability to utilise unstructured data for decision making and lastly
- Self-Learning tools – They can analyse and learn human activities

These are the four most common RPA tools being used in different industries. In their study, Alexovič et al. (2018) investigated the position of RPA in the pharmaceutical industry, highlighting how RPA can be used to improve accuracy in the production of medications. On the other hand, Schäffer et al., (2019) presented a pragmatic method of improving engineering processes that are considered knowledge-intensive by using RPA to concentrate on the progressiveness of knowledge bases. Additionally, there was also a study completed by Enriquez et al. (2020) that presented the status of RPA in the industrial and scientific industries, identifying gaps that are being resolved through the RPA lifecycle.

As mentioned previously, the digitisation journey became critical to the growth of any industry, even in wind and hydroelectric installations for example, where many of them are in rural areas (Kumar et al., 2021). Automation could assist in increasing this industry's efficiencies and maximise system performances. The smart sensors that are used daily made use of RPA to generate large amounts of data. Other uses for RPA can include creating reports based on data, generating shift charts for duties, load schedules, reports for energy generation, producing payslips, and even for the automatic submission of information to regulatory authorities where appropriate (Kumar et al., 2021). Table 1 below provides a summary of the application of RPA in various industries.

Table 1: The application of Robotic Process Automation (RPA)

Industry	**Usage**
Healthcare	Billing
	Patient registration
HR	New employee joining formalities
	Payroll process
	Hiring shortlisted candidates
Insurance	Claims Processing & Clearance
	Premium Information
Manufacturing & Retail	Bills of material
	Calculation of Sales
Telecom	Service Order Management
	Quality Reporting

Travel & Logistic	Ticket booking
	Passenger Details
	Accounting
Banking and Financial Services	Cards activation
	Frauds claims
	Discovery
Government	Change of Address
	Licence Renewal
Infrastructure	Issues Processing
	Account setup and communication

2.2.1 Uses for RPA in the financial sector

Robotics in the financial sector are mostly defined as making use of robotic automation software programs like UiPath and Automation Anywhere to install desktop and end-user device-level software system robots. Once RPA is implemented in the financial sector, it performed mouse and keyboard functions, repetitive tasks, and pasting or making use of data from web and application platforms (Vijai et al., 2020).

The financial sector, investment platforms included, is an industry that received a range of enquiries and requests ranging from information requests, account openings, and application progress enquiries (World Economic Forum, 2016). RPA has allowed enquiries that historically took days to be completed, to be finalised within seconds through various methods and platforms. RPA also addresses issues where decision-making is required with the use of artificial intelligence (Dey & Das, 2019). Chat robot automation makes use of natural language processing (NLP) to enable robots to grasp the natural language of speaking with clients and respond exactly as human beings would (Doguc, 2020).

2.3 Theoretical Basis of Research

2.3.1 Technology Adoption Theory

This research made use of an adoption theory as the basis for the investigation to be conducted because constant technological changes threaten business models (Kumar et al., 2021). There is a consistent need for newer, more improved service offerings that are sophisticated and dynamic, with the technological tools that become available it becomes important for customers to adopt and embrace these new technologies. This adoption relies on a variety of aspects such as the tool's availability, customer demand, security, and convenience. There are several researchers that have investigated the customer adoption of new technologies (Lai, 2017) (Chuttur, 2009). The Technology Acceptance Model (TAM) was utilised as the adoption theory for this research.

There are a variety of theories that have been developed to explain why customers embrace and adopt new technologies with the intention of using them. These theories include but are not limited to:

- The Theory of Diffusion of Innovations (DIT) which surfaced in 1960 (Rogers, 1995),
- The Theory of Task-technology Fit (TTF) (Goodhue, and Thompson, 1995),
- The Theory of Reasonable Action (TRA) (Fishbein and Ajzen, 1975),
- The Theory of Planned Behavior (TPB) (Ajzen, 1985, 1991),
- The Decomposed Theory of Planned Behavior (Taylor & Todd, 1995).
- The Technology Acceptance Model's final version (TAM), derived by Venkatesh and Davis (1996)
- Technology Acceptance Model 2 (TAM2), again derived by Venkatesh and Davis (2000)
- Technology Acceptance Model 3 (TAM3), derived by Bala and Venkatesh (2008)
- The unified Theory of Acceptance and Use of Technology (UTAUT) was derived by Venkatesh, Morris, Davis, and Davis (2003).

Generally, it is suggested that the implementation of RPA can be difficult, and this difficulty is largely attributed to the reduced acceptance (Zhang et al., 2022). Consultancies advise that implementing RPA requires a holistic change management strategy that focuses on aligning people, processes, and structures as closely as possible (Offerman & Van Leeuwen, 2020). The Technology Acceptance Model (TAM) is often used to evaluate system development applications for front-end use or automation technologies designed for back-end systems (Marangunić & Granić, 2014).

TAM is known as one of the best theories for mapping people's reactions to new technology into multiple dimensions of change, often known as constructs

(Marangunić & Granić, 2014). TAM, which is an adaption of the Theory of Reasonable Action, is designed primarily for modelling consumers' adoption of information systems or technologies. Davis (1989) introduced this behavioural model in 1986 to assist with predicting system usage. TAM was later refined to include and highlight relationships between several constructs that could be impacting technological acceptance (Offerman & Van Leeuwen, 2020).

Davis (1989) used TAM to explain the general drivers of technological adoption, which ultimately led to a better understanding of users' behaviour across a multitude of end-user computer systems and user groups. There are two important factors that a basic TAM accounts for, Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU is defined as a potential user's subjective likelihood to use a certain system (e.g., a platform's E-payment system, or a banking and investment application). The other important factor encompassed in TAM is PEU,) which describes the degree to which the potential user expects the system to be simple to use (Davis et al., 1989). Figure 1 represents the final version of TAM which includes a representation of an individual's belief that can be influenced by secondary factors, represented by "external variables" in the TAM.

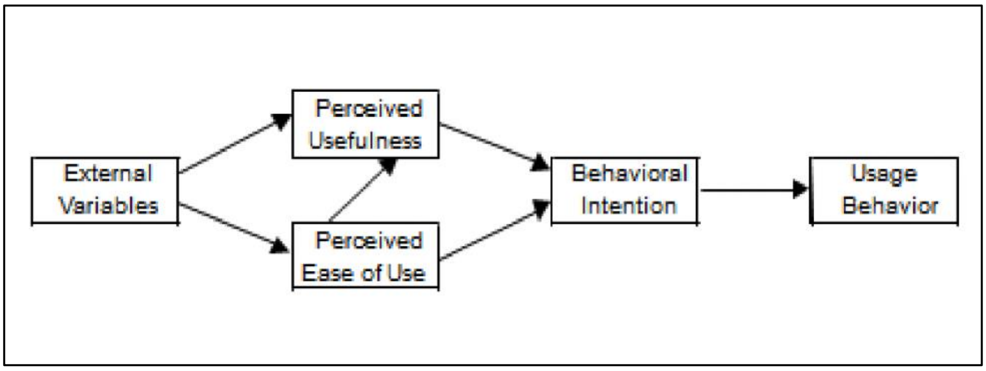

Figure 2: Final Version of the Technology Acceptance Model (Chuttur, 2009)

2.3.2 Customer Satisfaction Theories

Customer satisfaction is the most important factor for assessing the quality of a product or service along with the subsequent service provided to clients (Pizam et al., 2016). In the case of this research, the researcher will look to use customer satisfaction as a measure of the impact of RPA. Client satisfaction is critical to an organisation's long-term sustainability. According to a study done by Helm et al., (2006), attracting new customers has a cost of around five times as much in money, time and resources as retaining current customers. It is for this reason that maintaining high servicing standards, being aware of customer expectations, and good improvements are all an important part of any organisation's operations.

Lervik Olsen et al., (2014) also describes customer satisfaction as the end-user’s satisfaction with a service or product. Research by Angelova & Zekiri, (2011) defines customer satisfaction and contentment as stemming from a consuming experience. This can be a cognitive reward state, a comparison and cost reward to an expected outcome or an emotional response to an experience. Customer experience is an important element of any organisation and measuring it is pivotal if an organisation wants to be progressive and retain customers (Lervik Olsen et al., 2014).

Customer satisfaction can be measured for reasons that may differ from organisation to organisation. The following five reasons, according to, Naumann and Giel (1995), are the most prevalent:

- For the organisation to get closer and more personal with the consumer. This helps them discover which qualities customers consider the most essential; which attributes influence their decision-making; the relative significance of the attributes; and a performance rating of how effectively the company delivers each attribute and outcome.
- For the business to track progress throughout the customer journey. For the customer, important qualities are linked directly to the firm's value-added processes and put into a format that is compatible with the internal metrics used to evaluate the processes.
- For the organisation to achieve improvement that is driven by the customer. Customers are not all created equal when it comes to innovation. This needs an extensive database that records not only sales but also innovation sources.
- For the organisation to assess its competitive advantages and disadvantages. This is to determine how customers feel about competing options. This is accomplished through the use of questionnaires to sample both potential and present consumers, as well as current and previous customers.

- The organisation can also link Customer Satisfaction Measures (CSM) data to internal systems. This will mean a regular and more comprehensive sense of customer experience and satisfaction (Naumann, 1995).

As a form of measurement, a multitude of customer satisfaction surveys employs ordinal and discrete rating scales, such as Likert scales, which include an odd number of alternatives, generally 5 to 7. In this scale, the most positive end of the scale is labelled "most positive," and the same will apply to the "most negative" end, with "neutral" in the centre. "Agree" or "disagree" might be used as an alternative to "most positive" or "most negative" (Menold & Bogner, 2016).

It is important to note that making use of the Likert scale could result in what is known as acquiescence bias, also called agreement bias, where respondents tend to be more likely to respond positively (Angelova & Zekiri, 2011). A way to solve for acquiescence bias is to introduce items where agreement indicates disagreement, the reversal of items lessens the likelihood of bias, although doing this could cause respondents to answer differently than they intend to (Angelova & Zekiri, 2011).

The introduction of items in the negative, where agreement indicates disagreement with the construct, is one approach to solving this difficulty. Reversing items may lessen acquiescence bias, but this may create additional mistakes because people may respond differently to merely deleteriously phrased stimuli. Rosenvinge (2005) discovered that the semantic format matches measurement modes, model fit, and uni-dimensionality better than a Likert scale utilising inferential, structural equation, and reliability statistics.

Reichheld (2003) established another popular method of measuring customer satisfaction, the Net Promoter Score (NPS). This is a popular method used by organisations to quantify their consumers' inclination to suggest a product, service, or company to their friends or colleagues, based on their own experience.

Reichheld (2003) also states that for managers in some businesses, achieving a high NPS becomes almost as crucial as generating solid financial outcomes. It is for this reason that experimenting with an indicator such as NPS can assist with categorising qualitative data into classes that can be assigned numeric values and utilising user satisfaction data to identify services that may have influenced the users' skills, competencies, behaviour, and opinions. In the case of this research, the NPS will be used to identify if the adoption of RPA by organisations in the financial industry will result in increased satisfaction (a high NPS).

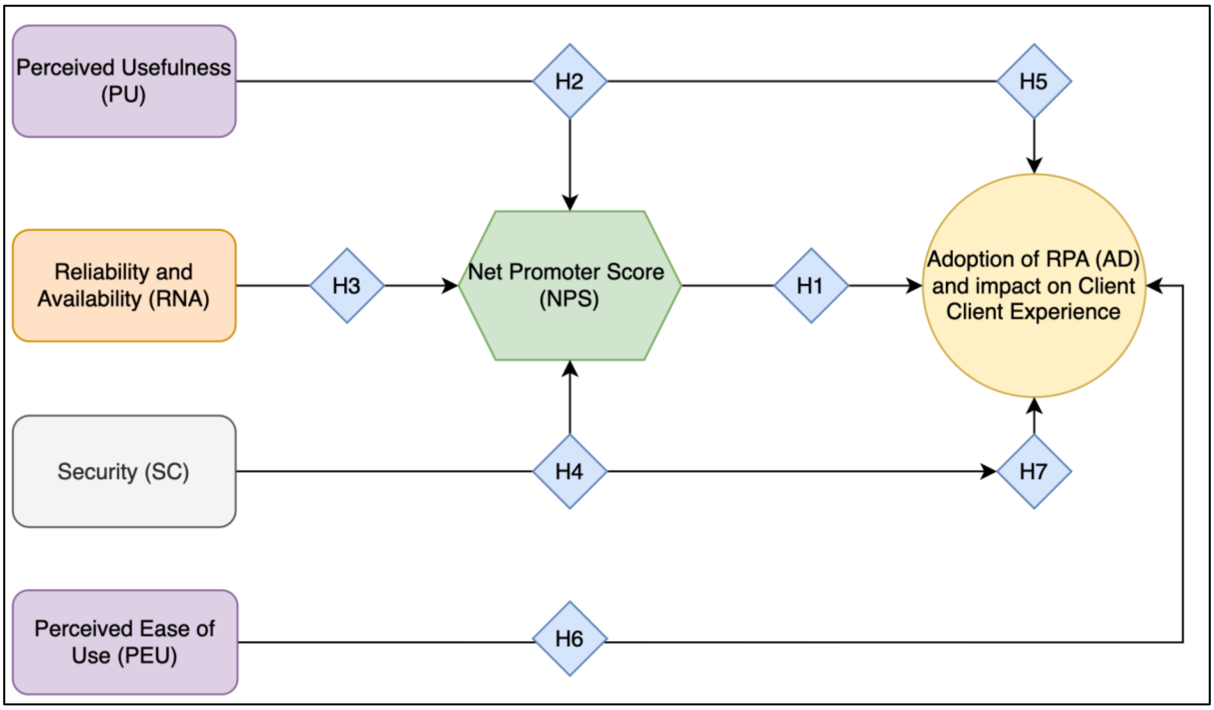

Figure 3: Research Model (Own Rendition, 2022)

3. RESEARCH MODEL AND HYPOTHESIS DEFINITION

The theoretical model that this research is based on is shown in Figure 3, representing the dependent variable as "RPA adoption by the finance sector to improve customer experience". The independent variables (the factors influencing the dependent variable) are listed below:

1. Net Promoter Score
2. Perceived usefulness
3. Reliability and Availability
4. Security
5. Adoption of RPA

The research model was created by establishing a link between these variables to better understand the function of each of them in affecting the adoption of RPA in the South African finance sector for the improving of their customer experience. Accompanying hypotheses are then derived and have been outlined below each of those sections.

3.1 Net Promoter Score

The literature review highlights the use of the Net Promoter Score (NPS) in measuring customer satisfaction. As a part of the model designed in this research, this theory is being used to measure and test the relationship between customer satisfaction and the adoption of RPA in the financial sector. The relationship will assist in determining the future adoption of RPA in financial organisations and what this will mean for their customers, and ultimately, their future income streams.

Hypothesis 1 (H1): A high Net Promoter Score (NPS) is positively related to RPA adoption and improved customer experience

Hypothesis 2 (H2): Perceived usefulness is positively related to the NPS

Hypothesis 3 (H3): Reliability and Availability are positively related and result in increased NPS

Hypothesis 4 (H4): Security is positively related to increasing NPS

3.2 Perceived Usefulness (PU)

An appropriate example of usefulness is the usefulness of using a banking application on a smartphone and how it is a factor that influences an individual's desire to stay with the bank in the future (Kumar et al., 2021). Examples of data mining include grouping, time series analysis, and classification. The difficulty of having access to or extracting enormous amounts of data is ensuring the security of sensitive information and dealing with data that is incomplete (Chen et al., 2015). In scenarios like these, RPA mixes the awareness linked to automation and the flexibility of AI and each job completed by the robot generates data that can be analysed.

The analysis leads to improved decision-making when automating processes (Casale et al., 2015). The main motivations for using AI are gaining insights from analysis, cost savings, and increased productivity (Rohde, 2016). Customers expect financial service providers to give them personalised products and services that are tailored to their specific needs (Susanto et al., 2016). The analysis of data and personalised offerings provide the usefulness of goods and services that influence a customer's propensity to make use of those financial services.

3.3 Reliability and Availability

Reliability and simplicity of use are said to have a significant impact on customer experience (Svilar & Zupančič, 2016). To improve regulatory compliance, efficiency, credibility, and customer experience, RPA can be used through integrated investment advice. RPA also reduces the risk of human error and improves business operations (Daga, 2016). It can also ensure prompt servicing, improved appearance, technical servicing, responsiveness, dependability, and trustworthy satisfaction - which are all factors that impact customer satisfaction (Zeinalizadeh et al., 2015). Reliability and availability are important variables to consider when looking at the adoption of RPA and how it impacts the customer, especially because the automation software has been said to save financial organisations up to 80% on processing expenditure, making measuring the customer experience of utmost importance (Casale et al., 2015). The usage of robotic process automation in the form of intelligent scripts improves a business's "digital efficiency" as well as the availability of services and consumers' access to them (Marciniak & Stanisławski, 2021).

3.4 Security

One of the most critical things that influence customer experience is security and privacy. According to the literature, customers often rate their top concerns in using financial services as privacy and security (Svilar & Zupančič, 2016). The general customers' expectations ontrust, adoption, and whether they will make use of said financial services are all influenced by their perception of the internet security (Rondovic et al., 2016). Large data gathering is necessary for innovation; big data remains a new source of enormous value (Tene & Polonetsky, 2013). Customers have a greater concern about the security and privacy of their personal data, as well as transactional security, fraud, and the social risk of making use of data available on the internet for discriminatory reasons (Chen et al., 2015). The above outline the reasons why security is an important variable in measuring the impact of adopting RPA in the financial sector and its impact on customer experience.

3.5 Adoption of RPA

The adoption and impact of RPA will be the focal point of this research and for this reason, it will be the dependent variable. The researcher will investigate and measure the impact of the NPS, perceived usefulness, reliability and availability and security, on RPA adoption.

The year "2018" is known as the "Year of Robotic Process Automation." The industry entered a new realm of technology when it comes to RPA. Its adoption has become a must in day-to-day processes and operations (Gartner, 2022). Companies that do not implement this technology in their operations may not be able to compete in the not-so-distant future (Mckinsey, 2017). RPA is a new type of business process automation technology that relies on software robots or artificial intelligence (AI) employees to complete tasks and its cutting-edge technology is considered the most powerful of the twenty-first century (Doguc, 2020). New hardware, software, and smart device technologies will dramatically assist with the way organisations do business, how people approach official employment, and how the public lives their everyday lives (Mckinsey, 2017). Worldwide collaborations, multinational organisations, and new IT/ITes breakthroughs which have been born from RPA technology, and human lifestyles are changing all over the world.

With adoption being so important for organisations, this research will show the impact of the independent variables on RPA adoption, define what customers deem important and help organisations in making decisions for the key areas of focus when ensuring the successful adoption of RPA.

Hypothesis 5 (H5): Perceived Usefulness is positively related to RPA adoption

Hypothesis 6 (H6): Perceived ease of use products that make use of RPA are positively related to RPA adoption and improved customer experience.

Hypothesis 7 (H7): Perceived security is positively related to RPA adoption and improved customer experience.

3.6 Summary of Hypotheses

Based on the literature review and the theoretical frameworks that have assisted in framing the research model, the following hypotheses were developed and the factors are applied to the adoption of RPA by the South African financial sector and its impact on customer experience:

1. Hypothesis 1 (H1): A high Net Promoter Score (NPS) is positively related to RPA adoption and improved customer experience
2. Hypothesis 2 (H2): Perceived usefulness is positively related to the NPS
3. Hypothesis 3 (H3): Reliability and Availability are positively related and result in increased NPS
4. Hypothesis 4 (H4): Security is positively related to increasing NPS
5. Hypothesis 5 (H5): Perceived Usefulness is positively related to RPA adoption and improved customer experience.
6. Hypothesis 6 (H6): Perceived ease of use of products that make use of RPA is positively related to RPA adoption and improved customer experience.
7. Hypothesis 7 (H7): Perceived security is positively related to RPA adoption and improved customer experience.

4. RESEARCH METHODOLOGY

4.1 Research Approach

The term research approach refers to research techniques and processes that explain the data collection, processing, and interpretation process. The primary purpose is to figure out which approach should be used for the given research (Creswell, 2018).

Quantitative research, which is framed with statistics and organised with open-ended and closed-ended questions, and qualitative research, which is framed with words rather than figures, are two different methods to do research (Ahmad et al., 2019). There is also a mixed-method approach which incorporates both qualitative and quantitative techniques (Creswell, 2018). The quantitative technique was used for this research as it allowed for the measuring of variables quantitatively. A deductive research technique was used since the online questionnaire was used to assess the seven hypotheses derived from the literature.

4.2 Research Design

Schindler (2019,) defines research design as "*a framework for gathering data that meets objectives and answers questions.*" The research design directed the procedures of the study in a specified way. A quantitative research strategy that is exploratory in nature was utilised to answer the research question. The goal of this research is to investigate the factors that measure the importance of RPA on client experience in the South African financial sector, and the research also determined the link between variables.

4.3 Sampling Design

In this section, the sampling strategy that was used in this research will be defined. Beginning with a description of the target population, followed by the sample frame, sampling size, as well as sampling methods.

4.3.1 Population

Schindler (2019,) defines population as "*people, events, or records with the needed information to address the study question*." The study's participants are South African e-commerce clients, over the age of 18. Participants must satisfy the following requirements to be considered for this study from the standpoint of a consumer: they must have prior experience with e-commerce platforms; they must have an internet connection, and they must have a device from which they can access the internet.

4.3.2 Sample Framing

"*The list of instances in the target population from which the sample is drawn; it is a complete and correct list of population members alone*," (Schindler, 2019,). The intended sample frame for this research consisted of all persons who interacted with a financial service provider using an application or on a web platform in South Africa.

4.3.3 Sample Size

The number of people in the sample and the processes used to obtain this number are indicated in the determination. The exact sample size was calculated using statistical techniques (Schindler, 2019). A trade-off was necessary since a bigger sample size would yield better accuracy, but recruiting volunteers was costly and time-consuming (Cresswel, 2018). A "good" sample-to-variable ratio is 5:1 for participants to items at a minimum and a 25:1 ratio maximum, this is according to Worthington and Whittaker (2006). This has become a popular rule of thumb. Memon et al., (2020) drive how crucial the sample size selection is, stating "*strength of samples derives from accurately picking samples.*" Consequently, the appropriate sample size for this data is between 175 and 200, given the items being investigated.

The aim was for a sample size of 200, this aligned with the literature advising that for multiple equation analysis, a sample size of 200 to 250 is acceptable Memon et al., (2020,).

Multiple variables are modelled and examined using multiple equation analysis, which described the relations between a dependent variable and a number of observed or investigated independent variables (Turóczy & Marian, 2012). These independent variables can be used for forecasting or as predictors. Compared to a uni-factorial regression model, the multiple regression model is often considered more realistic (Turóczy & Marian, 2012)

It is because of the above as well as the fact that confirmatory factor analysis is a statistical technique used to enhance the multiple equation analysis, that this methodology is appropriate for this paper. The goal of confirmatory factor analysis, which has its roots in psychometrics, is to assess hidden psychological qualities like attitude and satisfaction, on the other hand, path analysis began in biometrics and sought to identify the causal relationship between variables (Wright, 1921,). Confirmatory factor analysis was necessary to answer the research questions being investigated in this paper.

4.3.4 Sampling Methods

Probability and non-probability sampling techniques are the two categories of sampling procedures. What separates the two, according to Schindler (2019), is a random selection, which implies that "*any member in the population has an equal chance of being picked."*

Probability sampling, also known as random sampling, permits findings from the sample population to be extended to the population being investigated (Ahmad, Wasim, Irfan, Gogoi, et al., 2019). Non-probability sampling permits the researcher to choose samples based on their personal preferences (Cresswel, 2018). This study employed non-probability selection methods, which allowed for a selection process of participants based on convenience and availability.

4.4 Data Collection Methods

The online questionnaire built on the Microsoft Forms platform was used as the primary data-collecting tool for this project. A link was randomly distributed through platforms like Facebook, Twitter, LinkedIn, and WhatsApp, along with other social media channels. The questionnaire was distributed to a small number of participants first to test and ensure that they could reply without difficulty. Once this was completed, the final survey was sent out to all possible participants, the feedback obtained was closely considered and, where necessary, modifications to the questions were made.

4.5 Research Instrument

The research instrument used in this study was a questionnaire, administered as an anonymous survey that addresses the research questions as stated in Section 1. The breakdown of the proposed questions is encompassed in Appendix B. The instrument has four core sections, Section 1 gives a short description of the research, Section 2 is where the respondents completed demographic information, Section 3 is the screening information of the respondents and Section 4 is where the five variables of perceived usefulness, reliability and availability, perceived ease of use, security, adoption and NPS of RPA are addressed.

The research was constructed on a 7-point Likert scale to measure variables, the options ranged from strongly disagree to strongly agree. There were also NPS-specific questions to clearly measure the customer's experience using the NPS theory of if they would recommend the product or service.

4.6 Data Analysis

Once data collection was completed, the statistical analysis was completed by making use of the SPSS software. The following steps were followed when analysing the data:

1. Kept a record of the number of surveys sent out and responded to. Also, took note and tracked the number of "spoilt" questionnaires in the sample.
2. Made use of descriptive analysis when using the data to report the results of the standard deviation, means, scores as well as ranges. These statistics were noted and reported on for each variable and a 95% confidence level was utilised to test the reliability of the data, in accordance with the literature (Schindler, 2019).
3. The results of the study were interpreted and presented in figures and tables. Clear conclusions were drawn based on the results, these sought to prove or disprove the hypotheses that were constructed.

4.7 Validity and Reliability

This research made use of Cronbach's alpha to measure the consistency and reliability of the responses from the survey. There are varying reports about the appropriate value of alpha which ranges from 0.70 to 0.95.

Cronbach's alpha should be more than 0.7, according to Itwin and Fink, (2013), however, Chin (1998), suggests that a Cronbach's alpha value of 0.6 is adequate for confirming internal consistency. For the purposes of this research, the composite reliability score will be utilised and Kumar et al., (2021) confirm that an alpha of 0.70 or more is acceptable.

Convergent reliability was used to determine the correlation of the variables being tested, with an average variance of 0.5 implying a relationship between variables (Kumar et al., 2021).

4.8 Ethical Consideration

It is the researcher's job to ensure that ethical guidelines are followed and adhered to (Schindler, 2019).

The following procedure was implemented to guarantee that the research is carried out in an ethical manner:

1. The researcher sought ethical approval from the University's Ethics Committee beforehand.
2. To participate in the study, consent was requested from all participants.
3. The researcher did not link any replies to any specific respondent's name, ensuring that privacy and anonymity were respected.
4. The research aims were specified to maintain transparency.
5. The researcher did not discriminate against anyone and allowed participants that met the criteria stipulated in the research to participate in the study.

4.9 Chapter Summary

This chapter summarises the methodology of the research study in detail. It is a quantitative study that makes use of non-probability sampling techniques to share a survey, anonymously, through online platforms, aiming to get between 200 and 250 responses. These responses were from individuals 18 years or older, and from across different areas in South Africa. The theories and analysis of the data was completed by making use of multiple equation analysis and SPSS in the following chapter.

5. DATA PRESENTATION AND ANALYSIS

5.1 Introduction

This chapter will focus on statistical data analysis and the results obtained during the collection of data linked to the factors influencing the adoption of Robotic Process Automation (RPA) and its impact on customer experience in the financial services sector in South Africa. An overview of the descriptive statistics will be provided along with reliability and variability tests, and finally, a detailed multiple equation analysis and hypothesis testing.

5.2 Descriptive Statistics

This part of the research will provide the descriptive data that was collected through questions asked about the demographics of the survey participants, namely the respondents' gender, age, and level of education.

5.3 Sample Descriptions

The survey received 216 responses from data collected from individuals that make use of digital platforms linked to their finances, with one response being removed from the data set because the responses were blank. Tables 2 to 4 below provide a view of the demographic data collected.

Table 2: Demographic profile – Gender of respondents

Gender	Count of Gender	Percentage
Female	151	70,23
Male	64	29,77
Grand Total	**215**	**100**

Table 3: Demographic profile – Age of respondents

Age	Count of Age	Percentage
18 - 29 years	48	22,33
30 - 39 years	111	51,63
40 - 49 years	42	19,53
50 - 59 years	9	4,19
60 or over	5	2,33
Grand Total	**215**	**100**

Table 4: Demographic profile – Education Level of respondents

Row Labels	Count of Education Level	Percentage
Bachelor's Degree	61	28,37
Certificate	25	11,63
Grade 12/Matric	17	7,91
Honours/Postgraduate diploma	77	35,81
Masters	32	14,88
PhD	3	1,40
Grand Total	**215**	**100**

Table 2 shows the distribution of respondents by gender. Most of the study's respondents were female, making up for 70,23% of the individuals that completed the survey. The remaining 29,77% were male, with none of the respondents selecting others.

Table 3 showed the distribution of respondents by age. The majority of respondents were between the ages of 30 and 39 years old, making up 51.63%, followed by the ages 18 to 29 at 22,33%. The ages 40 to 49 followed closely with 19,53% of the respondents belonging to this group, and lastly were the ages 50 to 59 and 60 or over at 4,19% and 2,33% respectively.

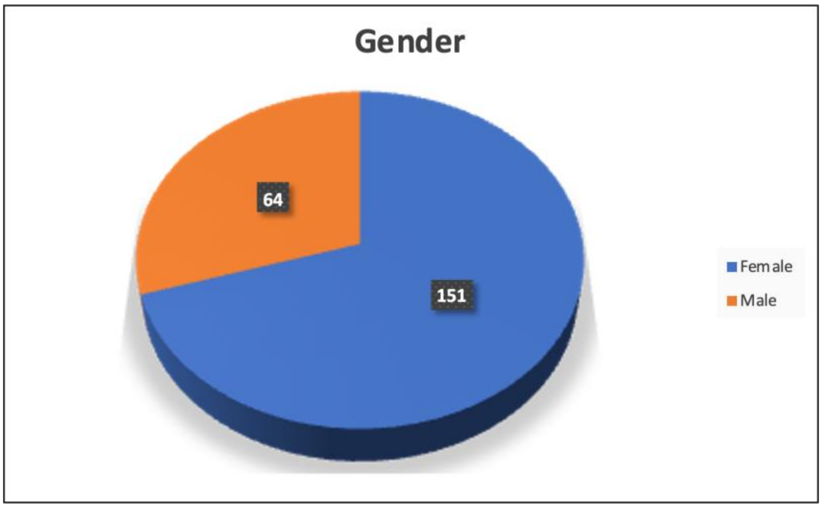

Figure 4: Pie chart representing gender distribution

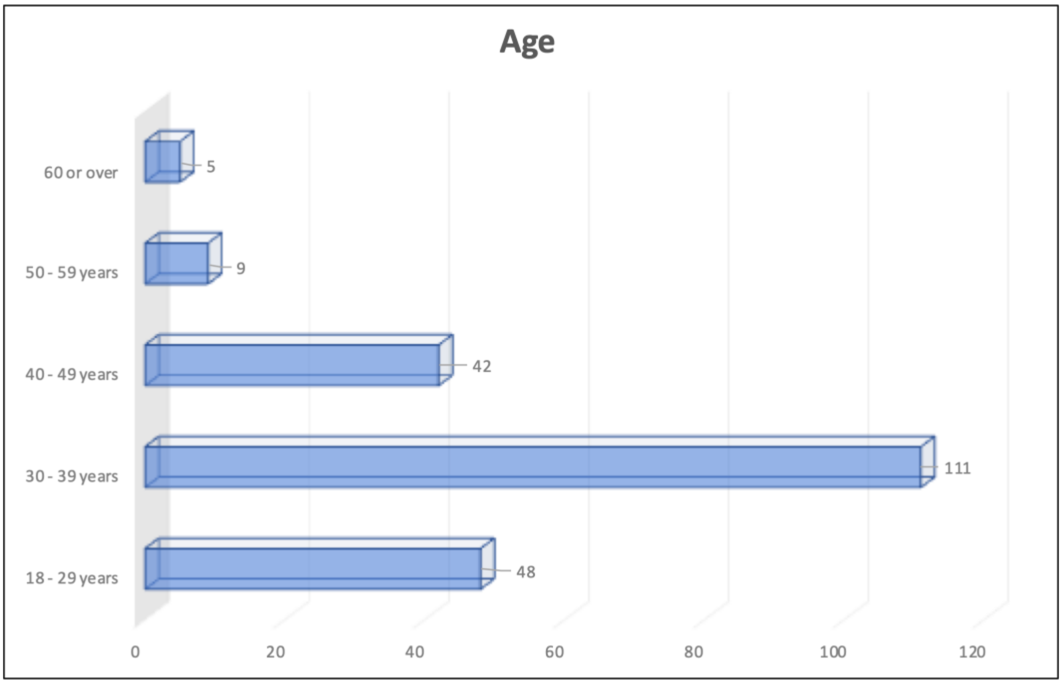

Figure 5: Pie chart representing age distribution

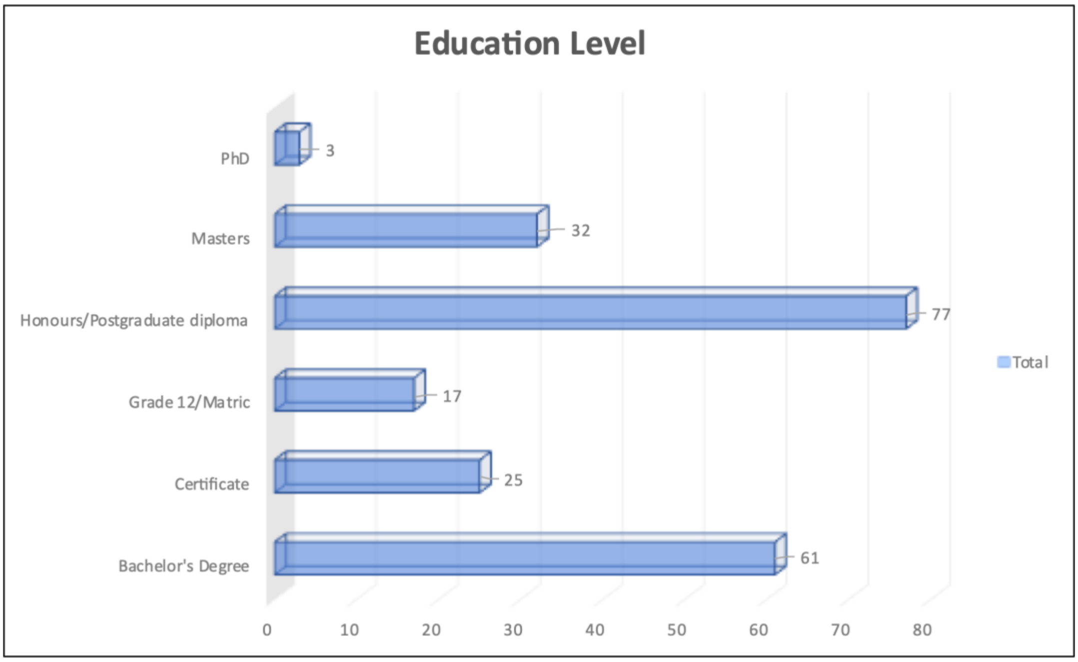

Figure 6: Pie chart representing distribution based on the education level

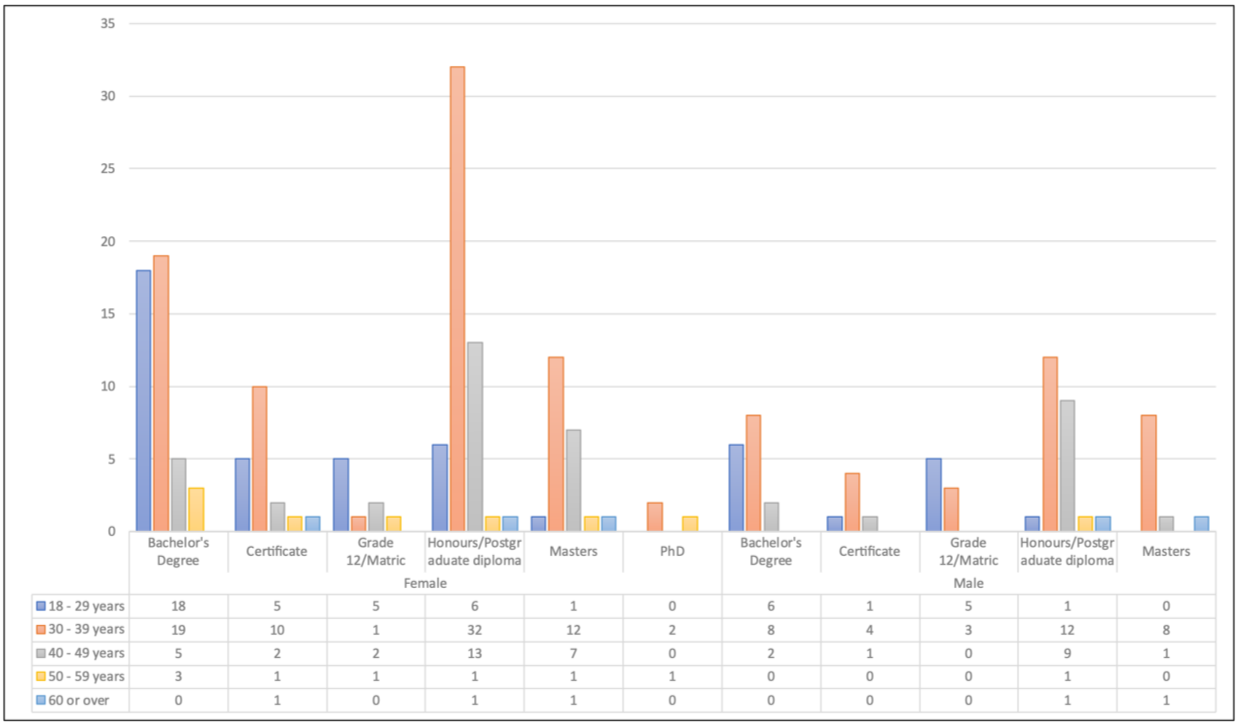

Figure 7: Bar graph of a combined view of demographic data

Figures 2 to 4 are a graphical representation of the demographic of the respondents broken down using real numbers. Figure 5 shows a combined view of the respondent's gender, age, and education level, providing a clear view that most of the respondents were females between the ages of 30 to 39 years old, with honours/postgraduate degrees and diplomas.

5.4 Statistical Analysis

In this section, an overview of the data analysis will be provided. A seven-point Likert scale survey was used to measure the research constructs (strongly disagree, slightly disagree, disagree, neutral, slightly agree, agree, strongly agree). Table 5 shows the breakdown of the coding used throughout the research analysis. It links the variables of perceived usefulness, reliability and availability, perceived ease of use, security, and adoption to their respective items in the questionnaire and the codes created for use throughout the analysis. Noting that the item linked to Reliability and Availability (RNA3) was dropped from the model fit and composite reliability testing due to having a factor loading that was less than 0.3.

Table 5: Likert scale questionnaire constructs and codes

Research Construct	Code	Items
Perceived Usefulness	PU1	Making use of the online application/web allows me to accomplish my tasks faster
	PU2	Making use of the online application/web made completing my task easier
	PU3	I consider making use of the online application/web convenient
	PU4	Using the application/web to complete my financial tasks increases how often I transact
Reliability and Availability	RNA1	The online application/web or website was available when I last made use of it
	RNA2	I find the online application/web to be easily accessible
	RNA3	I have experienced an error/mistake made on a transaction submitted through the online application/web
Perceived Ease of Use	PEU1	Learning to use the online application/web was easy for me
	PEU2	Becoming skilful at using the online application/web was easy for me
	PEU3	I find the online application/web easy to use
	PEU4	All the information I require to navigate the application/web is easy to find
	PEU5	I find using the online application/web "faster" because I can always visibly see where to click next to complete my tasks
Security	SC1	I input personal details onto the online application/web when completing tasks or transactions
	SC2	I trust that my data is safe when I input my data into the online application/web
	SC3	I believe that the security measures on the online application/web are of a high standard
	SC4	I feel safe making use of the online application/web
Adoption	AD1	I intend to keep using the online application/web
	AD2	I will always use this online application/web in my daily life
	AD3	I am using the online application/web for more than one type of transaction or function
Net Promoter Score	NPS1	On a scale of 0 to 10, how satisfied are you with the financial app you are using?
	NPS2	On a scale of 0 to 10, how likely are you to recommend the financial application/web you are using to friends and family?

Key: PU = Perceived Usefulness; RNA = Reliability and Availability; PEU = Perceived Ease of Use; SC = Security; AD = Adoption; NPS = Net Promoter Score

Table 6: Reliability and Validity statistics

Research Construct	Code	Descriptive Statistics				Cronbrach					
		Individual Mean Value	Overall Mean Value	Individual Standard Deviation	Overall Standard Deviation	Individual Cronbrach	Cronbrach Alpha	Composite Reliability Value	Average Value Expected	Highest shared variance	Factor loading
Perceived Usefulness	PU1	6,3023	6,1884	1,426	1.3657	0,914	0,946	0,94363	0,80818	28,948	1,001
	PU2	6,2698		1,388		0,914					0,928
	PU3	6,2791		1,442		0,914					0,829
	PU4	5,9023		1,622		0,914					0,826
Reliability and Availability	RNA1	6,0140	5,2993	1,518	1,3137	0,915	0,568	0,69535	0,53561	35,861	0,653
	RNA2	6,0977		1,512		0,914					0,803
	RNA3	3,7861		2,249		0,926					0
Perceived Ease of Use	PEU1	5,9814	5,94418	1,498	1,4016	0,916	0,963	0,96119	0,83301	66,863	1,006
	PEU2	5,9861		1,448		0,917					0,996
	PEU3	6,1116		1,413		0,917					0,862
	PEU4	5,7023		1,616		0,917					0,841
	PEU5	5,9395		1,526		0,916					0,843
Security	SC1	5,10697	5,2256	1,863	1,4624	0,916	0,885	0,88455	0,67520	73,649	0,392
	SC2	5,1628		1,679		0,914					0,884
	SC3	5,3395		1,595		0,914					0,953
	SC4	5,293		1,639		0,915					0,926
Adoption	AD1	6,1209	6,0930	1,490	1,4334	0,917	0,979	0,88626	0,72205	79,746	0,851
	AD2	6,0512		1,435		0,917					0,862
	AD3	6,10697		1,464		0,917					0,836
Net Promoter Score	NPS1	8,0279	8,05815	2,109	2.1383	0,916	0,971	0,96764	0,93739	84,782	1,004
	NPS2	8,0884		2,227		0,916					0,931

5.5 Reliability Test

The following statistics were gathered to measure the reliability of the data; Cronbach Alpha Coefficient, Composite Reliability, and Average Value Extracted. The results will be discussed below.

5.5.1 Cronbach Alpha Coefficient

According to researchers, in order to be regarded as reliable, Cronbach's Coefficient must be more than 0.7 (Hair, Bush, & Ortinau, 2009). However, other studies show that a Cronbach Alpha of greater than 0.6 is considered to have excellent reliability, this is according to Pallant (2001). Five of the six variables, namely PU, PEU, SC, AD and NPS have Cronbach alpha coefficients of over 0.88, all considered an extremely high level of reliability. The variable measuring reliability and availability (RNA) is close to the 0.6 reliability level at 0.57.

5.5.2 Composite Reliability (CR)

Another metric for evaluating internal consistency is composite reliability (CR) (Netemeyer, Bearden, & Sharma, 2003). According to Hair et al. 2009, the value of CR should be more than 0.7 for it to be approved. However, some academics believe that a CR value that is above 0.6 shows that the assessment items are highly consistent (Gu, et al., 2019). Based on the studies referenced the CRs linked to the research constructs used in this study, and shown in Table 7 below, are reliable with the lowest CR being 0.69535 and the highest at 0,96764.

Table 7: Estimated Composite Reliability

Research Construct	Code	Estimate			Error Terms	Summation of Error Terms	Composite Reliability	Average Variance Extracted
		λ	λ^2	(∑γi)^2	ε	(∑ε)	CR	AVE
Perceived Usefulness	PU1	1,001	1,002001	3,232702	-0,002001	0,76730	0,94363	0,80818
	PU2	0,928	0,861184		0,138816			
	PU3	0,829	0,687241		0,312759			
	PU4	0,826	0,682276		0,317724			
Reliability and Availability	RNA1	0,653	0,426409	1,071218	0,573591	0,92878	0,69535	0,57375
	RNA2	0,803	0,644809		0,355191			
	RNA3	0	0		0			
Perceived Ease of Use	PEU1	1,006	1,012036	4,165026	-0,012036	0,83497	0,96120	0,83301
	PEU2	0,996	0,992016		0,007984			
	PEU3	0,862	0,743044		0,256956			
	PEU4	0,841	0,707281		0,292719			
	PEU5	0,843	0,710649		0,289351			
Security	SC1	0,392	0,153664	2,700805	0,846336	1,29920	0,88455	0,67520
	SC2	0,884	0,781456		0,218544			
	SC3	0,953	0,908209		0,091791			
	SC4	0,926	0,857476		0,142524			
Adoption	AD1	0,851	0,724201	2,166141	0,275799	0,83386	0,88626	0,72205
	AD2	0,862	0,743044		0,256956			
	AD3	0,836	0,698896		0,301104			
Net Promoter Score	NPS1	1,004	1,008016	1,874777	-0,008016	0,12522	0,96764	0,93739
	NPS2	0,931	0,866761		0,133239			

5.5.3 Convergent Validity

To determine if a construct or factor that is expected to be related actually is, the researcher can make use of the Average Variance Extracted (AVE) column in Table 7. If the AVE is greater than 0.5, all independent variables are related to the dependent variable. All the AVE values in Table 7 are over 0.5, RNA being the lowest at 0,57375 and NPS being the highest at 0.93739.

5.5.4 Discriminant Validity

In cases where constructs or factors should not be related to one another, the researcher can make use of discriminant validity (Ronkko & Cho, 2020). The discriminant validity for the constructs used in this study is shown in Table 8, through the use of the inter-item correlation table and shows a lack of similarity. The values in the table below show a divergence from one, which is consistent with research that indicates that to prove discriminant validity, the correlations between the constructs should be diverging from one (O'Rourke & Hatcher, 2013).

Table 8: Inter-Item correlation matrix

Construct	PU	RNA	PEU	SC	AD	NPS
PU	1					
RNA	0,393	1				
PEU	0,098	0,003	1			
SC	0,45	0,352	0,116	1		
AD	0,012	-0,037	0,572	0,091	1	
NPS	0,455	0,218	0,035	0,397	0,543	1

**Correlation is significant at the 0.01 level (2-tailed)

Key: PU = Perceived Usefulness; RNA = Reliability and Availability; PEU = Perceived Ease of Use; SC = Security; AD = Adoption; NPS = Net Promoter Score

Table 8 illustrates the discriminant validity with the highest correlation being between PEU and AD with a value of 0.572, this value is acceptable. The values between RNA and AD are the furthest away from one, going into a negative value of -0,037, closely followed by PU and AD at 0.012.

5.6 Hypothesis Testing

5.6.1 Normality

The hypothesis testing for this research was completed following the Kolmogorov-Smirnov and Shapiro-Wilk tests, shown in Table 9 below. These tests show that all the variables utilised for this study have statistical significance, when making use of a significance level of 0.05, this indicates that these variables are not normally distributed. This is why the regressions that were run are linked to non-parametric data tests.

Table 9: Kolmogorov-Smirnov and Shapiro-Wilk Tests of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PU	.276	215	<.001	.629	215	<.001
RNA	.166	215	<.001	.899	215	<.001
PEU	.241	215	<.001	.734	215	<.001
SC	.120	215	<.001	.918	215	<.001
AD	.316	215	<.001	.651	215	<.001
NPS	.210	215	<.001	.815	215	<.001

a. Lilliefors Significance Correction

Key: PU = Perceived Usefulness; RNA = Reliability and Availability; PEU = Perceived Ease of Use; SC = Security; AD = Adoption; NPS = Net Promoter Score

5.6.2 Ordinal Logistic Regression Analysis

Ordinal logistic regression is a form of multiple regression statistical analysis that can be used to model the relationship between an ordinal response variable and one or more explanatory variables. An ordinal variable is a categorical variable for which there is a clear ordering of the category levels. The explanatory variables may be either continuous or categorical (CSCU, 2020). This matches the Likert scale data that was collected to conduct this study. Through the use of SPSS regression analysis, the study can use six key measures of assessment for each proposed hypothesis and determine if the outputs of the regressions support the hypothesis put forth in the study.

The six measures of Spear Correlation, Model Fitting Information, Goodness-of-Fit, Pseudo R-Squared, Parameter Estimate and the Test of Parallel Lines, are shown in Table 10 and were utilised to determine if the hypotheses, in the context of this study, were significant and supported or not.

5.6.3 Model fitting information

In SPSS, statistics that reveal information about how well a statistical model fits the data are referred to as model-fitting information (Yang, 2013). These statistics assist with assessing a model's goodness of fit and determining if it accurately captures the underlying relationship between the variables (Yang, 2013).

SPSS was used to provide model-fitting information, through the use of ordinal regression analysis. The likelihood ratio test is a statistical analysis that assesses how well a nested model fits in comparison to a more intricate model (Pearson, n.d.). The test can be used to determine whether the extra variables in the more intricate model actually make a meaningful difference in how well it fits the data. In general, model-fitting data assists in decision-making on the quality of statistical models, including which models to use and how well they fit the data.

5.6.4 Goodness-of-fit

Closely linked to the model fitting information is the measure of goodness-of-fit. The term "goodness of fit" describes how well a statistical model fits the collected data. It gauges how well the model's anticipated values and actual values match each other. The goodness-of-fit is a crucial component of statistical analysis since it aids in assessing a model's quality and predictive power.

This study makes use of the Chi-Square Test, a test that compares the observed and expected frequencies of a categorical variable to assess the goodness-of-fit of a model. A good fit is indicated by a non-significant chi-square test, this means that the goodness-of-fit will not be significant. Overall, the goodness-of-fit is a crucial component of statistical analysis in SPSS because it aids in assessing a model's quality and propensity to deliver accurate predictions. It allows for the identification of which models match the data collected and the best use of goodness-of-fit metrics to make more educated decisions.

5.6.5 Pseudo R-Squared

An indicator of how well a statistical model fits the data is pseudo R-Squared. Pseudo R-Squared is a measurement of the percentage of variation in the dependent variable that is explained by the independent variables in the model, as opposed to the usual R-Squared statistic, which is based on the ratio of the explained variance to the overall variance.

In this study, the use of the Nagelkerke R-Squared, one of the more popular varieties of pseudo R-squared in SPSS. In binary logistic regression models, this is another pseudo R-Squared value. Overall, pseudo R-Squared values can be used to compare the fit of our statistical models and provide information about the quality of a statistical model. Pseudo R-Squared values, however, should be evaluated cautiously because they may not have the same intuitive significance as conventional R-Squared values; it does however, still add value.

5.6.6 Parameter Estimates

The coefficients or weights given to each independent variable in a statistical model are referred to as parameter estimates. These estimates, which indicate the anticipated change in the dependent variable for an increase of one unit in the independent variable while maintaining all other variables constant, are computed using the technique of maximum likelihood estimation.

They also indicate the direction and degree of the relationships between the independent and dependent variables as well as the importance of those relationships statistically. In the case of this research, the parameter estimates in ordinal regression models were utilised. The ordinal regression also referred to as ordinal logistic regression is presented as odds ratios, which show how the odds of the dependent variable change as the independent variable increases by one unit (UCLA, n.d.).

Parameter estimates offer crucial details about how the variables in a statistical model relate to one another and can be used to predict the values of the dependent variable from the values of the independent variables. They are a crucial component and can aid in comprehending the underlying patterns in their data.

Table 10: Hypothesis testing results

Hypothesis	Effect	Spearman Correlation (%)	Model Fitting Information	Goodess-of-fit	Pseudo R-Squared (%)	Parameter Estimate	Test of Parallel Lines	Results
H1	AD--> NPS	4,2 (Very low)	Significant (invalid)	Significant (Valid)	8,4	Positive odds	Significant (Valid)	Not supported
H2	PU--> NPS	45,5 (Moderate correlation)	Not Significant (Valid)*	Significant (Valid)	31,4	Positive odds	Significant (Valid)	Supported
H3	RNA--> NPS	21,8 (low correlation)	Not Significant (Valid)	Significant (Valid)	24,7	Positive odds	Significant (Valid)	Supported
H4	SC--> NPS	39,7 (low correlation)	Not Significant (Valid)	Significant (Valid)	35,3	Positive odds	Significant (Valid)	Supported
H5	PU--> AD	1,2 (Very low)	Significant (invalid)	Significant (Valid)	9,9	Not significant	Significant (Valid)	Not Supported
H6	PEU--> AD	57,2 (Moderate Correlation)	Not Significant (Valid)	Significant (Valid)	55,1	Positive odds	Significant (Valid)	Supported
H7	SC--> AD	9,1 (Very low)	Significant (invalid)	Not significant (Invalid)	9,2	Not significant	Not significant (invalid)	Not Supported

Key: PU = Perceived Usefulness; RNA = Reliability and Availability; PEU = Perceived Ease of Use; SC = Security; AD = Adoption; NPS = Net Promoter Score

5.6.7 Test of Parallel Lines

A statistical technique called the test of parallel lines is used to assess the parallelism assumption in ordinal logistic regression models. When a dependent variable has a natural ordering, such as a Likert scale or a rating scale, ordinal logistic regression is utilised.

The link between each level of the independent variable and the dependent variable is parallel across all levels of the other independent variables, according to the parallelism assumption in ordinal logistic regression models (UCLA, n.d.). In other words, each level of the dependent variable should have the same impact as the independent variable.

By examining whether the slope of the relationship between the independent variable and the dependent variable is the same for each level of the dependent variable, the test of parallel lines in SPSS determines whether this assumption is true. By contrasting the likelihood of a model with variable slopes with a model with fixed slopes, this is accomplished.

The assumption of parallelism is satisfied, and the ordinal logistic regression model is adequate, as shown by the absence of significance in the test of parallel lines. The assumption of parallelism, however, has been violated if the test of parallel lines is significant, in which case alternative models or transformations of the data may need to be considered (UCLA, n.d.).

The test of parallel lines is a crucial tool for assessing the validity and assumptions of ordinal logistic regression models in SPSS and can assist with guaranteeing the appropriateness and accuracy of the analysis we are performing.

5.7 Hypothesis results

Hypothesis 1 (H1) highlights a better user experience will be influenced by the adoption of RPA by financial service providers. The data collected in this study showed a low correlation between adoption and the variable used to measure customer experience, Net Promoter Score (NPS). The regression also showed a significant P-Value under the model of fitting information column which means that the data observed, and the model is not a good fit, which means the null hypothesis must be accepted and the positive relationship between customer experience (NPS) and adoption (AD) could not be established from the data collected.

Hypothesis 2 (H2) tested the relationship between perceived usefulness and customer experience. The results for the Spear correlation were positive and at 45.5%, gave a moderate correlation between the two variables. The insignificant P-Value of less than

0.001 and significant goodness-of-fit means this data is a good fit for the model being tested and allows for the analysis of the Pseudo R-squared value which tests the variances between variables. In this case, it is determined that 31.4% of the total variance linked to the user experience can be explained by perceived usefulness.

Hypothesis 3 (H3) investigates if there is a positive relationship between Reliability and Availability (RNA) and customer experience (NPS). The regression analysis showed a P-Value of below 0.001, which is below our level of significance of 0.05 and a value higher than 0.05 for the Goodness-of-fit which means the data is a good fit for the model under investigation. A Pseudo R-Squared value of 24.7% is said to be a good indicator of how much the total variance in NPS is explained by RNA

Hypothesis 4 (H4) is linked to security (SC) and if there is a positive relationship with customer experience (NPS). There is indeed a positive correlation between the two variables with a Spear correlation of 38.7%, high enough for the assumption that SC and NPS move in the same direction. The P-Value is not significant as it is below 0.05 significance level and a goodness-of-fit level that is greater than 0.05. Pseudo R-Squared of over 35%, which is considered good.

Hypothesis 5 (H5) highlights the influence of Perceived Usefulness (PU) is positively related to RPA adoption (AD) the results of the goodness-of-fit tests are not in favour of the data fitting the model, P-Value is significant, and the goodness-of-fit value is not significant. The value of the Pseudo R-Squared is low at 9.9%, which means the model is not fit and the null hypothesis is accepted in this case.

Hypothesis 6 (H6) investigates the relationship between Perceived Ease of Use (PEU) and the products that make use of RPA and if there is a positive relationship with the adoption of RPA (AD). The question this hypothesis is attempting to test is if users believe the web or online applications are easy to make use of will drive up the adoption of RPA. The Spear correlation is the highest among the observed variables at 57.2, which is considered a good indicator that when PEU increases so does AD. The P-Value is not significant, and the goodness-of-fit is also significant which proves that the data is a good fit for the model presented. The Pseudo R-Squared is also high at over 55% of the variance in AD explained by PEU.

Hypothesis 7 (H7) highlights that Perceived Security (SC) is positively related to RPA adoption (AD), the regression results show that the goodness-of-fit statistics are not representative of SC impacting AD and the data presented does not fit the model being presented. The insignificance means that the null hypothesis is accepted.

An overall regression model was run, and the results show the impact of variables of PU, PEU, SC, AD and RNA on the NPS. There are stronger goodness-of-fit statistics than when the regressions were run on the individual impact of each variable and remained insignificant at less than 0.01 and the goodness-of-fit being significant. The Pseudo R-Squared of the combined model is over 65% along with the test of parallel lines being greater than 0.05, proving that the overall hypothesis linked to the model in its entirety can be accepted to be true.

Having run the individual regression, it is clear that the data linked to PU, RNA and SC are the highest contributors to the model fit and ultimately the significance levels investigated in the dependent variable (NPS).

5.8 Chapter Summary

This chapter provides statistical analysis and findings from the data gathered on the importance of Robotic Process Automation (RPA) on Customer Experience in the South African Financial Sector. Descriptive statistics, reliability, model fit assessment, regression analysis, and hypothesis testing were presented. There are at least four elements that can be deemed as important factors that contribute to robotic process automation’s impact on the customer experience and are linked to its adoption. These elements include perceived usefulness, reliability and availability, security, as well as the impact of perceived ease of use on adoption. The following chapter provides a critical analysis of the study's findings in light of the first chapter's stated research goals.

6. DISCUSSIONS

6.1 Introduction

The research findings are thoroughly explored in this chapter, assessing these to the existing literature. This section will outline the findings of the hypotheses, then connect those findings to previously published literature, and finally, examine the implications of those findings for the financial sector and its use of robotic process automation.

6.2 Findings

In this section of the research, the focus will be on the main findings of the variables highlighting the importance of Robotic Process Automation (RPA) on client experience in the South African financial sector.

$H1_1$: A high Net Promoter Score (NPS) is positively related to RPA adoption

$H1_0$: A high Net Promoter Score (NPS) is not positively related to RPA adoption

The findings for Hypothesis 1 are that there is no relationship between the net promoter score and the adoption of RPA. The null hypothesis, in this case, is accepted due to the significant value found through the model fit information, which differs from the value found in the goodness-of-fit statistic. However, all other statistics in the model show that NPS and adoption have a relationship. Research has shown this relationship with Filgueiras et al., (2022) stating that there are numerous touch points between customer experience and RPA adoption. This adoption can be influenced by elements that enhance the customer experience (Filgueiras et al., 2022). The structures of these models, when combined, can be useful for determining how individuals intend to use technology. In this study, however, the results displayed the opposite.

In this regression highest (significant) parameter estimate in the output is the positive odds of 19.562. This suggests that if there is a one-unit increase in the adoption of robotic process automation, there is a predicted increase of 19.562 in the log odds of being at a higher level for net promoter score which is the indicator of client experience.

Despite the above, given that the model that has been run for this research paper and the P-Value presented in the model of fit information, of 0.355, is above the significance level of 0.05, the results are not supported.

Literature by Sobczak, (2022) suggests that a reason for the lack of relationship between NPS and the adoption of RPA could be linked to a lack of knowledge, customers might not be aware of the impact or value of RPA in their contact with businesses, which could affect how the perceive RPA.

$H2_1$: Perceived usefulness is positively related to the NPS

$H2_0$: Perceived usefulness is not positively related to the NPS

The findings for Hypothesis 2 indicate a positive relationship between perceived usefulness and NPS. This means that if a web or digital application is perceived by users as useful then this will mean an increase in NPS, which, in this study, is used to measure customer experience

Perceived usefulness, according to the TAM, is the extent to which a person thinks that using a specific technology will improve his or her ability to accomplish their work. Perceived utility, according to Davis et al. (1992), refers to how customers view the conclusion of the encounter with a digital platform. According to Jahangir and Begum (2008), perceived usefulness is the belief that employing new technology will boost or improve a person's performance. Similarly, Mathwick et al. (2001) defined perceived usefulness as how much a person believes a specific system will improve his or her ability to accomplish their job.

$H3_1$: Reliability and Availability are positively related and result in increased NPS

$H3_0$: Reliability and Availability are not positively related and result in increased NPS

The results linked to Hypothesis 3 indicate a relationship between Reliability and Availability (RNA) and the NPS. The results are significant and prove a positive relationship and positive log odds, which means that when there is a one-unit change in RNA, there is a predicted increase of 19.762 in the log odds of obtaining a higher NPS. The most impactful significance level in the ordinal logistic regression that was run is 19.762. This positive result contributed to the variable RNA3 that was dropped due to the factor loading from the analysis when testing data reliability.

This shows that when individuals believe systems that make use of RPA are reliable and consistently available there is a greater chance of an increase in NPS, the measure for customer experience.

Despite the fact that the field of research is linked to the connection between Robotic Process Automation (RPA), reliability and availability, and customer experience, there are researchers like Kumar et al., (2021) that have conducted research that suggests that RPA automates repetitive and time-consuming procedures to improve efficiency and accuracy in financial processes. Tasks are accomplished efficiently and accurately when an RPA system is reliable and available, which can enhance productivity and result in cost savings for businesses. As a result, clients have a higher probability of having a pleasant customer experience due to the RPA system's improved efficiency and accuracy.

RPA is also being utilised more and more to improve the customer experience by automating processes that directly involve customers, like order processing, queries, and support. RPA can guarantee that customer requests are addressed promptly and accurately when it is reliable and available, improving the customer experience.

The effectiveness of RPA depends on a certain degree of availability and reliability, just like any other technology (Dey & Das, 2019). The customer experience may suffer when RPA systems are unreliable or frequently unavailable since they might cause delays and errors in corporate operations.

These elements imply that there is probably a good association between reliability and availability and customer experience for RPA, and further research is required to fully grasp the relationship in detail. The productivity, accuracy, and customer happiness of businesses that spend in maintaining the dependability and availability of their RPA systems are likely to grow.

$H4_1$: Security is positively related to increasing NPS

$H4_0$: Security is not positively related to increasing NPS

The findings for Hypothesis 4 indicate a significant relationship between security and NPS, which is the measure for customer experience. The results show that one-unit increase in perceived security would result in a predicted increase of 18.292 log odds of getting an increased customer experience. The more users believe that a financial services RPA system is secure and protects their data, the higher the expected customer experience.

Hypothesis 4 is based on research linked to Kumar and Balaramachandran (2018), who cited that the key elements that impact the consumer experience are security and privacy. According to the researchers, customers' top concerns with using financial services are security and privacy. Customers' expectations, trust, adoption, and use of the internet banking service are influenced by how secure they perceive the internet to be (Rondovic et al., 2016b). Large data collection is necessary for innovation, and big data is a brand-new resource with enormous economic and societal value. Customers are more worried about the security and privacy of their personal information, transactions, fraud, and the social dangers of using their online-accessible data for discriminatory purposes.

The above has led to a rising amount of research on robotic process automation (RPA) and that research reveals a beneficial connection between security and consumer experience (RPA). This is because ensuring client satisfaction and establishing consumer confidence depend heavily on security.

According to a Forrester Research (2018) survey, individuals and corporates prioritise security while selecting a vendor for RPA services. According to the report, customers are more likely to believe in vendors who place a high value on security and take precautions to safeguard their systems and data. According to PwC's 2020 report, security is crucial for fostering customer loyalty and trust.

These findings indicate that security and customer satisfaction for RPA are positively correlated. Customers' trust, loyalty, and good word-of-mouth are likely to rise for businesses that engage in robust security measures to safeguard consumer data and systems. This can therefore result in a better customer experience and more RPA market success.

$H5_1$: Perceived Usefulness is positively related to RPA adoption

$H5_0$: Perceived Usefulness is not positively related to RPA adoption

The results of Hypothesis 5 indicate that there is no relationship between perceived usefulness and the adoption of RPA. The results mean the level of perceived usefulness that users have of financial systems that make use of RPA does not impact the adoption of RPA.

Research linked to perceived usefulness has strongly indicated a positive relationship with adoption because when automating processes, analysis improves decision-making (Casale et al., 2015). Increasing productivity, cutting costs, and getting insights through analysis are the key reasons people use and find the usefulness in AI (Rohde, 2016). Customers anticipate that financial service providers will supply them with individualised goods and services that are catered to their unique requirements (Susanto et al., 2016). The usefulness of products and services that affect a customer's propensity to use financial services is provided through data analysis and personalised offerings.

The above means that perceived usefulness is frequently regarded as a crucial component in the adoption of technology, but several studies indicate that it might not be a reliable indicator of adoption for robotic process automation (RPA).

The perceived usefulness was not a significant predictor of RPA adoption, according to a study by Lacity et al. (2019). According to the study, which polled over 100 businesses, perceived usability, compatibility with current technologies, and organisational readiness were better predictors of adoption than perceived usefulness.

While perceived usefulness was positively correlated with the desire to implement RPA, it was not a significant predictor of actual adoption, according to a different study by Wamba et al. (2020). According to the study, which polled over 300 firms, perceived benefits, management support, and compatibility with current systems were better predictors of adoption than perceived usefulness.

RPA's frequent adoption for specific use cases or business processes rather than as a general-purpose technology is one explanation for these findings. In these circumstances, variables like organisational preparation and compatibility with current systems may play a bigger role in adoption than the perceived utility. So, while the data indicates that perceived usefulness may influence RPA adoption, it may not be a very important predictor of adoption (Juntunen, 2018). Adoption may be more influenced by other elements like perceived ease of use and security, which will be discussed through Hypotheses 6 and 7.

$H6_1$: Perceived ease of use of products that make use of RPA is positively related to RPA adoption

$H6_0$: Perceived ease of use of products that make use of RPA is not positively related to RPA adoption

The results for Hypothesis 6 illustrate the positive relationship between the perceived ease of use of the financial services web or online applications that utilise RPA and its adoption. This means that when users find it easy to use, they are likely to adopt it and continue its use.

Perceived ease of use was discovered to be a major predictor of intention to adopt RPA in the study by Fosso Wamba et al. (2020). According to the study, perceived usability, usefulness, and compatibility with current systems were all highly predictive of intentions to adopt RPA. The same was highlighted in a similar study conducted by Lacity et al. (2019). Perceived ease of use was found to be the most effective predictor of adoption among the technology-related characteristics and these results imply that when the technology is regarded as being simple to use, RPA adoption may be more likely. Given that RPA is frequently implemented by business users rather than IT specialists and might only need basic technical know-how to set up and utilise, this may be particularly crucial.

$H7_1$: Perceived security is positively related to RPA adoption

$H7_0$: Perceived security is not positively related to RPA adoption

The results linked to the relationship between security and adoption returned an insignificant value, failing both goodness-of-fit model tests. This means the null hypothesis will be accepted in this case, meaning that security does not have a relationship with the adoption of RPA.

According to research conducted by Kumar and Balaramachandran (2018), the relationship between security and adoption should be a positive one and Hypothesis 7 should by account have produced a significant output that clearly displays an appropriate goodness-of-fit and strong positive relationship.

There are studies that contend that the biggest obstacle to the adoption of RPA may not be security issues. For instance, a study by Fosso Wamba et al. (2020) indicated that perceived ease of use and compatibility were important drivers of RPA adoption intentions, but that security concerns were not significant predictors.

Research conducted by Lacity et al. (2019) also indicated that while security issues were a concern for some businesses, they were not the main focus for the majority of them. According to the study, organisational challenges like resistance to change, ignorance of the advantages of RPA, and a lack of enough resources for implementation were the biggest obstacles to RPA adoption.

6.3 Summary of Findings

In summary, this research investigation found evidence to support four of the assumptions. H2 received support and demonstrated a favourable correlation between perceived usefulness and the net promoter score. H3 was endorsed and shown a favourable correlation between reliability and availability and the net promoter score. H4 received support and demonstrated a favourable correlation between security and the net promoter score. H6 was significant and showed a favourable correlation between perceived ease of use and adoption.

Table 11: Hypothesis Testing Results

Code	Hypothesis	Result
H1	Net Promoter Score (NPS) is positively related to RPA adoption	Not Supported

H2	Perceived usefulness is positively related to the NPS	Supported
H3	Reliability and Availability are positively related and result in increased NPS	Supported
H4	Security is positively related to increasing NPS	Supported
H5	Perceived Usefulness is positively related to RPA adoption	Not Supported
H6	Perceived ease of use of products that make use of RPA is positively related to RPA adoption	Supported
H7	Perceived security is positively related to RPA adoption	Not supported

The results of hypotheses H2, H3, H4 and H6 supported previous research and supported the existence of a substantial positive link between the variables. H1, H5 and H7 were not supported, though, and this did not demonstrate a connection between NPS and adoption, NPS and perceived usefulness, as well as security and adoption in the models that were run in this research. The overview of the outcomes from the hypotheses is shown in Table 11.

6.4 Chapter Summary

The key research study findings were thoroughly discussed in this chapter. Existing literature was utilised to support the conclusions.

7. CONCLUSION AND RECOMMENDATIONS

The main conclusions of the study are summarised in this chapter, which also examines the study's contributions, limitations, and suggestions for further research.

7.1 Conclusion of Findings

Four out of the seven hypotheses were determined to be significant. As a result, there is a favourable correlation between the relationships of NPS and perceived usefulness, reliability and availability, and security along with the relationship between ease of use and the adoption of RPA. The correlation between NPS and perceived usefulness is 45.5%, the correlation between NPS and reliability and availability is 21.8%, and between security and NPS is 39.7%. The intensity of the relationships, however, varies with the highest correlation being between the ease of use and adoption at 57.2%. As a result, if a financial services company would like to increase their levels of customer experience, it will need to focus on these variables as a part of its strategic objectives.

Unexpectedly, it was discovered that there is no connection between NPS and the adoption of RPA. Along with the relationships between adoption and perceived usefulness as well as security. Due to the fact that they constrict the existing literature, these findings should be interpreted cautiously.

7.2 Implications for Financial Services Industry

There is room for improvement in the widespread adoption of RPA technology in the financial sector, despite the anticipation that it will deliver value and the growing number of use cases. The perceived usefulness and usability of any new technology are major determinants of its adoption, according to previous literature written from the customer perspective. Understanding the variables that affect RPA, its adoption, as well as its impact on the customer experience is crucial, but it's also crucial to comprehend how financial services companies can address and manage these variables in order to create a business model that will boost profitability and efficiency and provide a competitive edge (Kumar & Balaramachandran, 2018).

These fundamental theoretical and practical issues with the adoption of RPA serve as the foundation for this study. Our current study looks at the following aspects—adoption, perceived usefulness, reliability and availability, security, perceived ease of use, and net promoter score as a measure of customer experience—that affect RPA adoption and its impact on customer experience in the financial services sector. The research covers several significant research and practice implications.

While most banks are still in the early phases of RPA implementation, its use in the financial services sector is accelerating (internationalbanker, 2021). Through an understanding of customer acceptance and implementation of this cutting-edge technology, this study complements insights linked to information systems (IS). This study makes a theoretical contribution by laying the groundwork for subsequent research in this field. The report emphasises the variables that can affect the decision to implement a technology like RPA. By offering a study model that offers a theoretical foundation for understanding the antecedents of adoption intentions in the context of RPA, the findings of this study further the literature on several components as well as the literature on RPA itself. These traits can be further explored in future studies to increase the list. Lastly, a research model is presented in the study (Figure 1). This model can be used to research how different technologies are adopted in the financial sector.

7.3 Limitations

All the replies in this study were collected from a South African population. By gathering data from more regions, such as America and Europe, the findings can be developed further by including the element of the region and its implications. Customer experience, adoption, perceived usefulness, reliability and availability, security, and perceived ease of use, were the main topics of this study.

7.4 Future Research

This study contributes to the work being done in the field of robotic process automation (RPA) and the results can be utilised as a baseline for future research. Further research can be built on other aspects like user-friendliness, solution stability and robustness, resource optimisation, and worker productivity as well as effective measures for the impact of robotic process automation on customer experience in the financial sector and other industries**.**

7.4 Conclusion

In order to maintain their competitive advantage and boost profitability, financial services should be placing more strategic importance on robotic process automation (RPA). The study suggests and evaluates the use of RPA in the financial services industry to improve customer experience. In order to focus on the customer's perspective, financial service providers, IT specialists, senior management decision-makers, technology practitioners, and researchers are given guidance by the conceptualisation of elements impacting adoption and customer experience. Also, the regression analysis confirmed the link between a number of hypothesised elements and the intention to implement RPA, highlighting the urgent need to develop practical plans for the technology's adoption and creation of value by focusing on its impact on customer experience.

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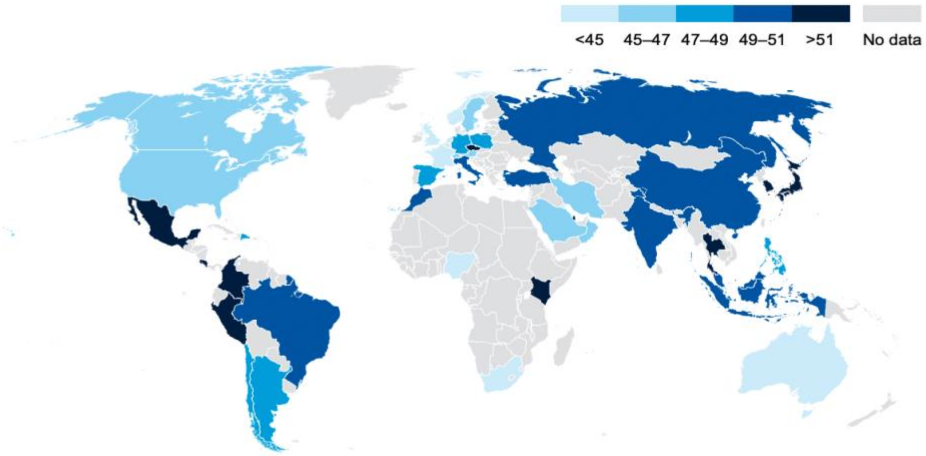
APPENDIX

Appendix A – Figure 1: Employee weighted overall % of activities that can be automated by adopting technologies that are currently available



Appendix B – Proposed Questionnaire

Section A: Demographic Information

Gender

Male		Female	

Age

18 – 29 years	
30 – 39 years	
40 – 49 years	
50 – 59 years	
60 or over	

Education Level

Grade 12/Matric	
Certificate	
Bachelor’s Degree	
Honours/Postgraduate Diploma	
Masters	
PhD	

Screening Information

The information below will allow me to find out more about you for the purposes of this research. Please select the option that best describes your response.

Do you have a mobile application linked to a financial provider, e.g., a Banking app or an Investment App?

Yes	
No	

Do you make use of a website linked to a financial provider, e.g., a Banking website or an investment website?

Yes	

No	

When last did you use the mobile app or website of a financial service provider?

Less than a week ago	
Less than a month ago	
6 months – 1 year ago	
1 year – 2 years	
More than 2 years	

What transactions or tasks do you complete on the mobile app or website?

Checking balances	
Statement request	
Completing an online purchase	
Purchasing airtime	
Purchasing electricity	
Completing a financial transaction	
Other	

<u>Section B: Customer Experience Questions</u>

LIKERT SCALE QUESTIONNAIRE									
Research Construct	Code	Questions	Scaling						
			SD	D	SLD	N	SLA	A	SA
			1	2	3	4	5	6	7
Perceived Usefulness	PU1	Making use of the online application/web allows me to accomplish my tasks faster							
	PU2	Making use of the online application/web made completing my task easier							
	PU3	I consider making use of the online application/web convenient							
	PU4	Using the application/web to complete my financial tasks increases how often I transact							
Reliability and Availability	RNA1	The online application/web or website was available when I last made use of it							
	RNA2	I find the online application/web to be easily accessible							
	RNA3	I have experienced an error/mistake made on a transaction submitted through the online application/web							
Perceived Ease of Use	PEU1	Learning to use the online application/web was easy for me							
	PEU2	Becoming skilful at using the online application/web was easy for me							
	PEU3	I find the online application/web easy to use							
	PEU4	All the information I require to navigate the application/web is easy to find							
	PEU5	I find using the online application/web "faster" because I can always visibly see where to click next to complete my tasks							
Security	SC1	I input personal details onto the online application/web when completing tasks or transactions							
	SC2	I trust that my data is safe when I input my data into the online application/web							
	SC3	I believe that the security measures on the online application/web are of a high standard							
	SC4	I feel safe making use of the online application/web							
Adoption	AD1	I intend to keep using the online application/web							
	AD2	I will always use this online application/web in my daily life							
	AD3	I am using the online application/web for more than one type of transaction or function							
Net Promoter Score	NPS1	On a scale of 0 to 10, how satisfied are you with the financial app you are using?							
	NPS2	On a scale of 0 to 10, how likely are you to recommend the financial application/web you are using to friends and family?	Scale of 1 to 10						

Key: SD = Strongly disagree, D = Disagree; SLD = Slightly disagree; N = Neutral; SLA = Slightly agree; A = Agree; SA = Strongly agree