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Integrating Internet of Things into household waste collection processes in Ekurhuleni.

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Abstract

Numerous South African regions face serious waste management difficulties as a result of urbanization, population increase, and ineffective collection systems. Backlogs and inappropriate garbage disposal techniques have resulted, endangering the environment and public health. Reducing inefficiencies and streamlining waste collection procedures are possible with the integration of Internet of Things (IoT) technology.

The aim of the study was to investigate how adopting IoT can improve household waste collection in Kempton Park, located in the Ekurhuleni municipality of Gauteng province, South Africa. A quantitative research approach was employed utilising a questionnaire to collect primary data from residents. The Technology Acceptance Model is used as the theoretical framework to examine factors influencing IoT adoption.

The results provided perceptions on how well-and poorly received IoT-enabled waste management systems are perceived. Difficulties in incorporating IoT into home waste collection mitigate the impact of perceived usefulness and perceived simplicity of use on the variables influencing technology adoption. By addressing hurdles, the study advances our understanding of how IoT might facilitate more effective waste collection. Policymakers and service providers can use the findings as a reference when deciding whether to use smart technologies to solve South Africa's waste management problems.

Declaration

I hereby confirm that this work is entirely original with full citations for all sources I have used or quoted.

Researcher

Signed:  Date: 26 February 2024

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List of Abbreviations

DoI - diffusion of innovation

IoT - internet of things

IT - information technology

PEOU - perceived ease of use

PU - perceived usefulness

QR - quick-response

RFID - radio-frequency identification

TAM - technology acceptance model

TISM - total interpretive structural modelling

TOE - technological organisational environment

TRA - theory of reasoned action

UTATU - unified theory of acceptance and technology usage

Wi-Fi - wireless fidelity

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CHAPTER 1: INTRODUCTION

1.1 Introduction

This study was aimed at investigating adoption factors when integrating smart technologies to household waste collection processes to reduce waste management challenges and environmental factors. At an estimated annual waste output of 108 million tons (Lebuso, 2022), South Africa presents an ample opportunity for internet of things (IoT) implementation into waste collection processes to increase efficiency, optimise resource allocation, and decrease environmental pollution. The following parts of this paper comprise the study's background and context, problem statement, research objectives, research questions, study significance, study limitation, context reflection and study outline.

1.2 Background and context of the study

In 2016, the world's expanding population, urbanisation, and lifestyle changes generated a record-breaking amount of waste: 2.01 billion tons (World Bank, 2022). Inefficient waste management processes are a significant problem in both industrialised and developing countries. Poor waste management, according to Igbal (2021), impacts lives and the environment. Waste management is a major part of sustainable environmental management (Derhab & Elkhwesky, 2022). Many countries are still developing recycling and waste management policies (Derhab & Elkhwesky, 2022). However, smart technologies have been used in a variety of applications to improve aspects of the integrated domestic waste management processes. Because of the rapid development of information technologies (IT) in recent years, such as the Smart City concept (O'Dwyer, Pan, Acha, & Shah, 2019), the implementation of IoT technologies and other engineering applications with a smart approach has sparked interest in the research community. There are undoubtedly new paths toward sustainability being opened by the quick development and application of smart technologies for numerous applications. There are moreover advantages to using smart technologies, and they may help to ensure ongoing technical advancement (Ismagilova, Hughes, Dwivedi, & Raman, 2019), to ensure efficient waste management processes.

Younesi (2022) asserts that IoT has proven to be one of the most desirable services technology yields across the globe that can be deployed to solve waste management problems in large metropolitan areas. Improper waste disposal, inadequacies in waste management plans, and inadequate policies for waste management prove to play an integral role in the consequences associated with waste management.

South Africa's waste management systems are insufficiently developed to establish an efficient and sustainable chain (Owojori, Mulaudzi, & Edokpayi, 2022). It is noted that smart technology adoption is still in its infancy stage (Aljerf, 2018), and therefore, the waste management chain necessitates innovative, resourceful, and shrewd approaches to reduce waste and increase recycling, thereby making it more efficient and environmentally sustainable. Municipalities in South Africa should focus on improving household waste management policies and strategies while maintaining environmental sustainability and improving socioeconomic well-being.

As a result of the various obstacles and difficulties discussed, it is valuable to understand what factors lead to adoption and use of smart waste management system. Tornatzky, Fleischer, and Chakrabarti (1990) indicated that effective innovation adoption hinges on proper technological, organisational, and environmental factors. Several variables affect technology adoption, making it a multifaceted process (Matandela, 2017). Tornatzky, Fleischer, and Chakrabarti (1990) listed four commonly accepted models that include Technological Organisational Environment (TOE); Technology Acceptance Model (TAM), Unified Theory of Acceptance and Technology Usage (UTATU) and Diffusion of Innovation (DoI). Individuals and organisations for different motives adopt smart technology. Technological Organisational Environment and Diffusion of Innovation are theoretical models for technology that are applicable to organisational adoption (Tornatzky, Fleischer & Chakrabarti, 1990). Other alternative theories are acceptable for individual adoption decisions (Baker, 2012; Ijab et al., 2019; Davis, Bagozzi, & Warshaw, 1989).

The research discusses the TAM model as a technology adoption model to address effective ways to determine adoption of smart waste management. The study aims to

assess the adoption of smart technology in emerging economies like South Africa and identify factors that influence adoption. The study provides a complete understanding of the problems experienced while adopting smart waste management, taking into account perceptions on the ground and determining the relationships between various aspects or challenges.

1.3 Problem statement

Backlogs in waste collection in Johannesburg have become an issue in recent years (Lebuso, 2022). This situation has been worsened by recent local government instability, which has hampered service delivery (Lebuso, 2022). Govender, Barnes, and Pieper (2011) indicated that instead of properly disposing of waste at waste collection stations, many people and households employ informal and often illegal waste disposal techniques include throwing trash in public places. Rapid population growth in the nation has also put strain on the infrastructure for waste management, causing a shortage of supplies needed for waste collection. This study provides insights to determine the adoption of factors when integrating smart technologies to household waste collection processes to reduce waste management challenges and environmental factors.

1.4 Research objectives

The primary research objective of this study was:

- To investigate how the adoption of integrating IoT to waste management systems will reduce inefficiencies when collecting household waste.

In addition, the secondary research objectives were:

- To investigate the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate challenges faced in Integrating IoT to household waste management in Kempton Park households.

- To investigate the factors that affect the adoption of IoT to waste management processes in Kempton Park.

1.5 Research questions

The main research question of this study was:

- How will the adoption of integrating IoT to waste management systems reduce inefficiencies when collecting household waste?

In addition, the secondary research questions were:

- How is the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality?
- How is the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality?
- What are the challenges faced in Integrating IoT to household waste management in Kempton Park households?
- What are the factors that affect adoption of IoT to waste management processes in Kempton Park?

1.6 Significance of the study

The purpose of the study was to explore whether smart technologies may reduce inefficiencies in waste management. South Africa's waste management systems are insufficiently developed to establish an efficient and sustainable chain (Owojori, Mulaudzi, & Edokpayi, 2022). Therefore, the results of the study can provide solutions to reduce waste management challenges.

1.7 Delimitation of the study

The research is delimited to household waste as disposable materials. The research is also delimited to Internet of Things and investigated integration to household waste collection. This study focused on addressing waste management in urban area in Kempton Park, Ekurhuleni municipality. The framework of choice to determine adoption is TAM. However, the results of other countries studied and the comparison with other studies indicated that the digitalisation process in the municipal waste sector is still in its

infancy.

1.8 Context reflection

At an estimated annual waste output of 108 million tons, South Africa presented ample opportunity for IoT implementation into waste collection processes to increase efficiency, optimize resource allocation, and decrease environmental pollution. Smart bin sensors can provide real-time information on fill levels within bins to allow waste collection companies to optimize collection routes while simultaneously decreasing frequency of trips and fuel consumption - an especially relevant solution in developing world environments where most households don't have access to professional waste services.

Integrating IoT into South African waste collection processes would require significant investments in technology infrastructure, data connectivity and training; social challenges must also be considered, particularly within informal settlements, and townships where infrastructure may be scarcer and business models for waste collection companies may be unprofitable.

As such, successful integration of IoT into waste collection processes in South Africa requires collaboration among government institutions, waste management companies, technology providers, and communities to develop an equitable waste management system that benefits all parties involved - especially the environment and local communities.

1.9 Outline of the study

The first chapter includes the introduction, and the background and context of the study, problem statement, research problem, research objectives, research questions, significance of the study, delimitation of the study, and the study outline.
The second chapter examines the relevant literature review on technology acceptance, and the application of IoT technology to waste management.
The third chapter describes the research methodology of the study.
The fourth chapter offers the data analysis results.

The fifth covers the results and findings, and

The sixth gives the conclusions and recommendations.

1.10 Conclusion

The first chapter introduced the study, covering its background and setting. The research objectives and questions were outlined. In addition, the study's importance and limitations were highlighted. Chapter 2 examines the literature on technology acceptability and the application of IoT technologies to trash management.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Chapter 2 reviews the relevant literature on technological acceptability and the use of IoT technologies in trash management. The study sought to investigate the factors that influence adoption when incorporating smart technologies into residential waste collection procedures in order to reduce waste management difficulties and environmental impacts. The following portions provide a theoretical review of this study and explain the Technology Acceptance Model (TAM). This is followed by IoT uses that are suitable for contemporary waste management; and how IoT is being used in household waste management. And the final section covers the cases where these technologies have been used; and this is followed by barriers to the adoption of these technologies, and conclusion.

2.2 Theoretical review

This section discusses the framework behind this study. The Technology Acceptance Model (TAM) and its recent applications are discussed in the subsections that follow.

2.2.1 Technology acceptance model (TAM)

This study used the Technology Acceptance Model (TAM). Davis, Bagozzi, and Warshaw (1989) proposed the Technology Acceptance Model to define IT users' application usage. According to Davis, Bagozzi, and Warshaw (1989), perceived usefulness has a direct influence on purpose and attitude, which may influence users' decision to utilise IT as well as their negative attitude towards it. Davis, Bagozzi, and Warshaw (1989) found a connection between ease of use and perceived usefulness. Individual skills, IT type, function, and status concerns have an indirect impact on users' intentions because they influence what is perceived as valuable and easy to use. TAM explains why people adopt or reject information technology (IT), particularly smart technology. TAM 2 and 3 were major improvements to TAM (Venkatesh, Morris, Davis, & Davis, 2003). The TAM model indicates that employees' beliefs and actions impact numerous decision outcomes, which is important to note. So, when people encounter new technology like smart technology,

several variables influence their choice to use it. TAM has been a significant extension of the literature supporting Ajzen and Fishbien's Theory of Reasoned Action (TRA) (LaCaille, 2013). The concept posits that a user's attitude towards a system plays an important part in determining whether the user would actually utilise or reject the system. Perceived effectiveness and perceived ease of use were identified as two major attitudes that influence the individual.

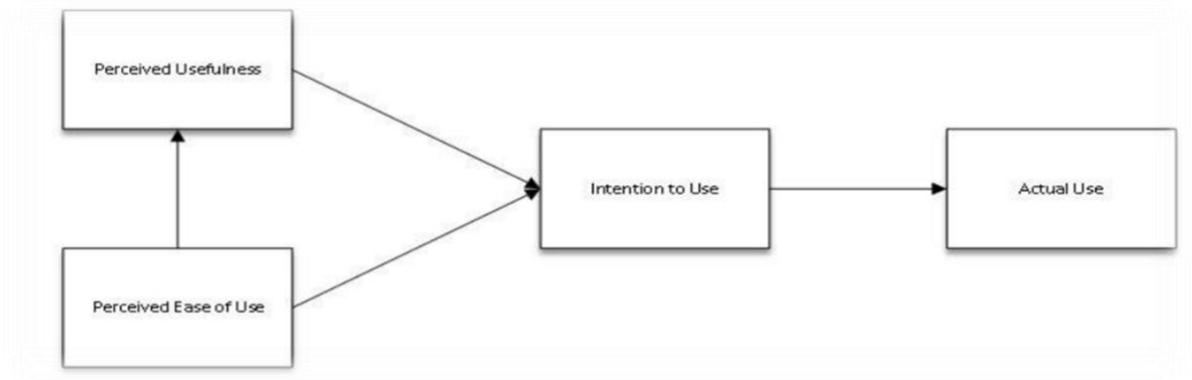


Figure 2.1: Original technology acceptance model (TAM)
Source: Davis, Bagozzi, and Warshaw (1989)

The user's encounter with the technology moderates its perceived usefulness and ease of use, influencing the user's decision to embrace or reject the technology. According to (Sherbib et al., 2012), a user who has a good attitude toward technology is more likely to be motivated to use it. Other studies confirmed the importance of beliefs in influencing technology use. Alharbi and Drew (2014) pointed out that the competency level that influences how much technology is used can be used to anticipate how much technology will be used. Organisational, technological, social, and demographic characteristics including gender, computer self-efficacy, and training levels can all have an impact on how well a technology is accepted. Researchers have used TAM to better understand and explain how people adopt new technologies. Although TAM is widely used, it might not be able to determine a user's readiness.

According to Davis, Bagozzi, and Warshaw (1989), the study's focus on the perceived usefulness (PU) factor was appropriate given that Kempton Park residents believe that using a computer system integrated with smart technologies such as IoT allowed them

the flexibility for waste pickups rather than using traditional methods, where the municipality predetermined a day when household waste should be collected.

Another aspect of the theory that is relevant to the inquiry is perceived ease-of-use (PEOU). The usage of smart waste applications by individuals in Kempton Park will be made easier by their capacity to accept and use electronic machine gadgets, which also has an impact on other social interactions. That is, using technology automatically reduces the need for conventional efforts.

2.2.2 Recent applications of TAM

Researchers used TAM to investigate user behaviour in technology adoption. Kalina and Marina (2017) used TAM to investigate the prevalence of online buying among Macedonian youths. The results showed that TAM was a suitable model for describing online purchase behaviour (Kalina & Marina, 2017). In another study, Lule, Omwansa, and Waema (2012) employed TAM to investigate mobile banking adoption behaviour in Kenya. The study's findings revealed that TAM concepts had a significant impact on the adoption of mobile banking services (Lule, Omwansa, and Waema, 2012). Mugo, Njagi, Chamwei, and Motanya (2017) used TAM to forecast the acceptance and utilisation of various technologies in teaching and learning environments. According to the findings, there were obstacles in attitudes towards technology, and teachers had to work hard to resolve issues raised by stakeholders.

Waleed et al. (2019) combined diffusion of innovation (DoI) and TAM to assess students' attitudes towards an online learning management system, recommending that online course managers and developers carefully review students' needs and ensure that the selected system effectively meets their expectations, as online course system characteristics have a significant impact on adoption (Waleed et al.). Furthermore, McCormack, Buckley, and Kelly (2021) found TAM to be a suitable model for analysing contemporary farming technology uptake in Ireland. Opoku and Enu-Kwesi (2020) looked into the significance of TAM in IT research and how the model has been expanded in terms of perceived usefulness and ease of use. According to the results, TAM is still regarded as the correct model for IT research. However, there are critics who have called

for further research on the model, and that the model is lacking the essential characteristics of a respectable theory for IT research.

Abu-Dalbouh (2022) used a modified TAM to study a learning management system and found that the model is still very useful in studying technology adoption. During the COVID-19 pandemic, Silvestre, Miranda, and Gutierrez (2022) used TAM to study student preferences of virtual classroom and traditional classroom in Dominica. The results proved that TAM is still very useful in studying technology adoption. Owusu, Asiedu, Ji, and Sarpong (2022) used TAM to study social media commerce in Ghana.

In addition, Kalayou, Endehabtu, and Tilahun (2020) used TAM to study the adoption of electronic health technologies and found the model very helpful in studying the subject. And lastly, Nasongkhla and Shieh (2023) used TAM to study the adoption of social networking technologies among college staff members in Thailand, and the model was found useful in studying the subject.

2.3 Waste collection in South Africa

Viljoen, Schenck, Volschenk, Blaauw, and Grobler (2021) asserted that South African waste management sector is marked by inadequate infrastructure, inefficient services, and insufficient regulations. In addition, Viljoen et al., (2021) explained that waste management must be reinvented with sustainable solutions that create jobs while simultaneously reducing inequality while strengthening both public health resilience and environmental resilience.

Nkosi (2014) maintained that though ultimately responsible, garbage collection services may currently be provided by the local authority or an established contractor, most municipalities in South African municipalities typically use one of two methods for household waste collection: communal collection in underdeveloped areas such as informal settlements, which requires residents to place waste containers provided by the municipality, and door-to-door collection in formal settlements.

Viljoen et al., (2021) offered an in-depth examination of South Africa's waste management industry as they consider its challenges posed by municipalities that attempt to provide sustainable waste services. South African waste management has made some progress over time; however, several challenges still need to be tackled, including inadequate

funding sources, human resource shortages and operational inefficiency issues. The authors assert that although South African waste management has seen progress so far, significant challenges still lie in store for sustainable service provision - such as inadequate funding or staff resources shortages as well as operational inefficiency issues which must be tackled head on.

Integrating technological solutions such as IoT (Internet of Things) into South African waste collection systems is also vitally important to their efficiency and optimization, with smart bins helping increase efficiency while decreasing fuel usage - contributing towards more eco-friendly practices (Munsamy, 2022).

2.4 An IoT solution

According to Ashton (2009), he was the first to use the phrase IoT (Internet of Things) in 1999. On the other hand, the idea of linking equipment and devices to the internet has been around far longer. The vending machine was one of the first internet-connected devices which was at Carnegie Mellon University in 1982. It could report its inventory as well as whether the drinks were cold or not. The internet was also connected to a variety of additional devices during the ensuing years, but not on the scale of today's IoT ecosystem (Masinter, 1998). These devices included printers, cameras, and scanners. IoT is a component of a communication system in which smart gadgets supplement communication for practical purposes. IoT development demonstrates dramatically new possibilities in numerous aspects of human life, and the major goal of IoT is to provide plug-and-play technologies that are simple to operate, allowing users to control equipment remotely (Rafsanjani & Lawal, 2022). Chinaka and Aba (2020) described IoT as an ecosystem that incorporates multiple digital services that communicate through the internet services. Evaluation indicates that in a year, 740 grams of solid waste is produced per person footprint. Population growth, and urbanization increase postulate an increase in the annual waste generation from these cities by almost 70 % by 2050, hence the need to develop strategies that ensure efficient management of waste, or else the adversities associated with improper waste management pose a threat (Zanella et al., 2014). The integration of IoT and smart technology in waste management demonstrates a crucial role in mitigating these dangers and providing a path to preserving a secure and

sustainable environment for future generations and human prosperity.

2.5 Integrating IoT to waste management

Institutional theory indicates that organisations are driven by social norms, values, and expectations from stakeholders (Scott & Meyer, 1991). Researchers have investigated how local and national policies impact adoption and implementation of IoT-based waste management systems (Pitner, 2019). Furthermore, TAM emphasises perceived usefulness and ease of use as important factors in technology acceptance (Davis, Bagozzi, & Warshaw, 1989); South African academics have investigated this element while adopting such systems (Munsamy, 2022).

Understanding how IoT integration in household waste collection might result in incremental innovation is made easier with the help of innovation management. This theory holds that incremental innovation happens when continual modest improvements are made to current goods, services, or procedures (Dolfsma et al., 2003). IoT can make it easier to design new bin-level monitoring sensors for domestic waste collection, which will result in small but considerable gains in waste management efficiency.

An empirical literature review can make significant contributions to theoretical framework by revealing trends, gaps, and patterns among existing empirical studies. Additionally, this type of literature review could offer evidence supporting or contradicting various propositions in theory as well as identify areas needing further theoretical development.

2.6 Trends and successful integration of IoT into waste collection

Studies on IoT integration into waste collection in South Africa indicate its great potential to optimize waste management processes. Munsamy (2022) conducted an empirical investigation on an IoT-based waste management system's ability to reduce operational costs while increasing collection efficiencies – thus significantly increasing environmental sustainability in waste collection processes. Likewise, Pitner (2019) performed a case study analysing how adopting and implementing an IoT waste collection and disposal solution improved collection and disposal practices in Namibia.

The smart wastebasket concept is one example of an IoT integration technique offered by Tripathi, Pandey, Narwal, and Negi (2018) to address trash management issues. Importance of the smart wastebasket model is its capability in preventing waste

overflow into landfills. This includes the deployment of a cloud-based rubbish monitoring system powered by solar panels. A cloud-based technology analyses garbage levels in household bins and sends the information to a server, which determines waste collection routes in cities. Such systems save on the costs associated with waste transportation and ensure households in no means suffer the adversities of holding massive wastes amounts in their household bins.

Andrade and Yoo (2019) identified problems associated with waste management such as the issues of transportation and scheduling pick-up times for wastes in municipalities and even communities and households, and these problems are precisely commonly associated with the traditional waste management systems. The development of a hybrid waste management system, namely one that merges smart technology with traditional waste management systems, enables efficiency in the routing of waste pick-up vehicles, avoiding waste fill-ups and the associated dangers. AirBin is a strategy that integrates IoT in waste management designed by Das, Islam, Billah, and Sarker (2021) and specifically aims to prevent the spread of infectious diseases such as COVID through wastes generated from infectious high-risk zones. Examples of these zones are clinics, healthcare facilities, quarantine zones and even garbage bins. IoT integration in this system ensures that remote garbage build-up monitoring is effective, and the clearing occurs at the right times and frequently. Accumulation of bio-medical wastes increases the risks of infectious diseases, and with such a system in place it is always integral to ensure frequent collection of wastes, efficient transportation, and disposal of the waste and the AirBin proves to provide quality and sustainable data to streamline all these processes.

While IoT-based waste collection in South Africa holds great promise, gaps still exist in its empirical literature. Notably, research on social, economic and environmental effects associated with IoT-based systems remains limited in South Africa; furthermore most case study analyses of their adoption or implementation are limited by case-study methodologies that limit generalizability of findings; finally there were greater insight into technological factors influencing success or failure for IoT waste collection systems within South Africa - these gaps represent directions for further empirical research studies.

The studies emphasised the need of adopting the notion of smart technology to give an

improved and more sustainable imminent future and to realize the aim of an effective system of waste management. Real-time container information improved waste collection by forecasting the ideal time to pick up trash and scheduling the amount of cars that pick-up garbage from containers. Thus, emerging nations must concentrate on delaying characteristics that result in ineffective application of smart technology. Studies conducted outside South Africa demonstrate the potential application of IoT in waste collection systems; those conducted locally have confirmed it as an effective means of meeting challenges associated with waste collection procedures. Yet gaps exist within empirical literature when it comes to understanding effectiveness, socio-economic influences on adoption as well as environmental, scalability and sustainability concerns of using this type of waste collection solution across South African contexts. It seems to be a political rhetoric which is marred by lack of acceptance of suggested smart technologies. The next part therefore covers the factors that affect adoption of technology in waste management.

2.7 Factors that affect the adoption of smart technologies in waste management

Based on previous studies, one of the common research gaps is a lack of clarity about what factors stop smart technologies from being used effectively in waste management. Other studies have shown that there is still room to find big problems with smart waste management. Here is an assortment of studies that show the problems or factors that make it hard for smart city technologies to be used in waste management.

Sharma, Joshi, Kannan, and Govindan (2020) use Decision Making Trial and Evaluation Laboratory and Total Interpretive Structural Modelling (TISM) to identify impediments to IoT adoption in India's smart city waste management system. The main obstacles, as determined, are a lack of regulatory standards, regulations, direction, and internet access. There is a need for a thorough investigation for the identification of barriers in South Africa's smart city initiatives.

Bui (2020) utilised a Fuzzy Delphi technique on the identification of factors that hinder sustainable solid waste management methods. The key factors identified as obstacles include technological challenges, a lack of knowledge, poor lines of communication between local authorities, and financial and economic uncertainty. As such critical

obstacles to achieving sustainable objectives would simply include a lack of personnel competency and an absence of a systematic procedure for data gathering and analysis.

2.7.1 Perceived usefulness

Smart cities can be characterised from a human or technological aspect, since nations have varied smart city objectives and perspectives. A smart city has no conventional description, and its notion cannot be described (Kim & Heesup, 2022). Additionally, smart cities could enhance response times, service delivery, and city life. Smart technologies in the city keep a watch on the city's environment, respond swiftly, and accumulate data to assist people in making wise decisions (Ibrahim, 2022). This maximises resident services while maximising resources and preventive maintenance (Ibrahim, 2022). In smart cities, waste management entails a flexible, efficient, real-time waste value cycle intake that primarily employs IoT to optimise refuse collection, reducing costs and open disposal (Shukla & Hait, 2022). The above gives context on the perceived usefulness in integrating IoT to household waste collection.

2.7.2 Perceived ease of use

The following describes the perceived ease of use for people who already use other social media platforms. Kang, Kang, Ilankoon, and Chong (2020) examined how smart electronic waste management systems may increase Malaysian home electronic waste recycling. Customers may use collecting boxes with mobile applications and data servers to bring cell phones and other smaller waste and add smart online features (Kang et al., 2020). To encourage recycling, mobile phone apps may give product-specific recycling instructions, and radio-frequency identification (RFID) tags and weights can alert the municipality when a pickup smart bin is full. Satyamanikanta and Madeshan (2017) proposed collecting boxes using ultrasonic sensors, Arduino circuit boards, and wireless fidelity (Wi-Fi) modules.

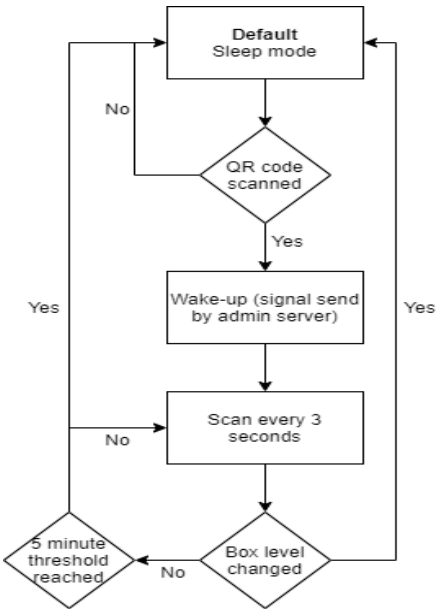


Figure 2.2: Process of electronic waste removal

Source: King et al. (2019)

The explanation of the above figure goes, scanning the quick-response (QR) code wakes up the waste collection box for five minutes, guaranteeing only electronic waste is dumped in. After scanning the QR code, the server wakes up the box, and its ultrasonic sensor checks the collecting box's surface every three seconds and transmits data to the server. The system runs until the user dumps electronic waste or the five-minute threshold. The smartphone app activates the system and locates the closest pickup place (Arya, 2021). A user then uploads a photo of the waste and the system recommend what to recycle. This may also be used to track how successfully individuals recycle and keep trash out of bins.

Table 2.1: Synopsis of literature gaps

Title	References	Research Gap
The article titled "Internet of Things (IoT) adoption barriers of smart cities'	(Sharma et al., 2020)	• Though this paper recognises the potential value of IoT adoption to

waste management: An Indian context"		improve waste management practices, it fails to offer an in-depth examination of its economic and societal advantages. • The study does not compare the situation with other countries. • The study does not propose solutions or recommendations to address adoption barriers.
The fuzzy Delphi approach is used to identify practical challenges to sustainable solid waste management. Resources, Conservation, and Recycling.	(Bui, 2020)	• Limited empirical research in developing countries • Lack of examination of solutions to these barriers • Limited focus on the stakeholder engagement

Despite the potential of integrating IoT into waste collection in South Africa, gaps still exist in the empirical literature. In South Africa, for example, there has been little research into the socioeconomic and environmental effects of IoT-based waste management systems.

Furthermore, a better knowledge of the technological aspects influencing the success or failure of IoT-based waste management systems in South Africa is required. These gaps represent directions for future empirical research studies.

2.8 Conceptual framework

Figure 2.3 shows the conceptual framework of this study and the model on which the data analysis is based. As displayed in Figure 2.3, perceived effectiveness and perceived ease of use both affect factors that affect the adoption of technology (factors affect). In addition, challenges faced in integrating IoT to household waste collection moderates the effects of perceived effectiveness and perceived ease of use on the factors that affect the adoption of technology (factors affect) as shown in Figure 2.3. The effect of perceived effectiveness on factors that affect the adoption of technology (factors affect) is represented by **a** while that of perceived ease of use is represented by **b**. In addition, the moderation effects of the challenges faced in integrating IoT to household waste collection are represented by **c** and **d** respectively. The study used the moderated multiple linear regression model (Cleary, 1968) to determine the moderation effects and the regression coefficients shown in Figure 2.3.

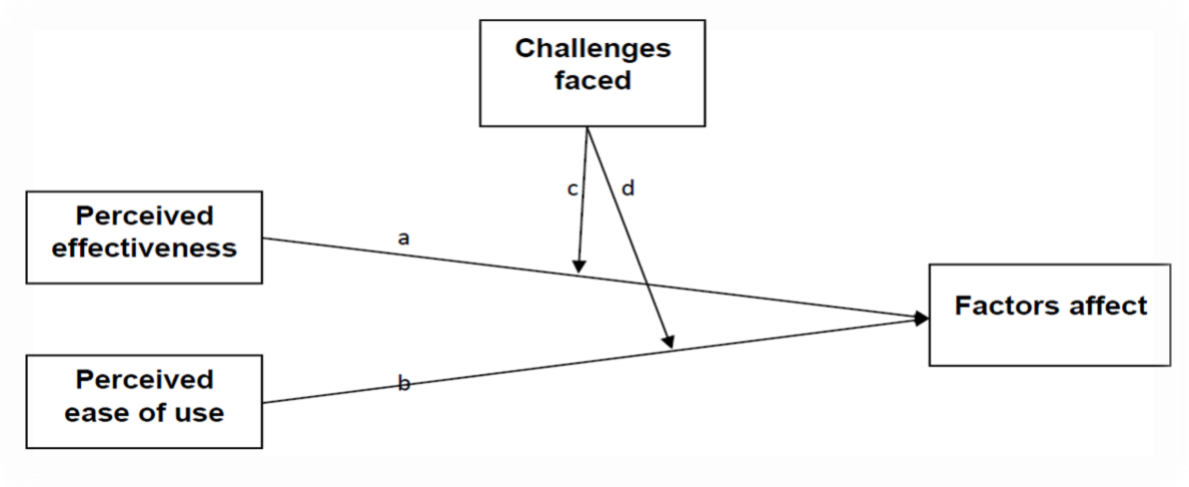


Figure 2.3: Conceptual framework

Source: Own

To determine the size of these effects **a**, **b**, **c**, and **d** using the moderated multiple linear regression analysis, the following hypotheses H1, H2, H3, and H4 were tested respectively.

2.8.1 Relationship between perceived effectiveness and factors that affect the adoption of technology (factors affect)

- H1: The factors that affect the adoption of IoT in waste management (factors affect) is explained by perceived effectiveness.

This hypothesis is tested by means of a simple linear regression model where the factors that affect the adoption of IoT in waste management (factors affect) is the dependent variable and perceived effectiveness is the independent variable.

2.8.2 Relationship between perceived ease of use and factors that affect the adoption of technology (factors affect)

- H2: The factors that affect the adoption of IoT in waste management (factors affect) is explained by perceived ease of use.

This hypothesis is tested by means of a simple linear regression model where the factors that affect the adoption of IoT in waste management (factors affect) is the dependent variable and perceived ease of use is the independent variable.

2.8.3 Moderation effect of challenges faced on the relationship between perceived effectiveness and factors that affect the adoption of technology (factors affect)

- H3: Challenges faced moderates the impact of perceived effectiveness on the factors that affect the adoption of IoT in waste management (factors affect).

This hypothesis is tested by means of a moderated multiple regression model where the factors that affect the adoption of IoT in waste management (factors affect) is the dependent variable and perceived effectiveness is the independent variable while challenges faced is the moderating variable.

2.8.4 Moderation effect of challenges faced on the relationship between perceived ease of use and factors that affect the adoption of technology (factors affect)

- H4: Challenges faced moderates the impact of perceived ease of use on the factors that affect the adoption of IoT in waste management (factors affect).

This hypothesis is tested by means of a moderated multiple regression model where the factors that affect the adoption of IoT in waste management (factors affect) is the dependent variable and perceived ease of use is the independent variable while challenges faced is the moderating variable.

2.9 Conclusion

Chapter 2 analysed relevant literature on technological acceptance and the use of IoT technology in trash management. The results of this literature review were used to create the theoretical framework in Figure 2.3, and the hypotheses stated below were offered. Chapter 3 of this study describes the research methodologies used to carry out this investigation with the goal of meeting the research objectives and hypotheses.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Chapter 3 details the research method that was used in this study. The chapter offers a background and justification to the study design and methodology. This study focused on investigating the adoption of factors when integrating smart technologies to household waste collection processes to reduce waste management challenges and environmental factors. The ensuing segments contain the research design and research philosophy, research methods, research philosophy, target population, sampling approach, research instrument, data collection, data analysis, validity and reliability, ethical considerations, and conclusion.

3.2 Research design

According to Adams, Khan, and Raeside (2014), research design is the blueprint for achieving research objectives, answering research questions, and ensuring that data acquired is relevant for solving a specific problem. The goal of research design is to develop a plan for guiding research to solve an issue by gathering relevant information. Furthermore, Adams et al. (2014) defined research design as a strategy for achieving research objectives and answering research questions while also ensuring that the data acquired is appropriate for problem solving. Research design is the plan that permits a researcher to do research in an appropriate, competent, and successful manner (Adams et al., 2014). The exploratory, explanatory, descriptive, and cross-sectional research designs can all be used to address study objectives (Saunders, Lewis, & Thornhill, 2016). A cross-sectional study strategy collects data from multiple entities at a single point in time while changing or influencing the environment (Saunders et al., 2016). As a result, a cross-sectional research design could provide light on assessing the adoption of elements when integrating smart technology into household waste collection procedures in order to reduce waste management difficulties and environmental impacts.

3.3 Research methods

Crossman (2017) defines research methods as the numerous actions used by researchers to carry out research initiatives. This study employed the quantitative research approach to evaluate the adoption of factors when incorporating smart technology into residential waste collection procedures in order to alleviate waste management difficulties and environmental factors. The quantitative research method frequently necessitates the use of questionnaires to collect valuable numerical data (Saunders et al., 2016), whereas qualitative research entails the collection of useful verbal information with the goal of gaining insights into human behaviour and the latent assumptions that govern such behaviour (Denzin & Lincoln, 2011). In this study, the researcher used the quantitative research approach to analyse the factors that influence the adoption of smart technology into household waste collection operations in order to reduce waste management difficulties and environmental factors. The quantitative research approach is empirical, accurate, and needs objectivity (Lee, 2000). As a result, the quantitative research method was deemed the most useful because it allowed the researcher to conduct a more scientific investigation into the adoption of factors when integrating smart technologies into household waste collection processes in order to reduce waste management challenges and environmental factors. Figure 3.1 compares quantitative and qualitative research methodologies based on their assumptions, aims, strategy, and researcher roles.

	Quantitative Method	Qualitative Method
Assumptions	Reality is single, tangible, and fragmentable. Social facts have an objective reality Knower and known are independent, a dualism Primacy of method. Variables can be identified and relationships measured Inquiry is objective, value-free	Realities are multiple, constructed, and holistic. Reality is socially constructed Knower and known are interactive, inseparable Primacy of subject matter Variables are complex, interwoven, and difficult to measure Inquiry is subjective, value-bound
Purposes	Generalisability (time and context free generalisations through nomothetic or generalised statements) Prediction Causal explanations	Contextualisation (only time and context bound working hypotheses through idiographic statements) Interpretation Understanding actors' perspectives
Approach	Begins with hypotheses and theories Manipulation and control Uses formal, structured instruments Experimentation and intervention Deductive Component analysis Seeks consensus, the norm Reduces data to numerical indices Abstract language in write-up	Ends with hypotheses or grounded theory Emergence and portrayal Researcher as the instrument Naturalistic or non-intervention Inductive Searches for patterns Seeks pluralism, complexity Makes minor use of numerical indices Descriptive write-up
Researcher Role	Detachment and impartiality Objective portrayal Etic (outsider's point of view)	Personal involvement and partiality Empathic understanding Emic (insider's point of view)

Figure 3.1: Quantitative and qualitative research methods

Source: Yilmaz (2013)

3.4 Research philosophy

Saunders et al. (2016) define research philosophy as the enhancement of knowledge and its features. A research philosophy is a set of principles for gathering, managing, processing, and using research data (Saunders et al., 2016). Figure 3.2 depicts the research model, which includes the several interdependent phases of the research process, from assuming a research philosophy at the outset to incorporating data collection methodologies directly into the model (Saunders et al., 2016). This model that was used for this investigation has five unique inter-reliant strata.

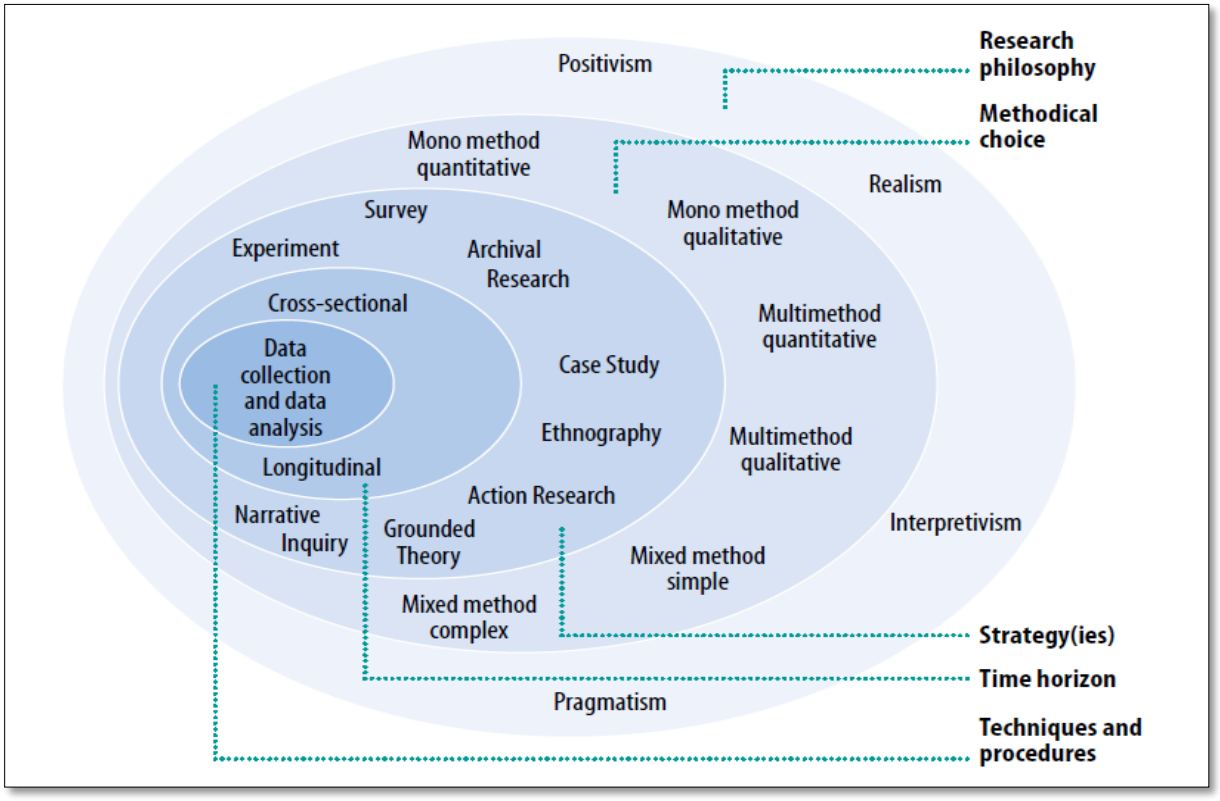


Figure 3.2: The research model

Source: Saunders and Tosey (2013)

Figure 3.2 exemplifies four research opinions specifically positivism, realism, interpretivism, and pragmatism (Saunders & Tosey, 2013).

3.5 Target population

Zikmund (2010) defines a population as a complete set of observations that have a common set of characteristics. Furthermore, Weiers (2011) defined a population as the entire set of people or items of interest. The population of interest were residents of Kempton Park, Ekurhuleni municipality, which has an estimated population of 171,565 (StatsSA, 2023) and had chosen to have lived in the area consistently for the previous 6 months as an inclusion condition.

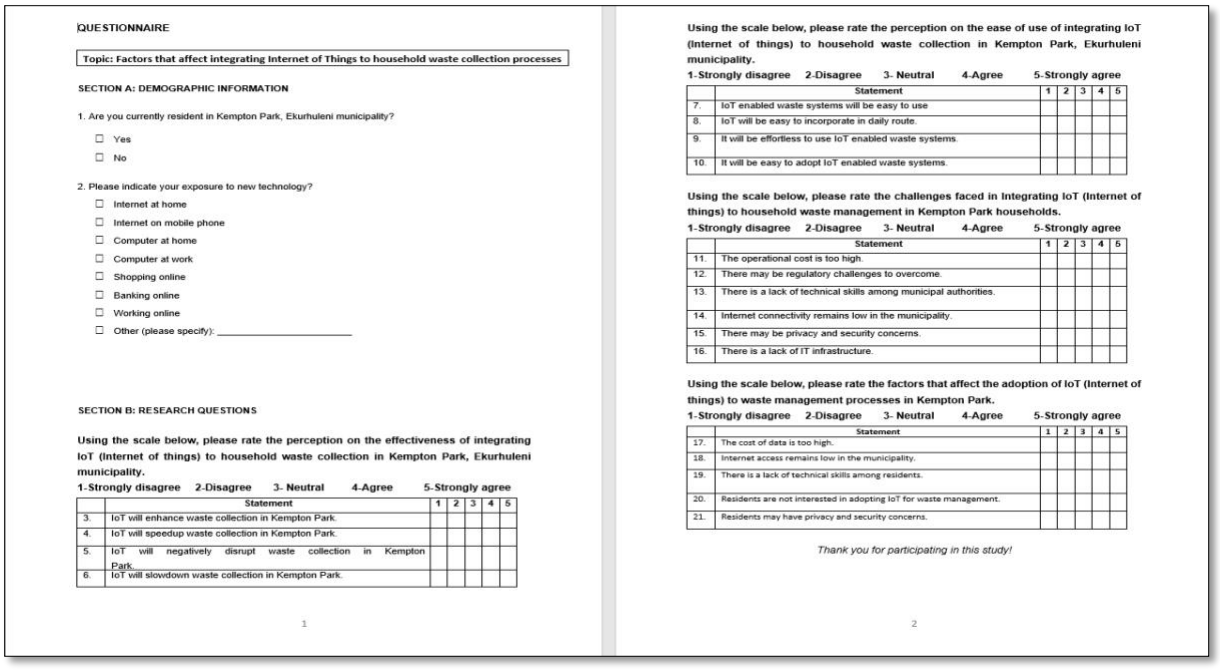
3.6 Sampling approach

Sampling is the methodical selection of units of a populace with the aim of collecting data about the whole populace (Weiers, 2011). Sampling methods are classified into two types: random sampling and non-random sampling. In random sampling, the selection process involves probability. Probability sampling always entails the random selection of samples from a population and ensures that all individuals in the population have an equal probability of being recruited into research (Bhardwaj, 2019). Random sampling also ensures the level of bias in the data collected or the research participants is low, and this is integral in improving the credibility and reliability of the research data. Bhardwaj (2019) explained that systematic sampling is a sampling strategy that draws samples randomly from a target population, and always ensures the selection of units from a population at random intervals and always from a random starting point. However, for survey data collection, the researcher used convenience sampling rather than probability sampling (Saunders et al., 2016).

Potential respondents were invited to participate in the survey by walking around Kempton Park's streets and directing them to an online questionnaire. The sample was over the age of 18, and the poll garnered 385 responses. The questionnaire includes study objectives and was hosted on Qualtrics (Qualtrics.com, 2023).

3.7 Research instrument

This study used an online questionnaire as its research instrument. For gathering information from the target population, a questionnaire is categorised as a primary research tool (Gillham, 2008). With an easier interaction and response structure for the responder, questionnaires are an efficient method of gathering data (Gillham, 2008). By posing a series of questions to a sample of respondents, a questionnaire will be used to gather data from them. Demographic traits, attitudes, perceived usefulness, satisfaction, and intention to adopt IoT-enabled devices for household trash management was assessed using the questionnaire. The 5-point Likert scale was used in the response format to assess the respondent's perceptions of the questions' usefulness and simplicity. Decision to choose questionnaires stems from the advantages of questionnaires in data collection, and examples of these advantages are cost saving, ability to reach a multitude of people in a short time, scalability aspect of survey that stems from the integration of internet services in the development of online questionnaires, and ease of maintaining respondents anonymity with questionnaires, an integral aspect of research ethics (Pozzo, Borgobello, & Pierella, 2019). Questionnaires also prove to exhibit a higher level of accuracy, and the flexibility in respondents answering these ensures a higher response rate. Questionnaires designed for data collection adopt a simple format for ease of answering and the language adopted also reflects the languages adopted by most of the respondents as a strategy to improve respondent and accuracy rates. Figure 3.3 shows the questionnaire that was used in this study. A copy of the questionnaire is shown at the Appendix.



QUESTIONNAIRE

Topic: Factors that affect integrating Internet of Things to household waste collection processes

SECTION A: DEMOGRAPHIC INFORMATION

1. Are you currently resident in Kempton Park, Ekurhuleni municipality?

- ☐ Yes
- ☐ No

2. Please indicate your exposure to new technology?

- ☐ Internet at home
- ☐ Internet on mobile phone
- ☐ Computer at home
- ☐ Computer at work
- ☐ Shopping online
- ☐ Banking online
- ☐ Working online
- ☐ Other (please specify): _____

SECTION B: RESEARCH QUESTIONS

Using the scale below, please rate the perception on the effectiveness of integrating IoT (Internet of things) to household waste collection in Kempton Park, Ekurhuleni municipality.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
3.	IoT will enhance waste collection in Kempton Park.					
4.	IoT will speedup waste collection in Kempton Park.					
5.	IoT will negatively disrupt waste collection in Kempton Park.					
6.	IoT will slowdown waste collection in Kempton Park.					

1

Using the scale below, please rate the perception on the ease of use of integrating IoT (Internet of things) to household waste collection in Kempton Park, Ekurhuleni municipality.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
7.	IoT enabled waste systems will be easy to use					
8.	IoT will be easy to incorporate in daily route.					
9.	It will be effortless to use IoT enabled waste systems.					
10.	It will be easy to adopt IoT enabled waste systems.					

Using the scale below, please rate the challenges faced in integrating IoT (Internet of things) to household waste management in Kempton Park households.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
11.	The operational cost is too high.					
12.	There may be regulatory challenges to overcome.					
13.	There is a lack of technical skills among municipal authorities.					
14.	Internet connectivity remains low in the municipality.					
15.	There may be privacy and security concerns.					
16.	There is a lack of IT infrastructure.					

Using the scale below, please rate the factors that affect the adoption of IoT (Internet of things) to waste management processes in Kempton Park.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
17.	The cost of data is too high.					
18.	Internet access remains low in the municipality.					
19.	There is a lack of technical skills among residents.					
20.	Residents are not interested in adopting IoT for waste management.					
21.	Residents may have privacy and security concerns.					

Thank you for participating in this study!

2

Figure 3.3: Questionnaire showing the survey questions
Source: own work

Figure 3.3 shows that Section A of the questionnaire comprised the study's demographic questions, whereas Section B had the study questions. The demographic questions questioned respondents if they lived in Kempton Park and how they were exposed to modern technology. Furthermore, the study questions were divided into four subsections: perceptions of the effectiveness of integrating IoT (Internet of Things) to household waste collection, perceptions of the ease of use of integrating IoT, challenges encountered in integrating IoT, and factors influencing IoT adoption. The study questions in Section B of the questionnaire in Figure 3.3 used the five-point Likert-like scale. In addition, the opening page of the online survey outlined the aim of the research and the directives for answering the questions. The researcher freely proclaimed and stressed to potential research participants that their participation was optional and that their privacy was protected during the investigation.

3.8 Data collection

Mkandawire (2019) defines data collection as the deliberate process of obtaining data from diverse sources in order to find answers to research questions and difficulties. Data collection is an essential component in research and an effective data collection process always ensures conclusions are perfectly drawn and inferences developed to answer a phenomenon. Data as a term is multiple kinds of information and adopts formats in multiple ways. Aguinis (2019) explain that data collection exists as a process, and in the process the activities of integral importance are gathering, measuring, and analysing data that is accurate. In this study, the data was collected using an online questionnaire hosted on Qualtrics (Qualtrics.com, 2023). The researcher visited potential research respondents' are and directed them to complete the online questionnaire shown in Figure 3.3. It is always important for researchers to identify the data types, sources of the data, and the precise methodology to use in the data collection process. Their responses were stored on the Qualtrics until the researcher decided to close the survey after receiving 385 responses.

3.9 Data analysis

The survey data was analysed using R and the R codes used in the data analysis are shown in the Appendix (R-project.org, 2023). The data was summarised, and percentages and frequencies were calculated. Additionally, Cronbach alpha results were computed to verify the validity and reliability of the study tool. To make the findings easier to grasp, the data was presented in tables and figures. Descriptive statistical analysis was conducted (Weiers, 2011). In addition, inferential statistical analysis was performed (Weiers 2011). Weiers (2011) conducted an inferential statistical analysis that included moderation analysis. The moderated multiple linear regression model was used to investigate whether the variable challenges faced in integrating IoT to household waste collection (challenges faced) moderates the impact of perception on the effectiveness of integrating IoT to household waste (perceived effectiveness) and perception on the ease of use of integrating IoT to household waste collection (perceived ease of use) on the factors that affect the adoption of IoT in waste management (factors affect). According to Cleary (1968), the moderated multiple linear regression model involves a three-step

differential prediction process that include the following:

i. Estimation of the criterion-related validity through a simple linear regression model.
ii. Intercept differences through an additive multiple linear regression model.
iii. Slope differences through a multiplicative multiple linear regression model.

3.10 Validity and reliability

According to Saunders, Lewis, and Thornhill (2016), validity is a measure of whether the findings are truly representative of their subject matter. External validity assesses whether the research findings are generalizable (Saunders, Lewis, & Thornhill, 2016). Reliability refers to the degree to which data collection procedures or analysis approaches produce consistent results (Saunders, Lewis & Thornhill, 2016). The researcher ensured content validity by asking various questions. Further, Cronbach alpha results were calculated throughout the data processing phase of the study to assess the research instrument's reliability. The reliability of the research instrument was determined by the Cronbach's alpha scores of the questionnaire subsections containing the study questions, which were typically more than 0.7. According to Cortina (1993), Cronbach's alpha values greater than 0.69 indicate that the research instrument is credible.

3.11 Ethical considerations

When conducting research to measure factors that affect the adoption of integrating IoT in household waste collection, researchers adhered to certain ethical principles to protect the participants' rights and enhance the credibility of the research. To conduct this study, the researcher obtained ethical clearance from Wits University. The Wits ethical clearance certificate is shown in Appendix D.

1. Informed Consent: Prior to gathering any information from individuals, the researcher sought the respondents informed consent. The goal of the study, participants' rights to opt out, and potential information security hazards were all explained to participants. Written in plain language, consent forms were clear, transparent, and free of coercion.
2. Participant Rights Protection: The researcher made sure that no participant rights are

violated at any point during the study. Confidentiality, privacy, and the availability of informed permission are all included in this.

3. Anonymity and Confidentiality: To prevent any harm to the participants – intentional or unintentional – the identities of the participants were and are kept confidential.

3.12 Conclusion

Chapter 3 has explained the research methods that were followed to carry out this study. The researcher utilised the online questionnaire to gather information and the sample contained of 385 research respondents. The study used a quantitative research methodology and a high ethical and professional standard was upheld during this study to investigate the adoption of factors when integrating smart technologies to household waste collection processes to reduce waste management challenges and environmental factors. The data was analysed using the R programming language. Chapter 4 is the presentation of the data analysis results.

CHAPTER 4: RESULTS

4.1 Introduction

Chapter 4 of this study presents the results and findings. The results are presented in tables, charts and figures to facilitate understanding of the findings. The questionnaire contained demographic information as well as study questions. The following was the main objective of this study:

- To investigate how the adoption of integrating IoT to waste management systems will reduce inefficiencies when collecting household waste.

And the secondary objectives of this study were as follows:

- To investigate the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate challenges faced in integrating IoT to household waste management in Kempton Park households.
- To investigate the factors that affect the adoption of IoT to waste management processes in Kempton Park.

The subsequent sections contain the demographic information, descriptive statistics, inferential statistics, and conclusion.

4.2 Demographic information

This segment presents the demographic information of the research respondents.

4.2.1 Residency of the research respondents

Table 4.1 and Figure 4.1 show the residency of the research respondents.

Table 4.1: Residency of the research respondents

Are you currently resident in Kempton Park, Ekurhuleni municipality?	Frequency	Percent
Yes	379	98.4
No	0	0
NA	6	1.6
Total	385	100

Source: R (R-project.org, 2023)

As shown in Table 4.1, 98.4% of the research respondents reside in in Kempton Park, Ekurhuleni municipality. However, 1.6% of the research respondents did not indicate their place of residence.

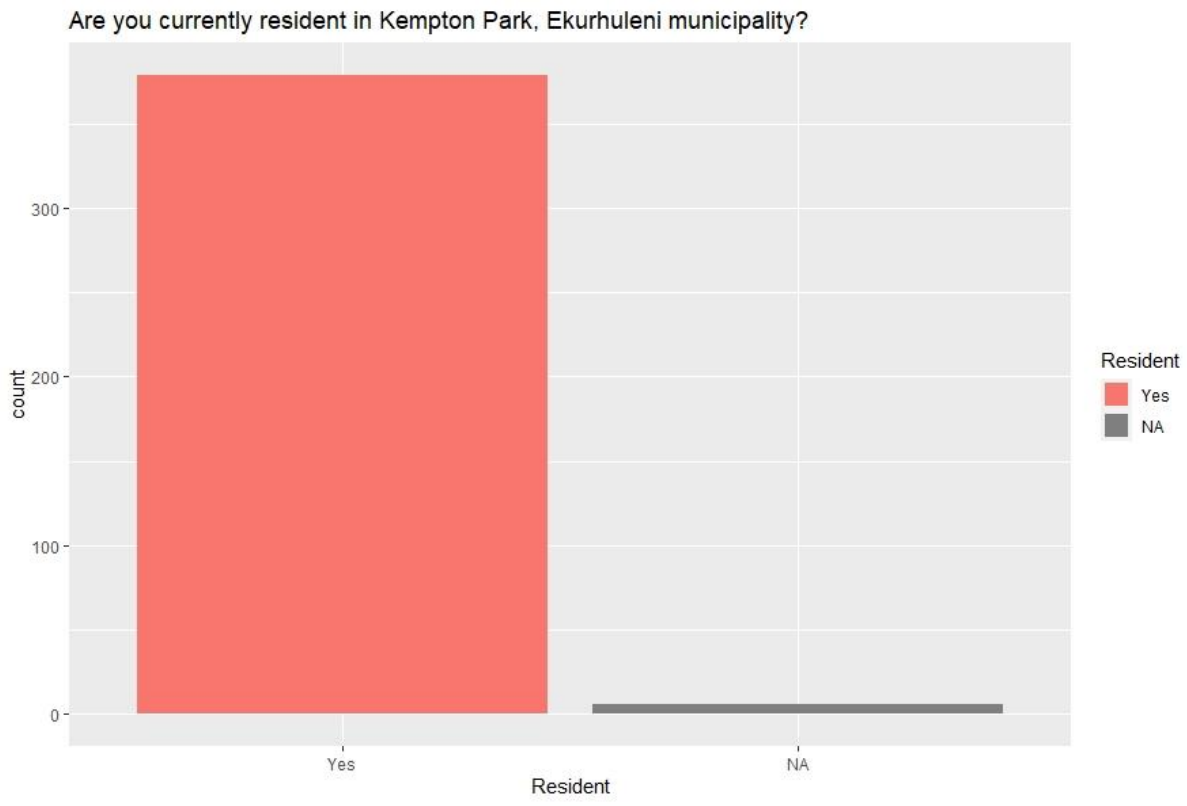


Figure 4.1: Residency of the research respondents

Source: R (R-project.org, 2023)

4.2.2 Exposure to new technology

In addition, Table 4.2 and Figure 4.2 show the research respondents' exposure to new technology.

Table 4.2: Research respondents' exposure to new technology

Please indicate your exposure to new technology?	Frequency	Percent
Internet at home	47	9.2
Internet on mobile phone	300	58.5
Computer at home	67	13.1
Computer at work	38	7.4
Shopping online	23	4.5
Banking online	21	4.1
Working online	12	2.3
NA	5	0.9
Total	513*	100

*The total frequency of 513 refers to the total number of responses and not to the total number of respondents because the respondents were allowed to make multiple responses.

Source: R (R-project.org, 2023)

As shown in Table 4.2, 58.5% of the research respondents are exposed to new technology through the internet on their mobile phones and 13.1% through computer at home. In addition, 9.2% of the research respondents are exposed to new technology through internet at home and 7.4% through computer at work. Further, 4.5% of the research respondents are exposed to new technology through shopping online and 4.1% through banking online. Also, 2.3% of the research respondents are exposed to new technology through working online. However, 0.9% of the research respondents did not disclose their exposure to new technology.

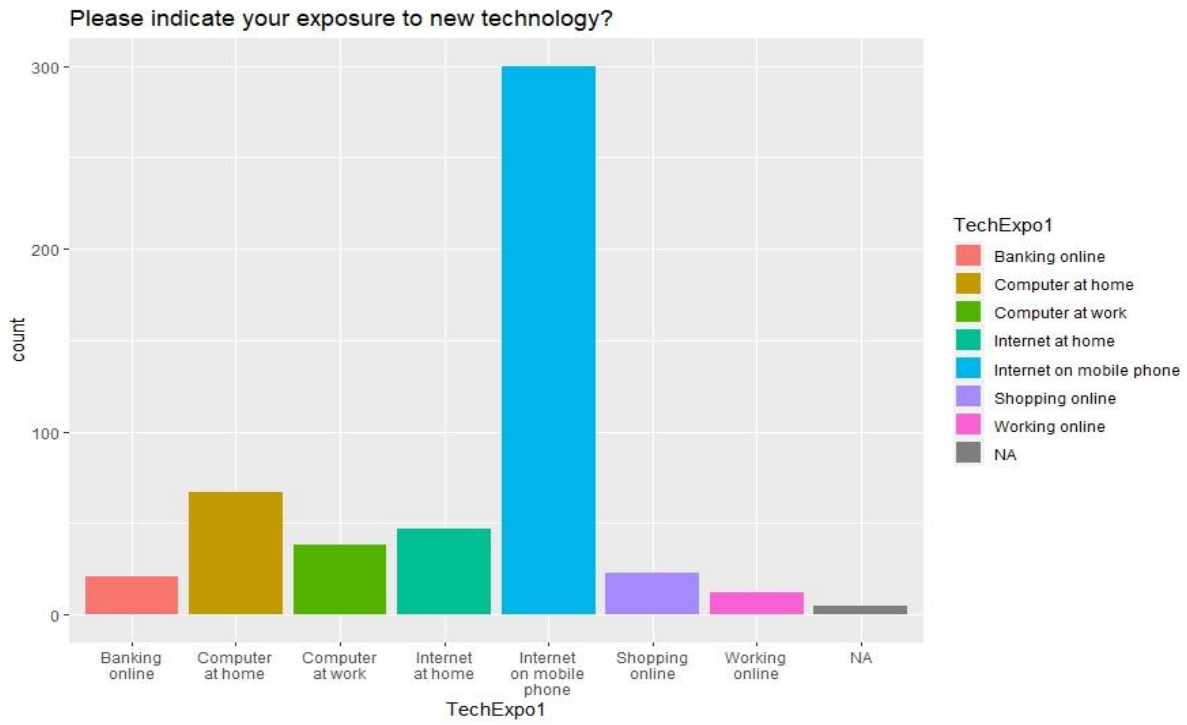


Figure 4.2: Research respondents' exposure to new technology

Source: R (R-project.org, 2023)

In addition, the research respondents were asked to specify their other exposure to new technology through an open-ended option in this questionnaire item. Table 4.3 and Figure 4.3 show the research respondents' other exposure to new technology.

Table 4.3: Research respondents' other exposure to new technology

Specify other exposure to new technology	Frequency	Percent
Laptop	1	0.3
TV	9	2.3
NA	375	97.4
Total	385	100

Source: R (R-project.org, 2023)

As shown in Table 4.3, 97.4% of the research respondents did not mention their other exposure new technology and 2.3% mentioned TV. In addition, 0.3% of the research respondents did mention laptop as their other exposure new technology.

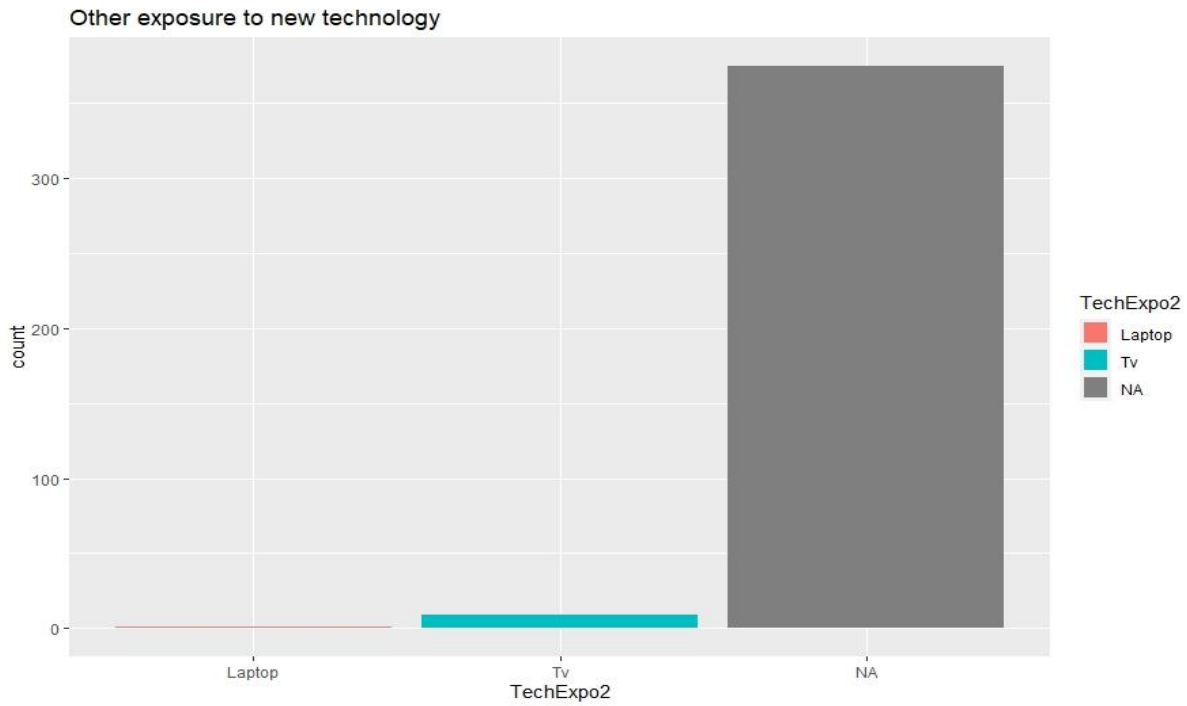


Figure 4.3: Research respondents' other exposure to new technology
Source: R (R-project.org, 2023)

4.3 Descriptive statistics

This segment of the study presents the results of the descriptive statistics. The participants were asked to respond to statements using the following five-point Likert scale:

1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree

4.3.1 Perception on the effectiveness of integrating IoT to household waste collection

This subsection of the study presents the results of perception on the effectiveness of integrating IoT to household waste. This subsection of the questionnaire had a Cronbach's alpha of -0.3. According to Cortina (1993), Cronbach's alpha values that are larger than 0.69 show that the research instrument is reliable. However, the Cronbach's alpha result for this variable is not very informative because the last two questionnaire items in Table 4.4 were framed to render an opposite response, and so they were negatively correlated with the total scale for this variable. According to Cortina (1993), a low value of alpha could be due to a low number of questions, poor inter-relatedness between items or heterogeneous constructs.

Table 4.4 presents the mean and standard deviation of these responses.

Table 4.4: Perception on the effectiveness of integrating IoT to household waste collection

Variable	Mean	Standard Deviation
IoT will enhance waste collection in Kempton Park.	3.49	1.09
IoT will speedup waste collection in Kempton Park.	3.52	1.12
IoT will negatively disrupt waste collection in Kempton Park.	2.48	0.99
IoT will slowdown waste collection in Kempton Park.	2.46	1.03

Source: R (R-project.org, 2023)

In Table 4.4, the mean values of the first two distributions are close to 4 thus indicating agreement to the questionnaire items. Consequently, the research respondents agreed that IoT will enhance waste collection in Kempton Park and that IoT will speedup waste collection in Kempton Park. However, the standard deviations of these first two distributions are greater than 1 and this shows that most of the respondents are far from the mean and that agreement is generally low among the respondents. Further, in Table 4.4, the mean values of the last two distributions are close to 3 thus indicating neutrality

to the questionnaire items. Therefore, the research respondents neither agreed nor disagreed that IoT will negatively disrupt waste collection in Kempton Park and that IoT will slowdown waste collection in Kempton Park. The standard deviations of these last two distributions are less than 1 and this shows that most of the respondents are close to the mean and that neutrality is generally high among the respondents.

To further investigate the variable perception on the effectiveness of integrating IoT to household waste collection, the mean of the individual variables in Table 4.4 was calculated to get the composite variable for perception on the effectiveness of integrating IoT to household waste collection. Table 4.5 shows the composite variable for perception on the effectiveness of integrating IoT to household waste collection.

Table 4.5: Composite variable for perception on the effectiveness of integrating IoT to household waste collection

Variable	Mean	Standard Deviation
Composite variable for perception on the effectiveness of integrating IoT to household waste collection.	2.99	0.48

Source: R (R-project.org, 2023)

In Table 4.5, the mean of the composite variable for perception on the effectiveness of integrating IoT to household waste collection is close to 3 thus indicating neutrality to the statements by the research respondents. In addition, the standard deviation in Table 4.5 is below 1 and this shows that most of the respondents are close to the mean, and therefore, neutrality among the research respondents is high. However, the results of this composite variable is not very informative because the last two questionnaire items in Table 4.4 were framed to render an opposite response, and so they were negatively correlated with the total scale for this variable. According to Cortina (1993), a low value of alpha could be due to a low number of questions, poor inter-relatedness between items or heterogeneous constructs.

4.3.2 Perception on the ease of use of integrating IoT to household waste collection

The subsection of the study presents the results of perception on the ease of use of integrating IoT to household waste collection. This subsection of the questionnaire had a Cronbach's alpha of 0.7. According to Cortina (1993), Cronbach's alpha values that are larger than 0.69 show that the research instrument is reliable. Table 4.6 presents the mean and standard deviation of these responses.

Table 4.6: perception on the ease of use of integrating IoT to household waste collection

Variable	Mean	Standard Deviation
IoT enabled waste systems will be easy to use.	3.48	1.09
IoT will be easy to incorporate in daily route.	3.17	1.22
It will be effortless to use IoT enabled waste systems.	2.89	1.14
It will be easy to adopt IoT enabled waste systems.	3.49	1.09

Source: R (R-project.org, 2023)

In Table 4.6, the mean values of the first and the last distributions are close to 4 thus indicating agreement to the questionnaire items. Consequently, the research respondents agreed that IoT enabled waste systems will be easy to use and that it will be easy to adopt IoT enabled waste systems. However, the standard deviations of these first and the last distributions are greater than 1 and this shows that most of the respondents are far from the mean and that agreement is generally low among the respondents. Further, in Table 4.4, the mean values of the second and third distributions are close to 3 thus indicating neutrality to the questionnaire items. Therefore, the research respondents neither agreed nor disagreed that it will be effortless to use IoT enabled waste systems. However, the standard deviations of these second and third distributions are greater than 1 and this shows that most of the respondents are far from the mean and that neutrality is generally not high among the respondents.

To further investigate the variable perception on the ease of use of integrating IoT to household waste collection, the mean of the individual variables in Table 4.6 was calculated to get the composite variable for perception on the ease of use of integrating

IoT to household waste collection. Table 4.7 shows the composite variable for perception on the ease of use of integrating IoT to household waste collection.

Table 4.7: Composite variable for perception on the ease of use of integrating IoT to household waste collection

Variable	Mean	Standard Deviation
Composite variable for perception on the ease of use of integrating IoT to household waste collection.	3.25	0.77

Source: R (R-project.org, 2023)

In Table 4.7, the mean of the composite variable for perception on the ease of use of integrating IoT to household waste collection is close to 3 thus indicating neutrality to the statements by the research respondents. In addition, the standard deviation in Table 4.7 is below 1 and this shows that most of the respondents are close to the mean, and therefore, neutrality among the research respondents is high.

4.3.3 Challenges faced in integrating IoT to household waste collection

The subsection of the study presents the results of challenges faced in integrating IoT to household waste collection. This subsection of the questionnaire had a Cronbach's alpha of 0.8. According to Cortina (1993), Cronbach's alpha values that are larger than 0.69 show that the research instrument is reliable. Table 4.8 presents the mean and standard deviation of these responses.

Table 4.8: Challenges faced in integrating IoT to household waste collection

Variable	Mean	Standard Deviation
The operational cost is too high.	3.86	0.88
There may be regulatory challenges to overcome.	3.61	1.14
There is a lack of technical skills among municipal authorities.	3.91	0.91
Internet connectivity remains low in the municipality.	3.85	0.94
There may be privacy and security concerns.	3.43	1.10
There is a lack of IT infrastructure.	4.22	1.00

Source: R (R-project.org, 2023)

In Table 4.8, the mean values of almost all the distributions except the penultimate distribution are close to 4 thus indicating agreement to the questionnaire items. Consequently, the research respondents agreed that the operational cost is too high and that there may be regulatory challenges to overcome. In addition, the research respondents agreed that there is a lack of technical skills among municipal authorities and that Internet connectivity remains low in the municipality. They further agreed that there is a lack of IT infrastructure. The standard deviations of these distributions are mostly less than 1 except that of the second distribution, and this shows that most of the respondents are close to the mean and that agreement is generally high among the respondents. In the second distribution, the standard deviation is greater than 1 and this indicates that the respondents are far from the mean and that agreement is not generally high among the respondents. However, in the penultimate distribution in Table 4.8, the mean value is close to 3, thus indicating neutrality to the questionnaire item. Therefore, the research respondents neither agreed nor disagreed that there may be privacy and security concerns. However, the standard deviation of this penultimate distribution is greater than 1 and this shows that most of the respondents are far from the mean and that neutrality is generally not high among the respondents.

To further investigate the variable challenges faced in integrating IoT to household waste collection, the mean of the individual variables in Table 4.8 was calculated to get the composite variable for challenges faced in integrating IoT to household waste collection. Table 4.9 shows the composite variable for challenges faced in integrating IoT to household waste collection.

Table 4.9: Composite variable for challenges faced in integrating IoT to household waste collection

Variable	Mean	Standard Deviation
Composite variable for challenges faced in integrating IoT to household waste collection.	3.81	0.72

Source: R (R-project.org, 2023)

In Table 4.9, the mean of the composite variable for challenges faced in integrating IoT to household waste collection is close to 4 thus indicating agreement to the statements by the research respondents. In addition, the standard deviation in Table 4.9 is below 1 and this shows that most of the respondents are close to the mean, and therefore, agreement among the research respondents is high.

4.3.4 Factors that affect adoption of IoT to waste management processes

The subsection of the study presents the results of the factors that affect adoption of IoT to waste management processes. This subsection of the questionnaire had a Cronbach's alpha of 0.8. According to Cortina (1993), Cronbach's alpha values that are larger than 0.69 show that the research instrument is reliable. Table 4.10 presents the mean and standard deviation of these responses.

Table 4.10: Factors that affect adoption of IoT to waste management processes

Variable	Mean	Standard Deviation
The cost of data is too high.	4.24	0.88
Internet access remains low in the municipality.	4.11	0.95
There is a lack of technical skills among residents.	4.04	0.94
Residents are not interested in adopting IoT for waste management.	2.68	1.09
Residents may have privacy and security concerns.	2.89	1.17

Source: R (R-project.org, 2023)

In Table 4.10, the mean values of the first three distributions are close to 4 thus indicating agreement to the questionnaire items. Consequently, the research respondents agreed that the cost of data is too high and that Internet access remains low in the municipality. The research respondents further agreed that There is a lack of technical skills among residents. The standard deviations of these first three distributions are less than 1 and this shows that most of the respondents are close to the mean and that agreement is generally high among the respondents. Further, in Table 4.10, the mean values of the last two distributions are close to 3 thus indicating neutrality to the questionnaire items. Therefore, the research respondents neither agreed nor disagreed that residents are not interested in adopting IoT for waste management and that residents may have privacy and security concerns. However, the standard deviations of these last two distributions are greater 1 and this shows that most of the respondents are far from the mean and that neutrality is generally not high among the respondents.

To further investigate the variable factors that affect adoption of IoT to waste management processes, the mean of the individual variables in Table 4.10 was calculated to get the composite variable for factors that affect adoption of IoT to waste management processes. Table 4.11 shows the composite variable for factors that affect adoption of IoT to waste management processes.

Table 4.11: Composite variable for factors that affect adoption of IoT to waste management processes

Variable	Mean	Standard Deviation
Composite variable for factors that affect adoption of IoT to waste management processes.	3.59	0.71

Source: R (R-project.org, 2023)

In Table 4.11, the mean of the composite variable for factors that affect adoption of IoT to waste management processes is close to 4 thus indicating agreement to the statements by the research respondents. In addition, the standard deviation in Table 4.11 is below 1 and this shows that most of the respondents are close to the mean, and therefore, agreement among the research respondents is high.

4.4 Inferential statistics

4.4.1 Moderated multiple linear regression

In this study, the moderated multiple linear regression model was used to investigate whether the variable challenges faced in integrating IoT to household waste collection moderates the effects of perceived effectiveness and perceived ease of use on the factors that affect the adoption of technology (factors affect). According to Cleary (1968), the moderated multiple linear regression model involves a three-step differential prediction process that include the following:

iv. Estimation of the criterion-related validity through a simple linear regression model.
v. Intercept differences through an additive multiple linear regression model.
vi. Slope differences through a multiplicative multiple linear regression model.

4.4.1.1 The effect of challenges faced on the impact of perceived effectiveness

This subsection presents the results of the moderation effect of challenges faced on the impact of perceived effectiveness on factors that affect the adoption of IoT in waste management. The model is shown in Figure 4.4 where the moderating variable is challenges faced and the independent variable is perceived effectiveness.

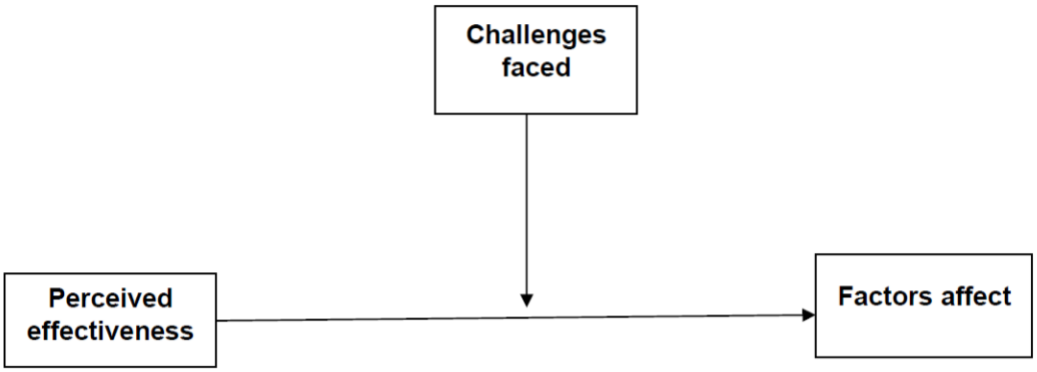


Figure 4.4: Moderation effect of challenges faced on the impact of perceived effectiveness on factors that affect the adoption of IoT in waste management

Source: Own work

4.4.1.1.1 Step 1: Criterion-related validity

H1: The factors that affect the adoption of IoT in waste management (factors affect) is explained by perceived effectiveness.

Step 1 of the three-step differential prediction process uses a simple linear model (1)

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon \qquad (1)$$

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the effectiveness of integrating IoT to household waste (Perceived effectiveness)

β_0 = Intercept

β_1 = Slope coefficient for perceived effectiveness, and

ε = Error term.

The results of the simple linear model (1) are shown in Table 4.12 and Figure 4.5.

Table 4.12: Simple linear model output I

	Estimate	Standard Error	t-value	p-value	Lower 95%	Upper 95%
Intercept	3.591	0.033	107.266	0.000	3.525	3.657
*c_Effectiveness	0.548	0.070	7.788	0.000	0.409	0.686

Source: R (R-project.org, 2023)

* c_Effectiveness refers to the grand-mean centre continuous predictor variable perceived effectiveness.

In Table 4.12, the low p-value of less than 0.05 shows that perceived effectiveness does predict factors that affect the adoption of IoT in waste management. Hence, the first hypothesis (H1) has been tested. The R-squared for this model is 0.137 meaning that 13.7% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived effectiveness. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor.

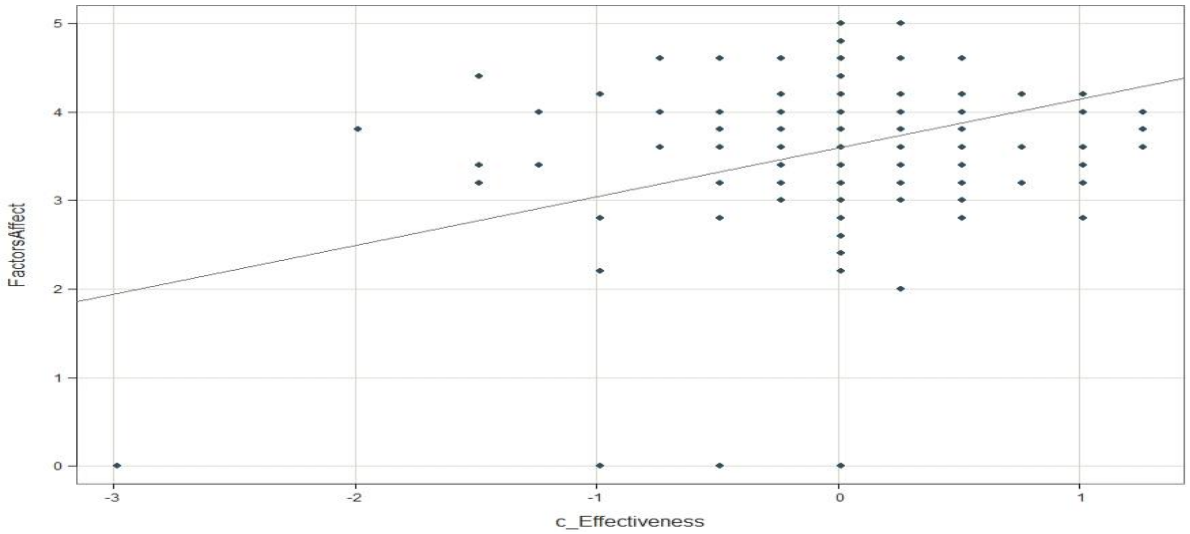


Figure 4.5: Scatterplot and simple regression model I

Source: R (R-project.org, 2023)

4.4.1.1.2 Step 2: Intercept differences

Step 2 of the three-step differential prediction process uses an additive multiple linear regression model (2)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (2)$$

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the effectiveness of integrating IoT to household waste (Perceived effectiveness)

X_2 = Challenges faced in integrating IoT to household waste collection (Challenges faced)

β_0 = Intercept

β_1 = Slope coefficient for perceived effectiveness

β_2 = Slope coefficient for challenges faced, and

ε = Error term.

The results of the additive multiple linear regression model are shown in Table 4.13 and Figure 4.6.

Table 4.13: Additive multiple linear regression model output I

	Estimate	Standard Error	t-value	p-value	Lower 95%	Upper 95%
Intercept	3.591	0.027	132.433	0.000	3.538	3.644
*c_Effectiveness	0.139	0.064	2.185	0.029	0.014	0.265
**c_ChallengesFaced	0.597	0.042	14.206	0.000	0.514	0.679

Source: R (R-project.org, 2023)

* c_Effectiveness refers to the grand-mean centre continuous predictor variable perceived effectiveness.

** c_ChallengesFaced refers to the grand-mean centre continuous predictor variable challenges faced.

Again in Table 4.13, the low p-value of less than 0.05 shows that perceived effectiveness does predict factors that affect the adoption of IoT in waste management. In Table 4.13, the low p-value for challenges faced provides evidence that there are intercept differences. The R-squared for this model is 0.435 meaning that 43.5% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived effectiveness and challenges faced. This shows an increase in the variability explained by the model. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor. As shown in Figure 4.6, the intercept for +1 standard deviation of challenges faced is higher than that of the mean, and the intercept for -1 standard deviation of challenges faced is lower than that of the mean. In addition, the p-values of all these three intercepts are less the 0.05, and this means that the simple slope analysis results shown in Figure 4.6 are all statistically significant.

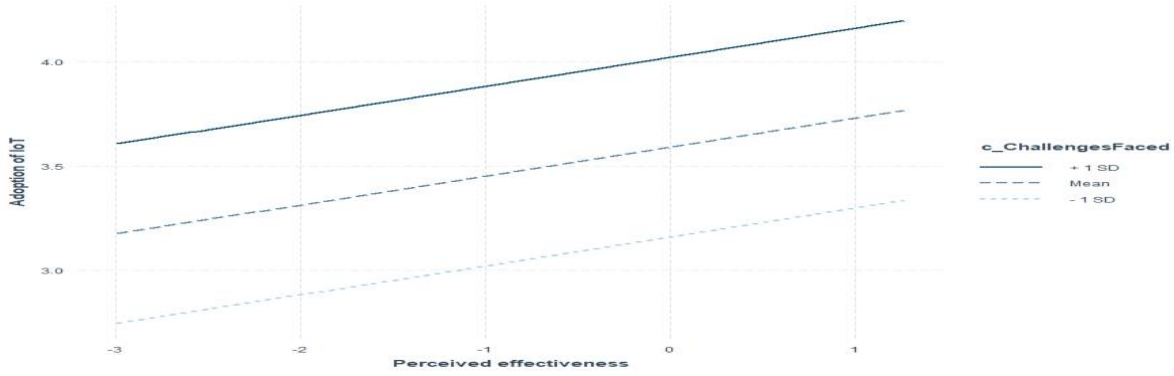


Figure 4.6: Simple slopes analysis 1a

Source: R (R-project.org, 2023)

4.4.1.1.3 Step 3: Slope differences

H3: Challenges faced moderates the impact of perceived effectiveness on the factors that affect the adoption of IoT in waste management (factors affect).

Step 3 of the three-step differential prediction process uses a multiplicative multiple regression model (3).

$Y = \beta_0 + \beta_1 X_1 * \beta_2 X_2 + \varepsilon$ (3)

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the effectiveness of integrating IoT to household waste (Perceived effectiveness)

X_2 = Challenges faced in integrating IoT to household waste collection (Challenges faced)

β_0 = Intercept

β_1 = Slope coefficient for perceived effectiveness

β_2 = Slope coefficient for challenges faced, and

ε = Error term.

The results of the multiplicative multiple linear regression model are shown in Table 4.14 and Figure 4.7.

Table 4.14: Multiplicative multiple linear regression model output I

	Estimate	**Standard Error**	**t-value**	**p-value**	**Lower 95%**	**Upper 95%**
Intercept	3.620	0.027	136.449	0.000	3.568	3.672
*c_Effectiveness	-0.079	0.072	-1.097	0.274	-0.221	0.063
**c_ChallengesFaced	0.473	0.046	10.327	0.000	0.383	0.562
*** c_Effectiveness: c_ChallengesFaced	-0.187	0.033	-5.746	0.000	-0.251	-0.123

Source: R (R-project.org, 2023)

* c_Effectiveness refers to the grand-mean centre continuous predictor variable perceived effectiveness.

** c_ChallengesFaced refers to the grand-mean centre continuous predictor variable challenges faced.

*** c_Effectiveness: c_ChallengesFaced refers to the interaction term of the two variables mentioned above.

In Table 4.14, the high p-value of more than 0.05 shows that perceived effectiveness does not predict factors that affect the adoption of IoT in waste management. As discussed in the previous model, the low p-value for challenges faced provides evidence

that there are intercept differences while the low p-value for the interaction term provides evidence of slope differences, and this shows that challenges faced moderates the impact of perceived effectiveness. Hence, the third hypothesis (H3) has been tested. The R-squared for this model is 0.480 meaning that 48% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived effectiveness, challenges faced, and the interaction these two variables. Again, this shows an increase in the variability explained by the model. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor. As shown in Figure 4.7, the slope for +1 standard deviation of challenges faced is steeper than that of the mean, and the slope for -1 standard deviation of challenges faced is less steeper than that of the mean. However, only the slope for the +1 standard deviation of challenges faced is statistically significant with a p-value that is less the 0.05.

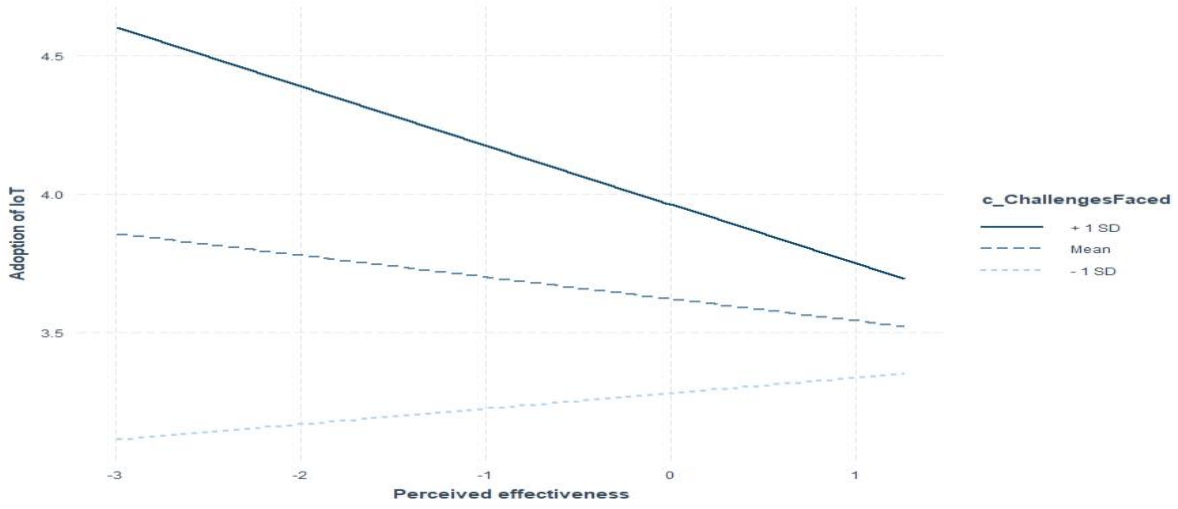


Figure 4.7: Simple slopes analysis 1b

Source: R (R-project.org, 2023)

4.4.1.2 The effect of challenges faced on the impact of perceived ease of use

In addition, this subsection presents the results of the moderation effect of challenges faced on the impact of perceived ease of use on factors that affect the adoption of IoT in waste management. The model is shown in Figure 4.8 where the moderating variable is challenges faced and the independent variable is perceived ease of use.

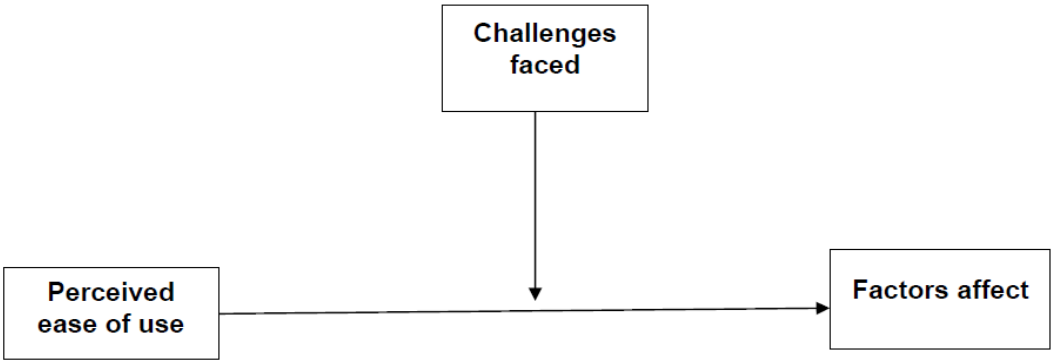


Figure 4.8: Moderation effect of challenges faced on the impact of perceived ease of use on factors that affect the adoption of IoT in waste management

Source: Own work

4.4.1.2.1 Step 1: Criterion-related validity

H2: The factors that affect the adoption of IoT in waste management (factors affect) is explained by perceived ease of use.

Step 1 of the three-step differential prediction process uses a simple linear model (4).

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon \qquad (4)$$

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the ease of use of integrating IoT to household waste (Perceived ease of use)

β_0 = Intercept

β_1 = Slope coefficient for perceived ease of use, and

ε = Error term.

The results of the simple linear model are shown in Table 4.15 and Figure 4.9.

Table 4.15: Simple linear model output II

	Estimate	Standard Error	t-value	p-value	Lower 95%	Upper 95%
Intercept	3.591	0.034	106.065	0.000	3.525	3.658
*c_EaseOfUse	0.313	0.044	7.126	0.000	0.226	0.399

Source: R (R-project.org, 2023)

* c_EaseOfUse refers to the grand-mean centre continuous predictor variable perceived ease of use.

In Table 4.12, the low p-value of less than 0.05 shows that perceived ease of use does predict factors that affect the adoption of IoT in waste management. Hence, the second hypothesis (H2) has been tested. The R-squared for this model is 0.117 meaning that 11.7% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived use. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor.

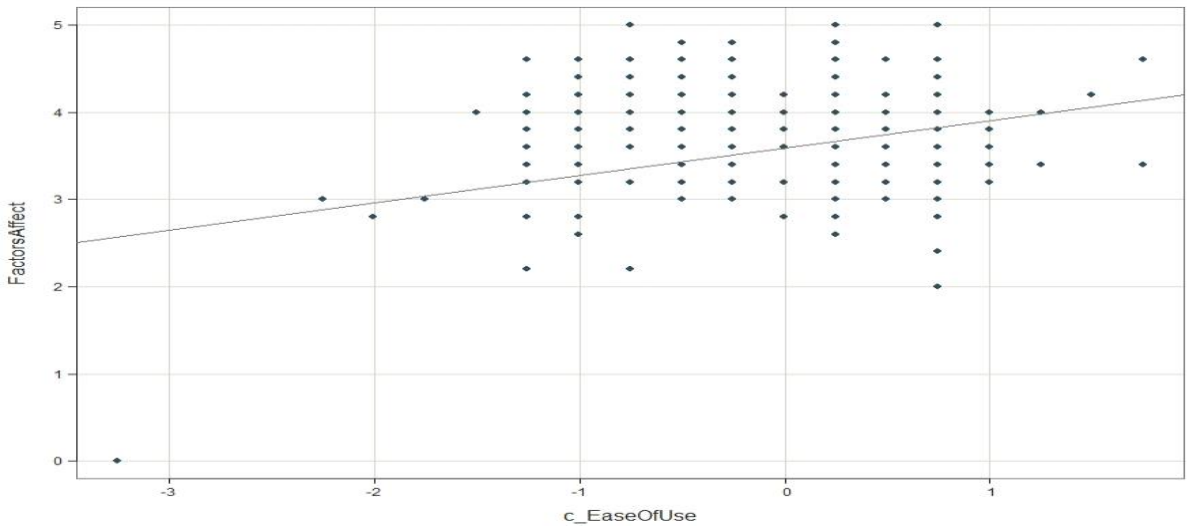


Figure 4.9: Scatterplot and simple regression model II

Source: R (R-project.org, 2023)

4.4.1.2.2 Step 2: Intercept differences

As mentioned earlier, Step 2 of the three-step differential prediction process uses an additive multiple linear regression model (5).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (5)$$

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the ease of use of integrating IoT to household waste (Perceived ease of use)

X_2 = Challenges faced in integrating IoT to household waste collection (Challenges faced)

β_0 = Intercept

β_1 = Slope coefficient for perceived ease of use

β_2 = Slope coefficient for challenges faced, and

ε = Error term.

The results of the additive multiple linear regression model are shown in Table 4.16 and Figure 4.10.

Table 4.16: Additive multiple linear regression model output II

	Estimate	Standard Error	t-value	p-value	Lower 95%	Upper 95%
Intercept	3.591	0.027	132.158	0.000	3.538	3.645
*c_EaseOfUse	-0.079	0.044	-1.780	0.076	-0.166	0.008
**c_ChallengesFaced	0.689	0.047	14.582	0.000	0.596	0.782

Source: R (R-project.org, 2023)

* c_EaseOfUse refers to the grand-mean centre continuous predictor variable perceived ease of use.

** c_ChallengesFaced refers to the grand-mean centre continuous predictor variable challenges faced.

In Table 4.16, the high p-value of more than 0.05 shows that perceived ease of use does not predict factors that affect the adoption of IoT in waste management. Also, Table 4.13,

the low p-value for challenges faced provides evidence that there are intercept differences. The R-squared for this model is 0.433 meaning that 43.3% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived ease of use and challenges faced. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor. As shown in Figure 4.10, the intercept for +1 standard deviation of challenges faced is higher than that of the mean, and the intercept for -1 standard deviation of challenges faced is lower than that of the mean. However, none of the p-values of all these three intercepts are less the 0.05, and this means that the simple slope analysis results shown in Figure 4.10 are all not statistically significant.

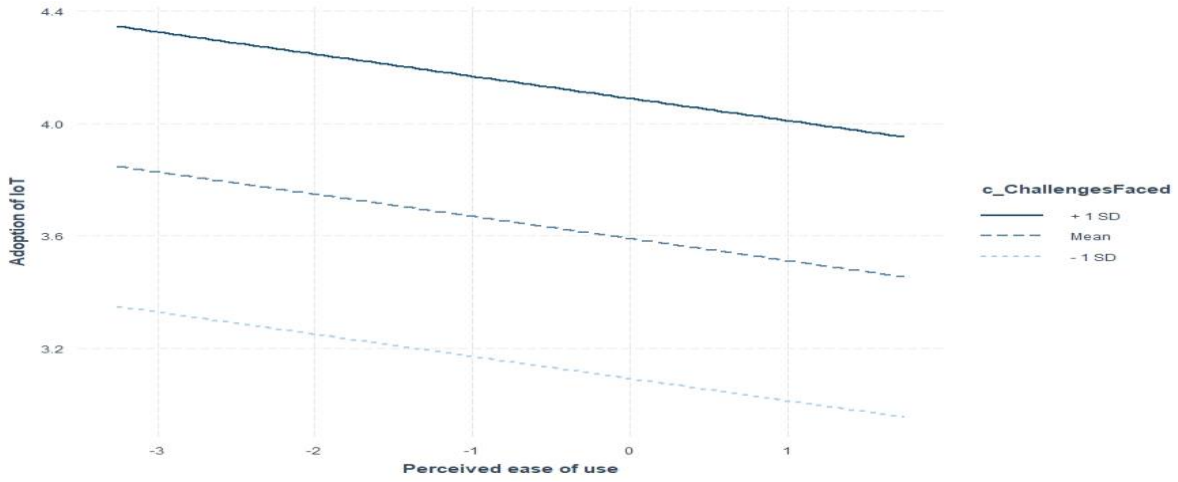


Figure 4.10: Simple slopes analysis 2a

Source: R (R-project.org, 2023)

4.4.1.3.3 Step 3: Slope differences

H4: Challenges faced moderates the impact of perceived ease of use on the factors that affect the adoption of IoT in waste management (factors affect).

Step 3 of the three-step differential prediction process uses a multiplicative multiple regression model (6).

$Y = \beta_0 + \beta_1 X_1 * \beta_2 X_2 + \varepsilon$ (6)

Where:

Y = Factors that affect the adoption of IoT in waste management (Factors affect)

X_1 = Perception on the ease of use of integrating IoT to household waste (Perceived ease of use)

X_2 = Challenges faced in integrating IoT to household waste collection (Challenges faced)

β_0 = Intercept

β_1 = Slope coefficient for perceived ease of use

β_2 = Slope coefficient for challenges faced, and

ε = Error term.

The results of the multiplicative multiple linear regression model are shown in Table 4.17 and Figure 4.11.

Table 4.17: Multiplicative multiple linear regression model output II

	Estimate	**Standard Error**	**t-value**	**p-value**	**Lower 95%**	**Upper 95%**
Intercept	3.665	0.026	143.600	0.000	3.615	3.715
*c_EaseOfUse	-0.186	0.041	-4.514	0.000	-0.267	-0.105
**c_ChallengesFaced	0.373	0.053	6.976	0.000	0.268	0.478
*** c_EaseOfUse: c_ChallengesFaced	-0.218	0.022	-9.703	0.000	-0.262	-0.174

Source: R (R-project.org, 2023)

* c_EaseOfUse refers to the grand-mean centre continuous predictor variable perceived ease of use.

** c_ChallengesFaced refers to the grand-mean centre continuous predictor variable challenges faced.

*** c_EaseOfUse: c_ChallengesFaced refers to the interaction term of the two variables mentioned above.

In Table 4.17, the low p-value of less than 0.05 shows that perceived ease of use does predict factors that affect the adoption of IoT in waste management. As discussed in the previous model, the low p-value for challenges faced provides evidence that there are

intercept differences while the low p-value for the interaction term provides evidence of slope differences, and this shows that challenges faced moderates the impact of perceived ease of use. Hence, the fourth hypothesis (H4) has been tested. The R-squared for this model is 0.545 meaning that 54.5% of the variability in the factors that affect the adoption of IoT in waste management is explained by perceived effectiveness, challenges faced, and the interaction these two variables. Again, this shows an increase in the variability explained by the model. The associated p-value for the model is less than 0.05 and this shows that the model does fit the data and it is a valid predictor. As shown in Figure 4.11, the slope for +1 standard deviation of challenges faced is steeper than that of the mean, and the slope for -1 standard deviation of challenges faced is less steeper than that of the mean. However, only the slopes for the +1 standard deviation and the mean standard deviation of challenges faced are statistically significant with p-values that is less the 0.05.

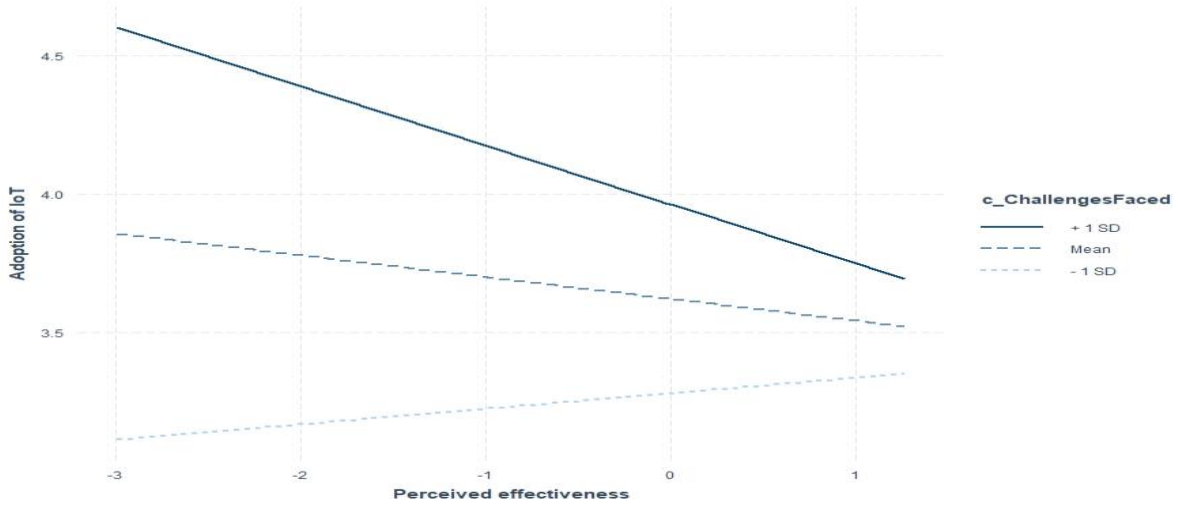


Figure 4.11: Simple slopes analysis 2b

Source: R (R-project.org, 2023)

4.5 Conclusion

Chapter 4 has presented the data analysis results of this study. The chapter presented the results of the demographic information of the research respondents, and this covered information on residency and exposure to new technology. In addition, reliability measurement of the research instrument was estimated using the Cronbach's alpha for each section containing interval or ordinal scale. Further, descriptive statistical analysis was carried out on each section of the questionnaire using the means and standard deviations. Next, inferential statistical analysis was carried out by using the moderated multiple linear regression model. The moderated multiple linear regression model was used to investigate whether the variable challenges faced in integrating IoT to household waste collection moderates the effects of perceived effectiveness and perceived ease of use on the factors that affect the adoption of technology (factors affect). The results show moderation effect of challenges faced in integrating IoT to household waste collection on the impact of the other two predictor variables on the factors that affect the adoption of IoT in waste management. Chapter 5 discusses the results of the data analysis with respect to the stated research objectives.

CHAPTER 5: DISCUSSION OF RESULTS

5.1 Introduction

Chapter 5 discusses the results of the study with respect to the research objectives that were stated earlier. The main objective of this study was to investigate how the adoption of integrating IoT to waste management systems will reduce inefficiencies when collecting household waste. In addition, the secondary objectives of this study were as follows:

- To investigate the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality.
- To investigate challenges faced in integrating IoT to household waste management in Kempton Park households.
- To investigate the factors that affect the adoption of IoT to waste management processes in Kempton Park.

The following segments of this chapter discusses the results with respect to the research objectives outlined above.

5.2 To investigate the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality

Based on the descriptive statistical analysis results, the research respondents agreed that IoT will enhance waste collection in Kempton Park and that IoT will speedup waste collection in Kempton Park. Further, the research respondents neither agreed nor disagreed that IoT will negatively disrupt waste collection in Kempton Park and that IoT will slowdown waste collection in Kempton Park. These findings on the perception on the effectiveness of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality is also supported by the results of criterion validity (step one) of the moderated multiple linear regression model. The results of the simple linear model show that perceived effectiveness does predict factors that affect the adoption of

IoT in waste management. However, the effect of perceived effectiveness on the factors that affect the adoption of IoT in waste management is moderated by the challenges faced in integrating IoT to household waste management. The results of the moderated multiple linear regression model show statistically significant intercept differences and slope differences for the moderating variable challenges faced in integrating IoT to household waste management.

Davis, Bagozzi, and Warshaw (1989) introduced Technology Acceptance Model to define IT users' IT application usage. Perceived usefulness directly influences purpose and attitude, according to (Davis, Bagozzi, & Warshaw, 1989), which may influence users' choice to use IT and their unfavourable attitude toward it. Further, a user's interaction with a technology moderates its perceived usefulness and simplicity of use, which in turn affects the user's choice to adopt or reject a technology. According to (Sherbib et al., 2012), a user who has a good attitude toward technology is more likely to be motivated to use it. Other studies confirmed the importance of beliefs in influencing technology use. Alharbi and Drew (2014) pointed out that the competency level that influences how much technology is used can be used to anticipate how much technology will be used. Organisational, technological, social, and demographic characteristics including gender, computer self-efficacy, and training levels can all have an impact on how well a technology is accepted. Therefore, the result of the simple linear model that perceived effectiveness does predict factors that affect the adoption of IoT in waste management is being supported by contemporary literature.

Researchers have investigated how local and national policies impact adoption and implementation of IoT-based waste management systems (Pitner, 2019). Further, TAM highlights perceived usefulness and ease of use as key aspects in technology acceptance (Davis, Bagozzi, & Warshaw, 1989), and South African researchers have explored this factor when adopting such systems (Munsamy, 2022). Understanding how IoT integration in household waste collection might result in incremental innovation is made easier with the help of TAM which holds that incremental innovation happens when continual modest improvements are made to current goods, services, or procedures (Dolfsma et al., 2003). IoT can make it easier to design new bin-level monitoring sensors for domestic waste

collection, which will result in small but considerable gains in waste management efficiency. Studies on IoT integration into waste collection in South Africa indicate its great potential to optimise waste management processes. Munsamy (2022) conducted an empirical investigation on an IoT-based waste management system's ability to reduce operational costs while increasing collection efficiencies – thus significantly increasing environmental sustainability in waste collection processes. Likewise, Pitner (2019) performed a case study analysing how adopting and implementing an IoT waste collection and disposal solution improved collection and disposal practices in Namibia.

An example strategy proposed by Tripathi, Pandey, Narwal, and Negi (2018) on IoT integration in waste management as a solution to the problems associated with waste management is that of the smart wastebasket model. Importance of the smart wastebasket model is its capability in preventing waste overflow into landfills. Integral to this is the use of a cloud-based garbage monitoring system that is powered by solar panels. Cloud-based system analyses garbage levels in the household bins and communicates the data to a server that dictates the waste collection routes in cities. Such systems save on the costs associated with waste transportation and ensure households in no means suffer the adversities of holding massive wastes amounts in their household bins.

Andrade and Yoo (2019) identified problems associated with waste management such as the issues of transportation and scheduling pick-up times for wastes in municipalities and even communities and households, and these problems are precisely commonly associated with the traditional waste management systems. Development of a hybrid waste management system, explicitly one that integrates, or smart technologies and the traditional waste management system ensures efficiency in the routing of waste pick-up trucks to avoid cases of waste fill ups and the adverse risks that come up from these cases. AirBin is a strategy that integrates IoT in waste management designed by Das, Islam, Billah, and Sarker (2021) and specifically aims to prevent the spread of infectious diseases such as COVID through wastes generated from infectious high-risk zones. Examples of these zones are clinics, healthcare facilities, quarantine zones and even garbage bins. IoT integration in this system ensures that remote garbage build-up monitoring is effective, and the clearing occurs at the right times and frequently.

Accumulation of bio-medical wastes increases the risks of infectious diseases, and with such a system in place it is always integral to ensure frequent collection of wastes, efficient transportation, and disposal of the waste and the AirBin proves to provide quality and sustainable data to streamline all these processes.

5.3 To investigate the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality

On account of the descriptive statistical analysis results, the research respondents agreed that IoT enabled waste systems will be easy to use and that it will be easy to adopt IoT enabled waste systems. In addition, the research respondents neither agreed nor disagreed that it will be effortless to use IoT enabled waste systems. These findings on the perception on the ease of use of integrating IoT to household waste collection for households in Kempton Park, Ekurhuleni municipality is also supported by the results of criterion validity (step one) of the moderated multiple linear regression model. The results of the simple linear model show that perceived ease of use does predict factors that affect the adoption of IoT in waste management. However, the effect of perceived ease of use on the factors that affect the adoption of IoT in waste management is moderated by the challenges faced in integrating IoT to household waste management. The results of the moderated multiple linear regression model show statistically significant intercept differences and slope differences for the moderating variable challenges faced in integrating IoT to household waste management.

The original Technology Acceptance Model (TAM) comprises of four components namely: perceived usefulness, perceived ease of use, intention to use, and actual use (Davis, Bagozzi, & Warshaw, 1989). Individual capabilities, IT type, function, and status concerns indirectly impact users' intentions by influencing what is viewed as valuable and easy to use. TAM explains why people adopt or reject information technology, particularly smart technology. TAM 2 and 3 were major improvements to TAM (Venkatesh, Morris, Davis, & Davis, 2003) . The TAM model indicates that employees' beliefs and actions impact numerous decision outcomes. So, when people encounter new technology like smart technology, several variables influence their choice to use it. TAM has been a fundamental extension of the Theory of Reasoned Action (TRA) by Ajzen and Fishbien

(LaCaille, 2013). The framework proposes that a user's attitude toward a system had a significant role in determining whether the user would really utilise or reject the system. Perceived utility and perceived ease of use were deemed to be two key beliefs that have an impact on the individual. The usage of smart waste applications by individuals in Kempton Park will be made easier by their capacity to accept and use electronic machine gadgets, which also has an impact on other social interactions. That is, using technology automatically reduces the need for conventional efforts. Consequently, the result of the simple linear model that perceived usefulness does predict factors that affect the adoption of IoT in waste management is being supported by current literature.

Ashton (2009) was the first to use the phrase "Internet of Things" (IoT) in 1999. However, the idea of linking equipment and devices to the internet has been around far longer. The vending machine was one of the first internet-connected devices which was at Carnegie Mellon University in 1982. It could report its inventory as well as whether the drinks were cold or not. The internet was also connected to a variety of additional devices during the ensuing years, but not on the scale of today's IoT ecosystem (Masinter, 1998). These devices included printers, cameras, and scanners. IoT is part of a communication framework where smart devices augment communication for practical benefits. IoT development proves to massively slew new capabilities in multiple areas of human life and the main aim of IoT is to offer plug-and-play technologies that are easy to operate, and users easily access control devices remotely (Rafsanjani & Lawal, 2022). Chinaka and Aba (2020) described IoT as an ecosystem that incorporates multiple digital services that communicate through the internet services. Evaluation indicates that in a year, 740 grams of solid waste is produced per person footprint. Population growth, and urbanisation increase postulate an increase in the annual waste generation from these cities by almost 70% by 2050, hence the need to develop strategies that ensure efficient management of waste, or else the adversities associated with improper waste management pose a threat (Zanella et al., 2014). Therefore, IoT and smart technologies integration in waste management prove to play a critical role in solving these risks and a leeway to ensuring a safe and sustainable environment for future generation and prosperity of humans.

5.4 To investigate challenges faced in integrating IoT to household waste management in Kempton Park households

The results of the descriptive statistical analysis show that the research respondents agreed that the operational cost is too high and that there may be regulatory challenges to overcome. Further, the research respondents agreed that there is a lack of technical skills among municipal authorities and that Internet connectivity remains low in the municipality. The research respondents further agreed that there is a lack of IT infrastructure in Kempton Park, Ekurhuleni municipality. However, the research respondents neither agreed nor disagreed that there may be privacy and security concerns. The results of the moderated multiple linear regression models showed that the challenges faced in integrating IoT to household waste management in Kempton Park households is a moderating factor that moderates the effect of perceived effectiveness and perceived ease of use on the factors that affect the adoption of IoT in waste management. These results are shown in both the additive and multiplicative models that are known as stage two and stage three respectively.

Viljoen et al. (2021) asserted that South African waste management sector is marked by inadequate infrastructure, inefficient services, and insufficient regulations. In addition, Viljoen et al. (2021) explained that waste management must be reinvented with sustainable solutions that create jobs while simultaneously reducing inequality while strengthening both public health resilience and environmental resilience. Nkosi (2014) maintained that though ultimately responsible garbage collection services may currently be provided by the local authority or an established contractor, most municipalities in South Africa typically utilise one of two methods for household waste collection: communal collection for underdeveloped areas like informal settlements requiring residents to place waste containers provided by the municipality while door-to-door collection is more common in formal settlements.

In addition, Viljoen et al. (2021) offered an in-depth examination of South Africa's waste management industry as they consider its challenges posed by municipalities that attempt to provide sustainable waste services. South African waste management has made some progress over time; however, several challenges still need to be tackled, including inadequate funding sources, human resource shortages and operational inefficiency

issues. The authors assert that although South African waste management has seen progress so far, significant challenges still lie in store for sustainable service provision such as inadequate funding or staff resources shortages as well as operational inefficiency issues which must be tackled head on.

Integrating technological solutions such as IoT into South African waste collection systems is also vitally important to their efficiency and optimisation, with smart bins helping increase efficiency while decreasing fuel usage and thus, contributing towards more eco-friendly practices (Munsamy, 2022).

5.5 To investigate the factors that affect the adoption of IoT to waste management processes in Kempton Park

According to the descriptive statistical analysis results, the research respondents agreed that the cost of data is too high and that Internet access remains low in the municipality. The research respondents further agreed that There is a lack of technical skills among residents. However, the research respondents neither agreed nor disagreed that residents are not interested in adopting IoT for waste management and that residents may have privacy and security concerns. The results of the moderated multiple linear regression models showed that the factors that affect the adoption of IoT to waste management processes in Kempton Park is predicted by the two variables perceived effectiveness and perceived ease of use of integrating IoT to household waste collection as shown in the criterion validity (step one) of the models. However, the effect of these predictive variables perceived effectiveness and perceived ease of use is moderated by the challenges faced in integrating IoT to household waste management.

Sharma, Joshi, Kannan, and Govindan (2020) employ decision making trial and evaluation laboratory and total interpretive structural modelling (TISM) to identify barriers to IoT adoption in India's smart city waste management. The main obstacles, as determined, are a lack of regulatory standards, regulations, direction, and internet access. There is a need for a thorough investigation into the identification of barriers in South Africa's smart city initiatives. In addition, Bui (2020) utilised a Fuzzy Delphi technique on the identification of factors that hinder sustainable solid waste management methods. The

key factors identified as obstacles include technological challenges, a lack of knowledge, poor lines of communication between local authorities, and financial and economic uncertainty. As such critical obstacles to achieving sustainable objectives would simply include a lack of personnel competency and an absence of a systematic procedure for data gathering and analysis.

Smart city can be defined from a human or technological standpoint. Because nations have diverse smart city objectives and perspectives there is no conventional definition of a smart city, and it is impossible to describe its concept (Kim & Heesup, 2022). Additionally, smart cities could enhance response times, service delivery, and city life. Smart technologies in the city keep a watch on the city's environment, respond swiftly, and accumulate data to assist people in making wise decisions (Ibrahim, 2022). This maximises resident services while maximizing resources and preventive maintenance (Ibrahim, 2022). In smart cities, waste management entails a flexible, efficient, real-time waste value cycle intake that primarily employs IoT to optimise refuse collection, reducing costs and open disposal (Shukla & Hait, 2022).

Kang, Kang, Ilankoon, and Chong (2020) examined how smart electronic waste management systems may increase Malaysian home electronic waste recycling. Customers may use collecting boxes with mobile applications and data servers to bring cell phones and other smaller waste and add smart online features (Kang et al., 2020). To encourage recycling, mobile phone apps may give product-specific recycling instructions, and RFID tags and weights can alert the municipality when a pickup smart bin is full. Satyamanikanta and Madeshan (2017) proposed collecting boxes using ultrasonic sensors, Arduino circuit boards, and Wi-Fi modules. Digital technology can track and predict waste in smart bins and cities. IoT sensors and AI image recognition apps are major smart technology municipalities should emulate in their waste management programmes. Optimising waste management systems over large areas may save money, and effective waste management might save labour and other resources.

5.6 Conclusion

The preceding sections of Chapter 5 have presented a discussion of the results and outcomes of this study. According to the outcomes of the study, IoT will enhance waste collection in Kempton Park and will speedup waste collection in Kempton Park. In addition, IoT enabled waste systems will be easy to use and it will be easy to adopt IoT enabled waste systems. Further, the operational cost of integrating IoT to household waste collection is too high and there may be regulatory challenges to overcome. In addition, there is a lack of technical skills among municipal authorities and also among the residents of the municipality. Internet connectivity remains low in the municipality. The study also found that there is a lack of IT infrastructure in the municipality and that the cost of data is too high while Internet access remains low in the municipality. In addition, the study found that the challenges faced in integrating IoT to household waste management is a moderating factor on the effect of the predictive variables perceived effectiveness and perceived ease of use on the factors that affect the adoption of IoT to waste management processes in Kempton Park. Chapter 6 presents the conclusions and recommendations of the study.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusion

Chapter 6 concludes and suggest recommendations on factors that affect integrating Internet of Things (IoT) to household waste collection processes. Based on the findings of the study, IoT will enhance waste collection in Kempton Park and will speedup waste collection in Kempton Park. In addition, IoT enabled waste systems will be easy to use and it will be easy to adopt IoT enabled waste systems. Further, the operational cost of integrating IoT to household waste collection is too high and there may be regulatory challenges to overcome. In addition, there is a lack of technical skills among municipal authorities and also among the residents of the municipality. Internet connectivity remains low in the municipality. The study also found that there is a lack of IT infrastructure in the municipality and that the cost of data is too high while Internet access remains low in the municipality. In addition, the study found that the challenges faced in integrating IoT to household waste management is a moderating factor on the effect of the predictive variables perceived effectiveness and perceived ease of use on the factors that affect the adoption of IoT to waste management processes in Kempton Park.

6.2 Recommendations

Based on the findings of the study, the following are recommendations on adopting the integration of IoT in waste management systems to reduce inefficiencies in collecting household waste:

- Continue to invest in modern infrastructure that support the integration of IoT in waste management systems and other systems in the municipality.
- Continue to invest in the training of municipality officials to ensure that they have the necessary IT skills to deploy IoT technology in the municipality.
- Collaborate with other stakeholders such as the provincial government, the national government, and the private sector to reduce the cost of data in the municipality.

- Convert the municipality into a smart city with modern infrastructure that supports the integration of IoT in waste management systems and other systems.

6.3 Evaluation of the study

The main objective of the study was to investigate how the adoption of integrating IoT to waste management systems will reduce inefficiencies when collecting household waste. The results of Hypothesis 1 and Hypothesis 2 showed that the factors that affect the adoption of IoT in waste management (factors affect) is explained by perceived effectiveness, and perceived ease of use respectively. Hence, a positive criterion-related validity step or validation test for using the three-step moderated multiple linear regression model (Cleary, 1968) to determine the moderation effects of challenges in integrating IoT to household waste collection. In addition, the results of Hypothesis 3 and Hypothesis 4 showed that challenges in integrating IoT to household waste collection moderates the effects of perceived effectiveness and perceived ease of use on the factors that affect the adoption of technology (factors affect). The study outcomes establish that all the research goals and propositions that were charted at the start of this study have been met, and consequently, the research objectives of this study have been addressed by the researcher.

6.3 Limitations

The study only engaged participants in Kempton Park, Ekurhuleni municipality in Gauteng, South Africa. Therefore, the results of the study may not be generalised to other countries or regions.

6.5 Suggestions for further research

The ensuing direction could be exploited for further studies:

- To evaluate the factors that affect integrating Internet of Things (IoT) to household waste collection processes through a qualitative study.

- To evaluate areas that can benefit from employing smart waste management processes in South Africa.
- To evaluate cost benefit analysis for IoT waste bins.

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ANNEXURE

ANNEXURE A: Participant Information Sheet (PIS)

Dear Sir / Madam

My name is Dikeledi Lisbeth Monobe I am a Masters student in Business Administration at the University of the Witwatersrand, Johannesburg. My supervisor is Dr Robert Venter. I am conducting a research study to determine adoption factors when integrating smart technologies to household waste collection process to reduce waste management challenges and environmental factors. The study title is Factors that affect integrating IoT to household waste collection.

I am inviting you to take part to answer a questionnaire to understand factors that may impact adoption of integrating IoT to household waste collection processes. If you decide to take part, your participation in this research study will last about 10 minutes to answer the questionnaire The process will take place at your convince anytime between 10 October 2023 – 10 December 2023. The questionnaire will take place online.

With your permission, I would like to record your response for further analysis This data will be stored on my personal laptop which is password encrypted. I will store data for 2 years to allow engagement with waste collection service providers and the municipalities thereafter the data will be deleted. Only the researcher will have access to the data.

During the research activity, I will need to ask for some personal information about you, including age, how you perceive use and usefulness of technology and previous experience you have with technology.

The questionnaire will be confidential and anonymous. When I share the results of the research study, I will not include your name or anything else that could identify you. With your permission, other researchers may use the data collected from this research study, but your name and any personal information will not be used or passed on.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits, or rights you would normally have if you decide not to join. Taking part in the research study will not cost you anything. You will not be paid for being in this research study.

The risks for this research study are no more than what happens in everyday life / some of the questions asked may make you feel sad or upset. If this happens, feel free to stop the questionnaire and continue another time.

This research study will be written up as a research report. The report will be available on

the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,

Researcher:
Dikeledi Monobe, 0792443779, 1530005@students.wits.ac.za

Supervisor:
Dr Robert Venter, Robert.Venter@wits.ac.za, 0117178090

ANNEXURE B: Consent to Participate in the Study

- I can confirm that as the participant I have been informed of the purpose for the study.
- I part take in the questionnaire on voluntary basis.
- As the participant I have been made aware of the process that we will be taken to collect the data and for data analysis.
- As the participant I have been informed that my personal informal will not be shared out of this study; and the inform will be stored safely.
- As the participant I have been informed that I may choose to stop with the questionnaire in the event I feel uncomfortable.
- I am aware there is no incentive to be part of the study.
- I will receive a copy of signed consent should I wish to have one.

Participant's signature……. Date……

Researchers' signature……. Date……

Witness's signature……. Date……

ANNEXURE C: Research Instrument

South Africa continues to generate enormous quantities of waste that is poorly managed and disposed, impacting not only the environment but also people's health and wellbeing. The research aims to determine if a proposed solution that employs a smart approach for waste disposal by offering efficient collection systems which monitor garbage levels, optimize bin collections, and offer real-time data insights for bin collection optimization and collection efficiency which will yield positively to environmental sustainability.

QUESTIONNAIRE

Topic: Factors that affect integrating Internet of Things to household waste collection processes

SECTION A: DEMOGRAPHIC INFORMATION

1. Are you currently resident in Kempton Park, Ekurhuleni municipality?

- ☐ Yes
- ☐ No

2. Please indicate your exposure to new technology?

- ☐ Internet at home
- ☐ Internet on mobile phone
- ☐ Computer at home
- ☐ Computer at work
- ☐ Shopping online
- ☐ Banking online
- ☐ Working online
- ☐ Other (please specify): _____

SECTION B: RESEARCH QUESTIONS

Using the scale below, please rate the perception on the effectiveness of integrating IoT (Internet of things) to household waste collection in Kempton Park, Ekurhuleni municipality.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
3.	IoT will enhance waste collection in Kempton Park.					
4.	IoT will speedup waste collection in Kempton Park.					
5.	IoT will negatively disrupt waste collection in Kempton Park.					
6.	IoT will slowdown waste collection in Kempton Park.					

Using the scale below, please rate the perception on the ease of use of integrating IoT (Internet of things) to household waste collection in Kempton Park, Ekurhuleni municipality.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
7.	IoT enabled waste systems will be easy to use					
8.	IoT will be easy to incorporate in daily route.					
9.	It will be effortless to use IoT enabled waste systems.					
10.	It will be easy to adopt IoT enabled waste systems.					

Using the scale below, please rate the challenges faced in Integrating IoT (Internet of things) to household waste management in Kempton Park households.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	1	2	3	4	5
11.	The operational cost is too high.					
12.	There may be regulatory challenges to overcome.					
13.	There is a lack of technical skills among municipal authorities.					
14.	Internet connectivity remains low in the municipality.					
15.	There may be privacy and security concerns.					

16.	There is a lack of IT infrastructure.					

Using the scale below, please rate the factors that affect the adoption of IoT (Internet of things) to waste management processes in Kempton Park.

1-Strongly disagree 2-Disagree 3- Neutral 4-Agree 5-Strongly agree

	Statement	**1**	**2**	**3**	**4**	**5**
17.	The cost of data is too high.					
18.	Internet access remains low in the municipality.					
19.	There is a lack of technical skills among residents.					
20.	Residents are not interested in adopting IoT for waste management.					
21.	Residents may have privacy and security concerns.					

Thank you for participating in this study!

ANNEXURE D : Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA1530005/778
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below)

Project title	Integrating Internet of Things technologies into household waste collection processes in Ekurhuleni
Investigator / Researcher	Ms Dikeledi Lisbeth Monobe
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2023/08/28
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature _____ Date: _____

ANNEXURE E : R Codes

```
### Load libraries
library(readxl)
library(tidyverse)
library(ggplot2)
library(ggthemes)
library(gplots)
library(gmodels)
library(summarytools)
library(psych)
library(stringr)

### Read in the data sets Data1 and Data2
Data1 = read_excel("C:/Users/Learner/Documents/Data/Dikeledi/Data1.xlsx")
Data2 = read_excel("C:/Users/Learner/Documents/Data/Dikeledi/Data2.xlsx")


### Demographic Analysis

### Resident
#### Tabulate resident
resident_table = table(Data1$Resident)
resident_prop = prop.table(resident_table)
resident_percent = resident_prop*100
table.resident = rbind(resident_table, resident_prop, resident_percent)
table.resident

#### Plot resident
resident = ggplot(Data1, aes(Resident))
resident = resident + geom_bar(aes(fill=Resident), size=3) +
  labs(title="Are you currently resident in Kempton Park, Ekurhuleni municipality?")
resident


### Technology Exposure I
#### Tabulate TechExpo1
techexpo1_table = table(Data2$TechExpo1)
techexpo1_prop = prop.table(techexpo1_table)
techexpo1_percent = techexpo1_prop*100
table.techexpo1 = rbind(techexpo1_table, techexpo1_prop, techexpo1_percent)
table.techexpo1

#### Plot TechExpo1
techexpo1 = ggplot(Data2, aes(TechExpo1))
techexpo1 = techexpo1 + geom_bar(aes(fill=TechExpo1), size=3) +
  scale_x_discrete(labels = function(x) str_wrap(x, width = 10)) +
```

```
  labs(title="Please indicate your exposure to new technology?")
techexpo1


### Technology Exposure II
#### Tabulate TechExpo2
techexpo2_table = table(Data1$TechExpo2)
techexpo2_prop = prop.table(techexpo2_table)
techexpo2_percent = techexpo2_prop*100
table.techexpo2 = rbind(techexpo2_table, techexpo2_prop, techexpo2_percent)
table.techexpo2

#### Plot TechExpo2
techexpo2 = ggplot(Data1, aes(TechExpo2))
techexpo2 = techexpo2 + geom_bar(aes(fill=TechExpo2), size=3) +
  scale_x_discrete(labels = function(x) str_wrap(x, width = 10)) +
  labs(title="Other exposure to new technology")
techexpo2


### Descriptive statistics
### Effectiveness of Integrating IoT to Household Waste Collection
#### Cronbach's alpha
alpha(Data1[, c("Enhance", "Speedup","Disrupt", "Slowdown")])

#### Descriptive statistics
Data1 %>% select(Enhance, Speedup, Disrupt, Slowdown) %>% descr()

#### Composite variable Effectiveness
Data1$Effectiveness = rowMeans(Data1[, c("Enhance", "Speedup","Disrupt", "Slowdown")],
na.rm = TRUE)

#### Descriptive statistics of composite variable Effectiveness
describe(Data1$Effectiveness)


### Ease of Use of Integrating IoT to Household Waste Collection
#### Cronbach's alpha
alpha(Data1[, c("EasyToUse", "EasyToIncorp","Effortless", "EasyToAdopt")])

#### Descriptive statistics
Data1 %>% select(EasyToUse, EasyToIncorp, Effortless, EasyToAdopt) %>% descr()

#### Composite variable EaseOfUse
Data1$EaseOfUse = rowMeans(Data1[, c("EasyToUse", "EasyToIncorp","Effortless",
"EasyToAdopt")], na.rm = TRUE)
```

```
#### Descriptive statistics of composite variable EaseOfUse
describe(Data1$EaseOfUse)


### Challenges Faced in Integrating IoT to Household Waste Collection
#### Cronbach's alpha
alpha(Data1[, c("CostTooHigh", "Challenges","LackTech1", "LowConnect", "PrivacySecurity1",
"LackIT" )])

#### Descriptive statistics
Data1 %>% select(CostTooHigh, Challenges, LackTech1, LowConnect, PrivacySecurity1,
LackIT) %>% descr()

#### Composite variable ChallengesFaced
Data1$ChallengesFaced = rowMeans(Data1[, c("CostTooHigh", "Challenges","LackTech1",
"LowConnect", "PrivacySecurity1", "LackIT" )], na.rm = TRUE)

#### Descriptive statistics of composite variable ChallengesFaced
describe(Data1$ChallengesFaced)


### Factors that Affect Adoption of IoT to Waste Management Processes
#### Cronbach's alpha
alpha(Data1[, c("CostData", "InternetAccess","LackTech2", "NotInterested",
"PrivacySecurity2")])

#### Descriptive statistics
Data1 %>% select(CostData, InternetAccess, LackTech2, NotInterested, PrivacySecurity2) %>%
descr()

#### Composite variable FactorsAffect
Data1$FactorsAffect = rowMeans(Data1[, c("CostData", "InternetAccess", "LackTech2",
"NotInterested", "PrivacySecurity2" )], na.rm = TRUE)

#### Descriptive statistics of composite variable FactorsAffect
describe(Data1$FactorsAffect)


### Moderated Multiple Linear Regression
#### Differential Prediction (Predictive Bias) in Selection Context

#### Grand-Mean Centre Continuous Predictor (or Moderator) Variables
Data1$c_Effectiveness = Data1$Effectiveness - mean(Data1$Effectiveness, na.rm=TRUE)
Data1$c_EaseOfUse = Data1$EaseOfUse - mean(Data1$EaseOfUse, na.rm=TRUE)
Data1$c_ChallengesFaced = Data1$ChallengesFaced - mean(Data1$ChallengesFaced,
```

```
na.rm=TRUE)

#### Three-Step Differential Prediction Process (Cleary, 1968; SIOP, 2003)
#### 1) Estimate the criterion-related validity (simple linear regression)
#### 2) Intercept differences: Additive multiple linear regression model
#### 3) Slope differences: Multiple linear regression model (multiplicative)

#### Perceived effectiveness / Challenges faced
#### Step 1: Criterion-related validity (simple linear regression)

#### Load libraries
library(lessR)

reg_brief(FactorsAffect ~ c_Effectiveness, data=Data1)

#### Step 2: Intercept differences: Additive multiple linear regression model
reg_brief(FactorsAffect ~ c_Effectiveness + c_ChallengesFaced, data=Data1)


### Load libraries
library(interactions)

intercept_M1 = lm(FactorsAffect ~ c_Effectiveness + c_ChallengesFaced, data=Data1)

probe_interaction(intercept_M1,
                  pred = c_Effectiveness,
                  modx = c_ChallengesFaced,
                  johnson_neyman=FALSE,
                  x.label="Perceived effectiveness",
                  y.label="Adoption of IoT")


#### Step 3: Slope differences: Multiple linear regression model (multiplicative)
reg_brief(FactorsAffect ~ c_Effectiveness * c_ChallengesFaced, data=Data1)

slope_M1 = lm(FactorsAffect ~ c_Effectiveness * c_ChallengesFaced, data=Data1)

probe_interaction(slope_M1,
                  pred = c_Effectiveness,
                  modx = c_ChallengesFaced,
                  johnson_neyman=FALSE,
                  x.label="Perceived effectiveness",
                  y.label="Adoption of IoT")
```

```
#### Perceived ease of use / Challenges faced
#### Step 1: Criterion-related validity (simple linear regression)
reg_brief(FactorsAffect ~ c_EaseOfUse, data=Data1)

#### Step 2: Intercept differences: Additive multiple linear regression model
reg_brief(FactorsAffect ~ c_EaseOfUse + c_ChallengesFaced, data=Data1)

#### Interactions
intercept_M2 = lm(FactorsAffect ~ c_EaseOfUse + c_ChallengesFaced, data=Data1)

probe_interaction(intercept_M2,
                  pred = c_EaseOfUse,
                  modx = c_ChallengesFaced,
                  johnson_neyman=FALSE,
                  x.label="Perceived ease of use",
                  y.label="Adoption of IoT")


#### Step 3: Slope differences: Multiple linear regression model (multiplicative)
reg_brief(FactorsAffect ~ c_EaseOfUse * c_ChallengesFaced, data=Data1)

slope_M2 = lm(FactorsAffect ~ c_EaseOfUse * c_ChallengesFaced, data=Data1)

probe_interaction(slope_M2,
                  pred = c_EaseOfUse,
                  modx = c_ChallengesFaced,
                  johnson_neyman=FALSE,
                  x.label="Perceived ease of use",
                  y.label="Adoption of IoT")


### END
```