Performance impacts of mobile carbon footprint calculators in South Africa

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NOVEMBER 2016

A dissertation presented to the Department of Information Systems, University of Cape Town,
In fulfilment of the requirements for the Masters of Commerce degree in Information Systems

DEDICATION

This dissertation is dedicated to the Munetsi family.

Thank you for your patience during the research period.

ACKNOWLEDGEMENTS

Thank you Professor Michael Kyobe for your supervision and for convening the class of 2015. Your comments and suggestions were priceless during this research.

I would also like to acknowledge the expert reviewers of the survey instrument and all the respondents of the survey.

Another heartfelt acknowledgment goes to the personnel that collected data in Cape Town.

DECLARATION

I,…Martin T Munetsi…, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Abstract

Modernization and advancement in technology have contributed towards the increased use of mobile phones in South Africa. The increased demand for services and energy has resulted in the increase in generation of electricity to meet the country's need. Consequently, South Africa now possesses the highest greenhouse gas (GHG) emission per capita relative to other developing countries. Conservation organizations in South Africa argue that the first step towards reducing carbon footprint is through its measurement.

In spite of the high penetration of mobile phones and the alarming GHG emission, there is hardly any research to investigate the fit and performance impacts of mobile carbon footprint calculators in South Africa. In fulfilment of this gap, the rationale of this study was to (1) investigate factors that are suitable to determine the fit of mobile technology for carbon footprint tasks, (2) adopt an existing model from the vast base of theories and models on technology usage and impact, (3) test the research model based on a South African sample within a mobile technology and carbon footprint context in order to determine the performance impacts on individual carbon footprint tasks.

Sample data were collected, through a survey instrument, and was analysed quantitatively. Partial Least Square Structural Equation Modeling (PLS-SEM) analysis was used to evaluate the study's outer and the inner model. The study revealed that only task-technology fit was the cause of performance impacts on individual carbon footprint tasks. In addition, there was no significant difference in the estimation and offsetting of carbon footprint between the users and non-users of mobile technology.

In conclusion, this study established that performance impacts on individual carbon footprint tasks are only determined by the fit of the mobile technology. The insignificant difference between users and non users of carbon calculators, in performance impacts on carbon footprint tasks, was an unexpected result but yet relevant to practitioners. Further implications to practice and theory are outlined in conclusion to this study.

Key words : performance impacts, carbon calculators, mobile technology, South Africa

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List of Acronyms

CF	-	Carbon footprint
CO2	-	Carbon dioxide
CO2e	-	Carbon dioxide equivalent
COP	-	Copenhagen Conference of Parties
CPI	-	Consumer price index
CDM	-	Clean Development Mechanism
CER	-	Certified Emissions Reduction
ERU	-	Emissions Reductions Unit
1G	-	First Generation
FTFA	-	Food & Trees for Africa
GHG	-	Greenhouse gas
GPS	-	Global Positioning System
ICT	-	Information and Communications Technology
IT	-	Information Technology
IS	-	Information Systems
JI	-	Joint Implementation
kWh	-	Kilowatt hour
PLS	-	Partial Least Squares
PDA	-	Personal Digital Assistant
SEM	-	Structural Equation Modeling
2G	-	Second Generation
TTF	-	Task-technology fit
TAM	-	Technology Acceptance Model
TPC	-	Technology-to-Performance Chain
3G	-	Third Generation
UN	-	United Nations
UCT	-	University of Cape Town

VER - Verified or Voluntary Emissions Reduction

WWF-SA - World Wide Fund For Nature South Africa

Chapter 1 : Introduction

This introductory chapter provides a background to the need for a mobile approach to estimate and offset carbon footprint within a South African context. To provide this background, the researcher introduces carbon calculators and greenhouse gas emissions in South Africa. This is followed with the presentation of the problem statement, research questions and objectives. The contribution of this research and its philosophical underpinnings are also introduced. Lastly, the structure this research will follow is outlined.

1.1 Background and Context

In the past decade, the African continent has experienced high mobile phone penetration compared to other continents (Hosman & Fife, 2012). This penetration of mobile phones is estimated to be over 65% of the African population (GSMA, 2015). The acceptance of mobile phones has enabled the extension of services to more members of the society. While some of the services are business focused, others fulfil personal needs. One such service in the personal space is the monitoring of individual or household carbon footprint through the mobile phone. Tools which estimate carbon footprint are commonly referred to as carbon calculators (Birnik, 2013). Apart from estimating carbon footprint, the calculators offer ways to reduce the carbon footprint as well as offsetting it (Bottrill, 2007). This allows carbon calculators to act as measurement tools as well as facilitators of awareness amongst their users.

The reliability of carbon calculators has been questioned by prior studies (Cucek, Klemeš & Kravanja, 2012; Kenny & Gray, 2008; Padgett et al., 2008). This has raised concerns over their effectiveness in light of the discrepancies of their results. However, the carbon calculators reviewed by these studies have not included tools from a developing nation, for instance South Africa. Therefore, such generalization on their effectiveness in estimating and offsetting carbon footprint will not be assumed. In South Africa, one of the climate change agendas is still to reduce carbon emissions as this is currently high when compared with other developing countries.

South Africa was the host of the 17th Conference of Parties ('COP17') aimed at reducing greenhouse gas emissions amongst the participating nations. The South African government set up climate change targets such as increasing electricity generation from renewable resources apart from fossil fuels (mainly coal) (Department of Environmental Affairs, 2015a). This change in the inputs for electricity generation would result in the reduction of the pollution and excessive carbon emissions that presently result from the combustion of coal.

Other strategies to deter against the soaring carbon emissions were through implementation of a carbon tax and cap and trade systems (Department of National Treasury, 2013). This pricing of carbon has since been a debatable issue between the government and the business stakeholders (Inglesi-Lotz & Blignaut, 2011). It is contended that the proposals to preserve the environment for future generations should consider the immediate impact of carbon tax on products to the consumers. Thus a balance between abiding to the commitments of COP17 (to be evaluated in 2020) and the mandate of the South African government to serve the people, who voted them into power, should be attained. That said, without individual participation in reducing consumption of energy and fuel, the government remains under pressure to achieve its greenhouse gas emission reduction targets.

South Africa has a high carbon emission per capita relative to other developing countries (Department of Environmental Affairs, 2015b). Given that electricity in South Africa is generated on demand, more demand for electricity entails more combustion of coal and thus a consideration amount of pollution and GHG emission attributable to individuals. Therefore, public participation in the reduction of carbon emission may be supplementary to the reduction efforts at a national level.

The participation of individuals in the use of carbon calculators to estimate and voluntarily offset their carbon emissions can result in behaviour change (Padgett et al., 2008). This change in behaviour is envisioned and supported by non-governmental organizations which provide carbon calculators on their websites for this cause. However, it should be noted that the number of carbon calculators on websites applicable to South Africa is argued to surpass the number of carbon calculators purposely made for mobile phones. This presents the need to determine whether a mobile approach to estimate and offset carbon footprint provides a fit for carbon footprint tasks in South Africa. The implication of this study is pertinent to practitioners in non-governmental organizations and information and communications technology (ICT), particularly mobile services for carbon footprint tasks.

1.2 Problem Statement

Conservation organizations in South Africa such as *World Wide Fund For Nature South Africa*, *Greenworks* and *Food & Trees for Africa* believe that the first step towards reducing carbon footprint is through voluntary measuring of an individual's carbon footprint. To enable the measurement, these organizations provides tools to monitor carbon footprint (FTFA, 2013; Greenworks, 2015; Nova Institute, 2015; WWF-SA, 2015). However, most of these carbon calculators are web browser based (Birnik, 2013) yet there are arguably more mobile phone users than there are internet web users in South Africa. In light of this, it might be expected to have more mobile technologies to monitor carbon footprint (CF) as this platform serves the majority of the users. Will the mobile technologies provide the awareness and monitoring these conservation organizations yearn for? Due to this limited discussion and practice of mobile CF calculators in a South African context, there is need to predict the impact of using these mobile technologies on individual carbon footprint tasks. The results of this predictive study can provide insights to practitioners with regards to climate change campaigns which require individual participation.

1.3 Research Questions

The research is conducted by answering two questions; both of which are relevant to the research title. The first question sets the scene of the theory to be tested through assessing the fit of technology and performance impacts on individual carbon footprint tasks. The second question probes into whether individuals who use mobile technology to estimate and offset carbon footprint achieve greater performance impacts on their tasks than individuals who use less of the mobile technology. The research questions are as follows:

1. How does fit of technology influence the performance impacts of mobile carbon footprint calculators for individuals?

2. What is the relationship between performance impacts on individual carbon footprint tasks and use of mobile phones amongst individuals in South Africa?

1.4 Research Objectives

The aim of this research is to investigate the impact of mobile applications on individual carbon footprint in the estimation and offsetting of carbon footprint in South Africa. In order to achieve this aim, the following objectives have been set:

1. To measure the relation between:
    a. Characteristics of carbon footprint tasks, mobile technology and individuals with the fit of mobile phones to perform carbon footprint tasks.
    b. Fit of mobile phones with performance impacts on individual carbon footprint tasks.
    c. Fit of mobile phones for carbon footprint tasks and the beliefs and attitude towards technology use.
2. To determine the impact of beliefs and surrounding conditions on utilization of mobile phones in performing carbon footprint tasks.
3. To measure the relation between mobile phone utilization and performance impacts on individual carbon footprint tasks.

1.5 Research Contribution

Given the general acceptance of mobile technology in the 21^{st} century, it is anticipated that tools to estimate and offset GHGs through this platform are deemed acceptable in South Africa. However, before investing effort in technology that individuals can use to monitor their CF, the present research seeks to investigate the impact of such technology on individual's carbon footprint tasks. The contribution of this research is shared between theory and practice.

This study utilises theory in information systems (IS) to explain the impact of a green IS initiative, at an individual unit of analysis, within a developing nation. This is achieved by identifying the constructs emerging from the literature on carbon footprint and mobile technology, selecting the appropriate theory capable of explaining these constructs, developing a research model based on the constructs, drawing an appropriate sample, conducting a survey, validating the model and testing the hypothesized model. Seven factors (task characteristics, technology characteristics, individual characteristics, task-technology fit, precursors of utilization, utilization and performance impacts on carbon footprint tasks) extracted from the survey data were linked in the causal relationships that were hypothesized.

An important contribution to the theory is the influence of the factors on performance impacts on carbon footprint tasks. The technology-to-performance chain model posits that both task-technology fit and utilization influence individual performance (Goodhue & Thompson, 1995). Contrary to this, only task-technology fit influenced the outcome variable (in the study's case - performance impacts on carbon footprint tasks). Another theoretical contribution is the testing of a relationship proposed by past research between task-technology fit and the precursors of utilization. This study found support that task-technology fit positively influences the precursors of utilization of mobile carbon footprint calculators.

The testing of the technology-to-performance chain model within the carbon footprint and mobile technology context brings new knowledge, about the impact of green IS initiatives, to the information systems discipline. Further discussion of the theoretical contributions of this research is presented in the Conclusion Chapter.

This study also brings practical contributions to practitioners identified to be conservation organizations and the developers of mobile technology. As revealed by the supported causal relationships, the conservation organizations can benefit from educating the target population on their contribution to greenhouse gases and the tools available to them for sustainable living. With regards to mobile technology, the development of mobile carbon calculators that are reliable and easy to use is argued to retain its users.

1.6 Philosophical Underpinnings of Research

The aim of this research is to investigate the impact of mobile applications on individual carbon footprint with regards to the estimation and offsetting of carbon footprint in South Africa. To achieve this aim, the research identified the objectives which were specific and measurable. The approach was to uncover factors in the literature which result in the fit of mobile technology for carbon footprint tasks i.e. estimating and offsetting carbon footprint.

The identified factors were operationalized to ensure that they could be measured. These factors were modelled to show their relationships and to ultimately determine the impact of the technology on the individual's performance on carbon footprint tasks. This required testing causal relationships between identified factors in the hypothesized model. The causal relationships are presented in the form of hypotheses which were either accepted or rejected. A model of this nature relays the presence of a scientific method which embodies a deductive approach, to test the underlying theory.

This scientific approach follows the view that the greenhouse gas emissions can be estimated through emission factors and actions to offset the carbon footprint exists. In light of this, survey individuals have ratings on technology, attitudes, frequency of use and achievements on their carbon footprint tasks. These ratings are quantified. The quantified observable variables are then collated to represent latent variables which characterize the unobservable constructs. Validation of the constructs was performed and the constructs were analysed quantitatively. The research is presented to ensure reproducibility through accounting for the choice of each decision from research model development, dimension reduction, validation of constructs to hypothesis testing.

The target population was selected such that the carbon footprint tasks were relevant to the selected sample and that the results of the quantitative analysis could be generalised to this population. Data were collected through questionnaires which were administered using structured interviews. The questionnaire items were all closed-ended questions and the responses were quantified and analysed statistically.

In light of the ontological notion that the evaluations of attitudes and mobile technology exists and the use of a scientific process to acquire knowledge, the research follows the positivism paradigm. Further explanation of the positivist philosophical stance is discussed in Chapter 3, section 3.1.

1.7 Research Structure

The research structure takes the form of an empirical research. This structure is outlined as follows:

1. **Chapter 1: Introduction**

   The introduction gives a background to the research problem; presents the research questions, contribution of the research and its theoretical underpinnings.

2. **Chapter 2: Literature Review**

   This chapter provides a critical review of the literature in order to find the research gap in the estimation and offsetting of carbon footprint in South Africa. The review of the literature presents the research context, namely South Africa and its resource profile, particularly energy and fuel. Mobile services and related literature in carbon footprint are assessed. The underlying concepts from the literature are discussed. Use of Information and Communications Technology (ICT) towards environmental sustainability is analysed and the negative impact of technology is reviewed. An account of carbon footprint, its estimates, and impediments is provided. Also carbon offsets and their impediments are discussed. Based on the reviewed literature, some of the factors that could potentially affect the fit of mobile technology for carbon footprinting are discussed. These factors result in the search for a theory to answer the research questions. The review of existing theories is then used to develop the research model, based on existing theory. At the end of the review is the presentation of the research model, its constructs and research hypotheses.

3. **Chapter 3: Research Design**

   The research design chapter starts with explaining the research philosophy and research purpose. Other areas presented are time horizons, research approach and strategy. Research design also contains the methodology, target population and sample. Data collection procedures and design of the research instrument is also provided. Also, data analysis techniques relevant for the research are explained.

4. **Chapter 4: Data Analysis and Results**

   This chapter starts by presenting the survey and its responses. The chapter also contains screening of data and data transformations. Construct validity and reliability is also conducted and presented. The survey data are then described through descriptive statistics. The results of normality testing, correlation analysis, evaluation of the inner model and its fit are presented. An account of the hypothesis testing is also provided.

5. **Chapter 5: Discussion and Conclusion**

   The chapter begins by discussing the results and illustrating a refined model. Then conclusions identified from this study are presented. Limitations and contributions to theory and practice are discussed. Recommendations for future studies are also provided.

6. **References**

   This section lists references using the APA style of referencing.

In the next section, a literature review is explored to highlight the main concepts in carbon footprint, carbon offsets and mobile technology. This review also includes theory selection and leads to the development of the research model.

Chapter 2 : Literature Review

In order for the present research to determine the impact of mobile technology on performing carbon footprint tasks, an analysis of previous work is completed and presented in this chapter. This literature review chapter is organized as follows: *Section 2.1* introduces the research context with an overview of South Africa, its resource profile in terms of energy and fuel, mobile services, prior studies in carbon footprint and the gap in the literature. *Section 2.2* outlines underlying concepts; mobile technology, sustainability, green IT and green IS. *Section 2.3* summarises the use of Information and Communications Technology (ICT) towards environmental sustainability. *Section 2.4* identifies the negative impact of technology. *Section 2.5* presents carbon footprint, its calculation and impediments in its estimation. *Section 2.6* elaborates on offsetting carbon footprint, nature of offset projects and the impediments to some of the relevant offset projects. *Section 2.7* presents the factors towards the fit of mobile technology for carbon footprinting. *Section 2.8* discusses relevant theories, namely technology acceptance model, task-technology fit and technology-to-performance chain model. *Section 2.9* shows the development of the research model using the selected theory. *Section 2.10* presents the research model, definitions of constructs and research hypotheses.

2.1 Overview of South Africa

South Africa is formally known as the Republic of South Africa (Kaplan, 1970) and is situated at the southern part of Africa. This country's neighbours are Botswana, Mozambique, Namibia, Swaziland and Zimbabwe (Mwakikagile, 2008). Lesotho is an independent nation that is surrounded by South Africa. With regards to capital cities, Pretoria is the capital city, Cape Town forms the legislative capital and the judicial capital city is Bloemfontein (Mwakikagile, 2008; South Africa Info, 2015). While Johannesburg buzzes with business and is the largest city in South Africa it is not the capital.

The population of South Africa is estimated to be 53 million people (Factbook, 2014). This exceeds the 52 million that Roux (2005) forecasted to be the population by 2015. Given the 2011 census in South Africa yielded a population of 51 million, the growth rate in the last four years is an estimated two million people. This increase in population may be attributed by a number of factors, but migration from the neighbouring countries cannot be ignored. Roux (2005) suggests that education levels and relevant skills are low and need to increase in order to meet the demand for goods and services caused by the growing population. This need for scarce skills in South Africa can be argued to be a catalyst in the influx of economic migrants from the neighbouring Zimbabwe and other migrants seeking better opportunities.

The economy of South Africa is depended on contributing sectors such as mining, manufacturing industry, agriculture, construction and services (South Africa Info, 2015). South Africa is a fortress of minerals such as gold, platinum and chromium. However, the contribution of the mining and agriculture sectors to the gross domestic product (GDP) has been dwindling since the 1960s (Roux, 2005). It rests to be seen whether these sector's contribution to the GDP takes a different trend in the near future due to the controversies of indigenization posed by the political arena. On the other side of the sectors, the manufacturing and service industry contribute more towards the GDP.

Consumer price index (CPI) is often used as an indicator of inflation. The past five years have seen a slight increase in the CPI in South Africa (Band, Headline and Core, 2015). This entails that the past five years have experienced a corresponding increase in inflation. The same period has experienced a continuous decrease in the household expenditure while the Rand has weakened against the major currencies such as the US dollar on a year to year basis (Band et al., 2015). This suggests that the weakening South African Rand and the decrease in South African household expenditure might be related.

The road and rail network in South Africa connects major cities (Kaplan, 1970) and is the finest in Africa (Mwakikagile, 2008). Most major cities are also linked by air transport, which also has international routes mostly through Johannesburg. South Africa has the most extensive bill of rights in the world (Mwakikagile, 2008). The constitutional bill of rights governs the rights of every citizen in a wide range of areas such as equality, freedom, labour, environment, education and culture (Currie & De Waal, 2013). The bill grants the right for everyone to have the environment protected though such measures as pollution prevention, conservation of resources and sustainable development. Hence, the residents in South Africa need to participate in protecting the environment for current and future generations.

The Table 2.1 gives a summary view of South Africa based on landscape, provinces, people, economy and telecommunications. This information presents the South African context for the present research. The geographical location of South Africa, in relation to Southern Africa, is shown in Figure 2.1.

Figure 2.1 South Africa's geographical location relative to Southern Africa

Table 2.1 The Information about South Africa (South Africa Info, 2015).

Landscape	**Total Area:** 1 219 090 km^2 **Arable land:** 12.1% of total area **Rainfall:** Mostly in summer except Western Cape with winter rainfall **Surrounding Oceans:** The Atlantic Ocean is on the west flank and the Indian Ocean is on the east of South Africa.
Provinces	Nine provinces namely: Eastern Cape, Gauteng, KwaZulu-Natal Mpumulanga, Northern Cape, Limpopo North West, Free State and Western Cape
People	**Population:** 51 770 560 people (2011 census) **Gender:** females (51.3%) and males (48.7%). **Languages**: Eleven official languages namely: Afrikaans, English, isiNdebele, isiXhosa, isiZulu, Sesotho sa Leboa, Sesotho, Setswana siSwati, Tshivenda and Xitsonga **Education:** 20% of the total state expenditure is invested in education. **Education Levels:** Grade zero to Grade 12 (Matric). After grade 12, tertiary or university entry begins. **Illiteracy Rate:** 19.1% of people older than 15 years have either no education or have the highest education level lower than grade seven.
Economy	**Currency:** Rand (R) **Ranking:** 25th largest economy in the world **Main Industries:** mining, automotive assembly, machinery, textile, iron and steel, chemical, food and ship repair. **Employment:** 15.7 million people **Unemployment:** 5.2 million people and 15.1 million not economically active.
Telecommunications	**Total fixed lines:** 4.9 million

	Mobile phone usage: 76% of adults (in 2010) **Mobile operators:** MTN, Vodacom, Cell C, 8ta and Virgin mobile.

2.1.1 A profile on Energy and Fuel in South Africa

2.1.1.1 Energy

South Africa generates electricity for itself as well as other African nations. Most of South Africa's electricity is generated, by Eskom, using locally mined coal. This local coal is of low quality and produces a lot of ash. Coal combustion, like other fossil fuels, emits carbon dioxide (Hong & Slatick, 1994) and therefore contributes to global warming. Most of the electricity generated is demanded by the industrial sector in South Africa that is quite energy intensive (Nkomo, 2005). As more demand for electricity is requested, so is the generation. This entails that more demand is associated with more carbon dioxide emission.

Since the industrial sector is huge and makes a substantial contribution to the GDP of South Africa, this use may be justifiable. However, this sector can benefit from renewable and more energy efficient technology (Winkler, 2005) to ease the increasing demand for electricity – especially in a time when more goods and services are requested by a growing population. Failure to make plans for the future, in light of the growing demands for electricity, has seen residential areas suffering as a result of Eskom' s load shedding procedures.

Most households in South Africa have prepaid electricity meters. Weiss, Mattern, Graml, Staake and Fleisch (2009) proposed integrating a mobile phone with such smart meters to alert individuals of their electricity consumption. This proposal suggests that informing users in real time could assist them in reducing their energy consumption. In the same vein of monitoring energy, Mankoff, Matthews, Fussell and Johnson (2007) assessed an approach to utilise social networking websites to provide reminders about user's individual performance in energy monitoring. This approach can be argued to enforce mandatory system use amid voluntary technology usage - which can be regarded as intrusive by some users. In addition, this technology is restricted to websites usage or mobile devices with access to the internet at the time of use.

The measurement of energy consumed by household devices has been investigated and this has allowed individuals to identify devices that are energy-intensive (Yun, 2009). However, a gap revealed by the literature is to explore whether mobile approaches to energy measurements would result in improved energy conservation and ultimately reduce carbon footprint.

2.1.1.2 Fuel

The dwindling resources for fossil fuels is necessitating the need for alternative fuels to be considered (Demirbas, 2009). In 2007, the government of South Africa released a biofuel strategy to allow production of fuel, but this only took place two years later (Letete & von Blottnitz, 2012). Although biofuel emit more carbon dioxide than the fossil fuels (Agarwal, 2007), the growth of the plants used for biofuel extraction absorbs the carbon dioxide in the atmosphere (Puhan, Vedaraman, Ram, Sankarnarayanan & Jeychandran, 2005). This results in a balance in the atmosphere, to some extent.

Biofuel projects in South Africa are faced with challenges of acceptance, especially when there are potential threats of relocation of communities (Amigun, Musango & Brent, 2011) and food shortage (Nasterlack, von Blottnitz & Wynberg, 2014). The South African locals are wary of the possibility of land displacements in light of their colonial history. In this case, public engagement, in line with the benefits offered, is paramount to the success of large scale biofuel production.

Another alternative source of energy is solar power. The Department of Environmental Affairs (DEA) launched a pilot of electric cars, in 2013, in their response to reduce greenhouse gas emissions following an undertaking during the 17th Conference of the Parties (COP 17). The purpose of the pilot was intended to pave the way to the commercial availability of the electric cars that would be recharged using solar energy.

Suzuki (2006) uncovered that the intricacies of global warming are barely understood by the general public. This limited understanding result in people assigning less value to environmental issues that are particularly important. Although the impact of individual carbon estimation and monitoring can be minimal, collective monitoring through social networking in a competitive way has a greater impact in reducing global warming (Foster, Lawson, Blythe & Cairns, 2010). This suggests that, if monitoring is done in a socially acceptable way, this social impact can be more effective in reducing energy and transport usage and therefore reduce the carbon footprint.

2.1.2 Mobile phone services in South Africa

South Africa has 38 million unique mobile subscribers (GSMA, 2015). This penetration rate makes it the largest market for mobile devices in Southern Africa. With a 30% adoption of smartphones, South Africa also the highest number of application downloads in the region (GSMA, 2015). These high download volumes are associated with the number of smartphones in the population. The utilization of mobile phones in South Africa is more widespread in urban areas than in rural areas (Porter, 2012). This infiltration of mobile devices has been facilitated by their availability and increased network coverage. As such, this has seen more adoption of mobile phones by younger generations in South Africa (Koutras, 2009) than in other sub-Saharan African countries (Porter, 2012).

Mobile phones are primarily used for communication (Katz & Aakhus, 2002; Koutras, 2009). In addition, they have also been found useful to provide entertainment (Kreutzer, 2009). This usage has been facilitated by the development of applications on mobile phones such as mobile phone games. Developed applications are easily downloaded onto mobile phones using the internet (Donner, Gitau & Marsden, 2011). Internet on mobile phones can also be used for email, instant messaging, calling, browsing for news and other content. The provision of services through mobile phones, namely m-services, in agriculture, education and health has also been adopted (Baumüller, 2012).

Extant studies in the use of m-services within a South African context are found in m-learning (Kyobe & Shongwe, 2011; Visser & West, 2005), m-health (Curioso & Mechael, 2010; Davey, Davey & Singh, 2014), m-commerce (Jobodwana, 2009; Joubert & Belle, 2009), m-banking (Donner, 2007) and m-finance (Anong & Kunovskaya, 2013). The financial service offered through m-finance has attracted the attention of the un-banked members of the population.

South Africa is exposed to mobile money platforms such as WIZZIT (Richardson & Callegary, 2008) and MTN mobile money (Mishra & Bisht, 2013). These mobile money platforms provide cell phone banking at costs that offer a competitive edge to formal banks while requiring minimal paperwork and turnaround times (Borg & Persson, 2010). However, mobile money has become more widespread in other African countries that are faced with more limited banking services (Porter, 2012). In Kenya, Mpesa is one mobile money facility which is widely used by individuals (Hughes & Lonie, 2007) and even retailers accept it as a method of tender (Maritz, 2011). In South Africa, Mpesa did not yield success (Lal & Sachdev, 2015) and this resulted in the facility to be discontinued by Vodacom, the mobile communication provider that was offering the service.

The adoption of these mobile services and technology is influenced by numerous factors. Some factors determining the adoption may be technological, social and economical (Sarker & Wells, 2003). Features on the mobile devices, the social status the mobile phone gives and the cost of the mobile phone can contribute to its acquisition. The use of the mobile service may be affected by the ability of the individual to comprehend the ins and outs of the service. This may be a technical case of computer self-efficacy (Lee et al., 2007) or a social case of literacy.

Nearly 19.1% of the South African population is considered to be illiterate (South Africa Info, 2015). This entails that approximately 19.1% of the population might affect the adoption of technology that requires some degree of literacy. For instance, illiteracy has an adverse effect on the adoption of internet on mobile devices (GSMA, 2015). In less developed countries, illiteracy is an existing inhibitor to the acceptance and usage of mobile technology (Imran, Quimno & Hussain, 2016). This has hampered the adoption of services such as mobile commerce (Saidi & Mgt, 2010). Matyila, Botha, Alberts and Sibiya (2013) suggest that there is a need to design mobile services which can be easily adopted by low literacy individuals.

2.1.3 Monitoring carbon footprint using mobile technology

South Africa has a relatively high greenhouse gas (GHG) emission per capita compared to other developing countries (Department of Environmental Affairs, 2015). The GHG emission, per capita, is estimated to be approximately 10 metric tons per annum. This is mainly attributed by the intensive use of private transportation and heavy reliance on electricity, which is generated through combustion of fossil fuel. For an individual to offset their carbon footprint there is a need to change towards a lifestyle that consumes less energy, planning trips, and wise choices about food and other products purchased. However, should individuals fail to minimize their footprint in certain areas; this footprint should ideally be offset. Individuals can offset their footprint by donating to projects that result in lowering the amount of GHGs emitted into the atmosphere such as growing trees and use of renewable energy resources.

An example of a mobile technology that can be adopted by individuals to measure carbon footprint (CF) in South Africa is provided by WWF-SA (2015). WWF-SA provides a mobile service to measure an individual's carbon footprint based on travel and energy usage (WWF-SA, 2015). The mobile service expects to receive an SMS named "CO2", in order to start the measuring process (WWF-SA, 2015). The mobile phone, sending the SMS must be WAP enabled and the SMS costs the user two South Africa Rands (WWF-SA, 2015). The fulfilment of these requirements can contribute towards its use. Therefore, four key attributes extracted from this service are worth discussing.

First, the mobile service depends on SMS based mobile communication. Therefore, input methods are relevant for the successful evaluation of mobile message communication (Gebauer & Ginsburg, 2009). Users rate mobile devices highly when they can input data with ease. Second, there is a cost attached to the use of the service. Without the full cost of the SMS a user is unable to measure their CF. In addition, a user pays each time they need to measure their CF. Therefore, it might be reasonable for the user to expect value for the money spent on the service. Third, the mobile network is required to send and receive a response from the mobile service. Fourth, the carbon footprint is measured based on input of transport and energy usage.

South African conservation organizations argue that the first step towards reducing carbon footprint is through its measurement. To facilitate this measurement, they have provided a number of carbon calculators. However, most of the calculators are web based with the exception of WWF-SA (2015). This is peculiar given that South Africa has the highest number of mobile phone holders of 34 mobile phones per 100 individuals in Africa (Vodafone, 2007). Due to this limited practice of mobile CF calculators in a South African context, there is need to predict the theoretical impact of using mobile technologies on individual carbon footprint.

The huge market for mobile phones in South Africa has invited a number of 'unproven' initiatives into the society. Duncombe (2014) argues that impact analysis of mobile initiatives should precede their implementation in the society. This analysis can be in conjunction with understanding the economic drivers in relation to the livelihood of the users.

2.1.4 Prior studies on carbon footprint

This section assesses research that has been conducted relating to individuals and households as a precursor to identifying gaps in the literature.

In order to achieve green lifestyles, there is a need for individuals to change their behaviour as well as change towards energy efficient technology (Lewis & Jooste, 2012). Since life choices and consumption patterns heavily impact an individual's carbon footprint, the City of Cape Town has identified projects to assist in carbon footprint reduction. These include new bus transport system, energy saving campaigns, greener housing units and solar water geysers.

Lewis et al. (2011) conducted a survey research in the City of Cape Town for low income housing to investigate the impact of solar water heaters on their carbon footprint. The results revealed that the use of solar water heaters results in a lower carbon footprint in households which use them compared to households that use electricity based geysers (Lewis et al., 2011). Although the research showed cost savings for households using solar water heaters, this result was expected. In hindsight, the research does not show how the sample size was derived. Also the sample size of 30 which was used can be argued to be relatively low for any generalizations to be made on the low income households in the City of Cape Town.

Davis (2011) conducted a research to empower South African household electricity consumers to invest in projects that would effectively manage their energy efficiency and consumption. Davis findings show that there is a need for a balance between the energy consumption feedback, pricing, technology and awareness. Due to the prevalence of Eskom power utility based initiatives, he raised the need to also focus on consumer related interventions. Davis (2011) suggests future research to be based on determining the best way to provide consumers with relevant feedback to allow them to manage their consumptions. In addition, he suggested the need to measure the success of energy reduction interventions citing a gap in the measurement of performance and success of such interventions.

Liu et al. (2012) used fuel efficiencies and carbon emissions of liquid fuel to compare the carbon emissions of fuel based combustion engines and electric vehicles in a South African context. Their findings revealed that due to the majority of South African electricity being generated from low quality coal and less clean technology, South African electricity generation has a high greenhouse gas emission. As a result, the use of electric vehicles would result in a higher greenhouse gas emission than the emission as a result of the combustion of liquid fuel in combustion engines. In addition, the use of electric vehicles would emit a relatively higher amount of sulphur and nitrogen pollutants than combustion engines.

Fakoya (2013) carried out a quantitative research to determine the effect of applying a carbon tax policy on the consumer price index in the context of South Africa. By reviewing literature from countries which introduced a carbon tax, his review showed that carbon tax did not have an effect on carbon dioxide emission reduction. He argued that an increase in the prices of energy related products through carbon tax would have a negative effect on 25% of the South African population living on government grants for basic survival needs. Although Fakoya supports the polluter must pay principle, the results of his research showed that the introduction of a carbon tax on energy-related products increased the consumer price index and thereby impoverishing lower income households. His recommendation to policy makers is to consider voluntary options aimed at reducing carbon dioxide emissions.

Letete et al. (2011) developed a methodological framework to estimate the carbon footprint for the University of Cape Town (UCT). Emission factors were used to estimate carbon footprint based on units of energy and fuel consumed. In cases when consumed units could not be determined, costs of energy were used to derive the quantity of units utilized. Loss in transmission of electricity was also considered (Letete et al., 2011). Although Letete et al. (2011) determined that the per capita carbon footprint of UCT was higher than local South

African institutions, but lower than some European based institutions, there were some issues associated with the research. To start with, the research focused on direct emissions. However, for a more comprehensive carbon footprint both direct and indirect emissions should be considered (Pandey et al., 2011). Also, the research concluded that the highest GHG emitter was the energy sector, yet sufficient data could not be collected from other sectors such as the transport sector. Actual details of flights were difficult to collect such that estimates were computed on flights completed by staff. In addition, data were difficult to collect from student's residential buildings.

Tomaschek et al. (2012) revealed that although use of biofuel in South Africa would result in reduced GHG emissions by the transport sector, the production costs for biofuel extraction would be relatively high when compared to the import of fossil based fuels. Apart from the high production costs, biodiesel production is faced with concerns such as impacting the scarce water supplies, high consumer costs and potential resistance on use of arable lands for fuel rather than food (Tomaschek et al., 2012). These challenges raise questions about the sustainability of biodiesel, taking into consideration the basic human needs such as water and food.

Within a South African context, Pillay et al. (2014) purported that there is a causal relationship between the income distribution and the electricity consumed within residential areas. Pillay et al.'s research acknowledged the possibility of other factors which may influence the consumption patterns of electricity in households and recommended future work to consider such factors as education on income distribution and household electricity consumption. The importance of Pillay et al.'s research is to inform policy formation in residential planning, especially when South Africa's gross domestic product is taken into account.

Tait and Winkler (2012) studied whether there is a compromise between providing electricity to the poor households and the climate change mitigation initiatives in South Africa. Their findings revealed that providing the underprivileged population of the economy with electricity would only add a minor demand for electricity and not a substantial amount of GHG emissions. Providing electricity to low income household would not warrant building another coal-fired power station (Tait & Winkler, 2012). According to their findings, the electricity consumption of these residential households would only add minimal demand to the power grid.

The research related to carbon footprint in South Africa, at a household or individual level has been useful in informing policy formation. The next section deliberates on the research gap identified within this literature.

2.1.5 Research Gap

The alarming rate of climate change is resulting in local governments to meet with other international parties and negotiate ways that can be taken by governments to reduce the adverse effect of human activities on the environment. In line with this quest to reduce global warming, environmentalists advocate to an involvement at a level lower than the governmental level. This is the level of individuals or households. To promote their proposals, conservationists run campaigns over their websites to educate the public about ways the public can conserve resources in order to minimize the impact caused by the production and use of products.

According to Ba et al. (2013), the sale of personal computers is being surpassed by the sale of mobile devices such as mobile phones and tablets. Therefore, it can be argued that the number of people being reached by these campaigns on personal computers is dwindling as more people prefer mobile devices more than personal computers. The shift in preference does not suggest that mobile phones are more superior, but that their portability offers an uncontested advantage when compared to personal computers.

Given the huge penetration of mobile phones, this mobile technology platform can be utilized to reach the majority of the population for disseminating environment related campaign programs. However, the technology running on mobile phones often needs to be customized to meet the specifications of a mobile phone and be relevant to the problem being resolved. This begs the question whether the mobile technology is fit for individual carbon footprint tasks. In spite of the question of fit, it might not be guaranteed that the availability of such campaign programs on individual's phones will result in individual's participation. Even when the individuals utilize mobile phones to monitor their resources, through estimating and offsetting carbon footprint, would this use of mobile phones result in them yielding greater performance in managing their resources?

According to the researcher's knowledge, as reviewed in section 2.1.2 and section 2.1.4, there is limited research in assessing the fit and impact of mobile phones in performing carbon footprint tasks for individuals in South Africa. The reviewed literature, in relation with individuals within a South African context, was limited to the assessment of the impact of energy efficient technology, carbon offsetting policies and different sources of energy and fuel. However, there is no evident research on the impact of carbon footprint calculators on the performance of individual carbon footprint tasks given the proliferation of mobile devices (GSMA, 2015) and applications in South Africa (section 2.1.2). Therefore, this research thrives to answer two queries: (1) how the fit of technology influences the performance impacts of mobile carbon footprint calculators for individuals, (2) whether individuals who use mobile phones more frequently, to perform their carbon footprint tasks, achieve greater performance impacts on individual carbon footprint tasks than individuals who use mobile phones less frequently.

2.2 Underlying Concepts

2.2.1 Mobile Technology

Mobility manifests in three forms namely; travelling, wandering and visiting (Sarker & Wells, 2003). Each of these forms of movement is concerned with time, location, distance and purpose. As stated by Sarker and Wells (2003), use of mobile technology can be affected by these different types of mobility as well as the extent of mobility. For example, it is illegal in South Africa to use handheld mobile phones while driving. In this case, user mobility is seen to reduce the use of mobile phones and can open doors to the use of other technology.

Mobile technology refers to devices which can be used in motion, such as laptops, global positioning system (GPS), tablets, personal digital assistant (PDA) and mobile phones. In this study, mobile technology will be focused on the use of mobile phones and its supporting communication technology. The latter has developed significantly from analog to digital over the past decades (Liikanen et al., 2004). This technology improvement has come with improved security in communication as well as improved processing speed and storage enhancements in the devices.

In a mobile context, Liikanen et al. (2004) purported that the diffusion of new technology affects the continued technology diffusion of older technology. Within a mobile technological context, the introduction of second generation (2G) mobile telecommunication slowed down the diffusion of first generation (1G) technology. In the same way, the introduction of third generation (3G) telecommunication affected the diffusion of 2G networks. In addition, the diffusion of technology is also affected by factors that are economic and demographic in nature (Liikanen et al., 2004). The introduction of new technology comes at a cost and this can affect the purchase of such technologies by consumers. Furthermore, older members of the population may be less enthused by technology changes when compared to the younger generation. Also, diffusion of mobile technology may be different in rural and urban areas based on the relevance of the technology to the users and the availability of supporting infrastructure.

Due to these technological developments, mobile technology has enjoyed increased implementations in mobile commerce (Dorflinger et al., 2009; Lee et al., 2007), mobile learning (Motiwalla, 2007; Sharples et al., 2005), mobile banking (Brown et al., 2003; Ivatury & Pickens, 2006), and mobile communication (Castells et al., 2009; Sarker & Wells, 2003). Although a number of innovations are developing, Sarker and Wells (2003) argue that without user adoption of mobile technology mobility innovations are meaningless. By this argument, Sarker and Wells (2003) challenge manufacturers to consider the factors affecting mobile technology adoption when introducing new technologies in order to achieve success in mobility.

2.2.2 Green and Sustainability

Based on the numerous ways of saving the planet suggested by Bach and Rosner (2008), being *green* can be defined as any individual act which conserves the use of resources such as water, paper, electricity, fuel, gas and other forms of energy. Yanarella et al. (2009) warns against acts of saving the world by unsustainable organizations and refers to this as *green washing*. Going green is characterized by individual changes in making and use of devices, products and techniques to make the planet less unsustainable (Yanarella et al., 2009).

Daly (2006) defines sustainability in terms of throughput; which is the amount of things passing through a system. For an economy, these things could be human populations, livestock, buildings and assets (Daly, 2006). He argues that sustainability is a way of defending and increasing the use of renewable resources and a desire to share non-renewable resources over future generations. This definition of sustainability acknowledges that resources are finite and should be utilized while considering the need of generations to come.

Sustainability is often viewed with the aim to drive towards sustainable development. The latter is a subject of much debate and confusion as it may involve reforms which end up being political (Hopwood et al., 2005). Technological changes are seen by reformists as necessary to provide efficiencies in energy, protect the environment and also through use renewable energy. Sustainable development is interplay between environmental and socioeconomic issues imposed by humans to support themselves while preserving the environment (Hopwood et al., 2005).

The arguments raised by Yanarella et al. (2009) on the difference between the terms *green* and *sustainability* are appropriate for this review and have been presented in Table 2.2.

Table 2.2 Green vs Sustainability (Yanarella et al., 2009)

Green	**Sustainability**
Improving the environment	Preventing harm and protecting the environment, ensuring wellness of the economy and equality in the society
The focus is on individual components	The focus is on individual components and the entire system
Promoting changes in individual lifestyles which maintain a balance in the ecosystem	Designing cost effective strategies to implement a self- balanced ecosystem
Conventional and supports gradual reform	Innovative and is revolutionary
Smaller scale, such as devices, products and buildings	Larger scale, such as cities and regions.

Green practices are relatively easy to enforce as they focus on a micro-level and are less radical than sustainability measures which take a holistic approach to ensure the balance in the ecosystem, economy and the society. The distinction between green and sustainability is important for the research as it guides that the mobile approach to estimate and offset carbon footprint is a green initiative. Next, is a review of green IT and green IS.

2.2.3 Green IT and Green IS

Green IT is the efficient and effective design, production, use and deposal of IT equipment resulting in minimal impact on the environment (Murugesan, 2008). Since the production, use and disposal of computing equipment has a threat of impacting the environment through pollution and emission of greenhouse gases, the use of green IT alleviates the harm through use of renewable energy, power management, virtualization of servers and recycling. The components which characterize green IT are shown in Figure 2.2.

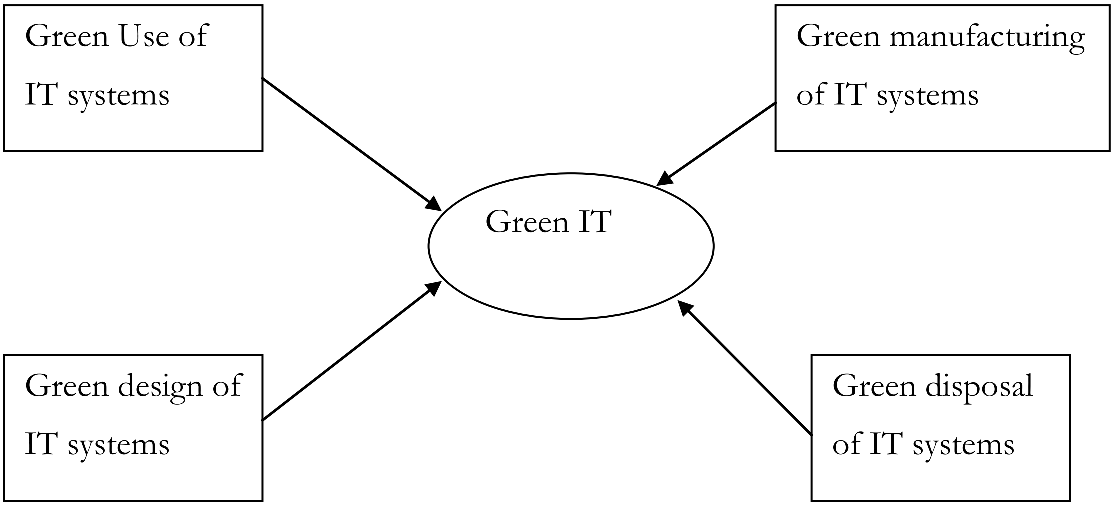

Figure 2.2 Holistic approach to Green IT (Murugesan, 2008)

Figure 2.2 shows a holistic approach which must be taken to alleviate the impact of IT on the environment;

Green use; calls for the reduction in the use of computers in order to reduce energy consumption.

Green disposal; refers to the recycling, upgrading and reuse of unwanted computer equipment.

Green design; requires the designing of energy efficient computer equipment.

Green manufacturing; this is the manufacturing of computer equipment from reusable parts or reprocessed material.

Although Green IT plays an important role in developing technology which results in lower energy consumption, users of the technology remain a key factor in determining success of environmental sustainability (Andreopoulou, 2012). Lamb (2011) explored the application of Green IT in South Africa through efficient data centres and cloud computing. He suggests that everyone should take part in saving the planet and measurement of energy used should be done in data centres as well as in homes.

Green IS "refers to the design and implementation of information systems which contribute to sustainable business processes" (Boudreau et al., 2008). This involves the use of technology or systems to perform tasks while minimizing the degradation caused by such tasks on the environment. Green IS focuses on the broader scale of environmental sustainability (Boudreau et al., 2008) as it includes improving efficiencies in operations which emit GHGs such as in energy, industrial and transport sectors (Dedrick, 2010).

Although sustainability is partly aimed at preventing and reducing pollution, an important goal is to use clean technology (Boudreau et al., 2008). This technology results in harmless emissions or waste and can be applied at all levels, such as individual, organizational and societal. At an individual level, clean technology can be utilized in the form of paperless interactions (Boudreau et al., 2008) such as electronic banking, electronic books, electronic mail and digital media.

The most significant driver for the adoption of Green IT is cost (Molla et al., 2009). Most organizations are driven to use Green IT when they need to reduce their production or running costs. Dedrick (2010) foresees research in Green IT to fade once energy prices fall and other emerging topic, for IS researchers, emerges. However, he urges IS researchers to continue in their pursuit for more innovative solutions towards environmental sustainability as the threat of degradation of the environment is still present.

A number of Green IS frameworks have been developed to address environmental sustainability (Howard & Lubbe, 2012). One framework worth noting is ecological thinking, which is based on three approaches, namely eco-efficiency, eco-equity and eco-effectiveness (Boudreau et al., 2008). Eco-efficiency is the use of resources to produce goods and services which are competitively priced while reducing the impact on the environment; eco-equity refers to the distribution of the earth's resources equally within the current generation and without depriving the future generation; and eco-effectiveness entails that the waste of a process should be used as the input to another process. With regards to eco-effectiveness, Information Systems can be used to facilitate trading of waste between people or organizations.

Having identified a number of Green IT research in recent studies, Esfahani et al. (2015) recommended future research to be on Green IS rather than Green IT. These future studies should focus more on the individual-level as the unit of analysis and including the influence of personal values and norms in investigating the adoption of Green IS initiatives (Esfahani et al., 2015). Micro-level based Green IS studies are intended to offer solutions towards the development of information systems which hopefully change the way individuals interact with the environment.

Therefore, the aim of the present research is well in line with an investigation of a green IS initiative, at an individual unit of analysis, as recommended by prior research.

2.3 Use of Information and Communications Technology (ICT) towards Environmental Sustainability

Environmental problems such as greenhouse gas emission can be reduced through the use of information systems which control how energy is utilized (Dedrick, 2010). Examples range from the use of smart grid technology to distribute electricity more efficiently, use of sensors in building to adjust temperature based on the environment to use of smart meters in households to adjust energy usage (Dedrick, 2010).

There are also a number of online ecological footprint calculators to assist individuals to visualize how their use of resources impacts the environment. However, Franz and Papyrakis (2011) argue whether the use of these calculators leads to behaviour change or merely delays the individual's negative impact on the environment.

Given that Information Technology is contributing towards environmental issues through production, transportation, use and disposal of its devices, Green IT is being employed to ensure devices are energy efficient and refurbished. Better cooling mechanisms are also being adapted for data centres to reduce the energy used. In addition, virtualization of servers is becoming increasingly utilized than before and this consequently results in less physical servers and therefore less utilization of energy.

2.4 Negative Impact of Technology

Although technology makes life easier through automation, it is also part of the problem when it comes to trending towards environmental sustainability. Data centres are known to consume relatively more energy than smaller devices as they need to be up all the time and also require high computing power. As a consequence, data centres contribute towards the emission of greenhouse gases, which in turn results in climate change (Dedrick, 2010).

Technology has also presented criminals another platform to commit crime. Wall (2007) identifies and elaborates on a wide range of cybercrime activities ranging from hacking, denial of service, scams to theft. All these criminal activities have been made possible, at least without requiring physical presence, through the use of information technology.

Communication has been made easier and effective, be it through emails, voice communication, SMS or chats. Therefore, families have found it much easier to stay connected in this information age. Albeit this communication privilege, it has also contributed towards social issues such as cyber bullying.

Dedrick (2010) argues that IT is part of the problem as it impacts the environment during its production, use and disposal. The disposal of electrical and electronic equipment, which is referred as electronic waste or e-waste is becoming a huge negative effect of technology (Robinson, 2009). Although e-waste can be salvaged, it still releases chemicals harmful to the environment.

2.5 Carbon Footprint

In the preceding sections, much reference has been made to the importance of green IT/IS in ensuring that products and processes are energy efficient. The resultant benefits being the reduction of greenhouse gas emission, which is one of the causes of climate change.

In 1997, the Kyoto protocol was endorsed to put a stop to climate change as a result of greenhouse gas emissions (UN, 1998). In order to achieve this, the protocol identified sectors that proved to be the sources of the GHGs and these were; energy, industry, agriculture and waste. The protocol also identified relevant economies to reduce GHG emissions by 5% in the period between 2008 and 2012 (UN, 1998). In addition, the greenhouse gases to be reduced were identified. Due to the target set by the protocol and the newness of the field of carbon footprint, a number of research papers were published.

Most of the literature that appeared during the early years of carbon footprint was non-scientific (Pandey et al., 2011). These studies were driven by the desire of business organizations to explore how they would save costs and improve their business rather than the environment. However, with progressive years of studies, academic bodies started to call for papers in the field and academic studies on the environment have increased remarkably.

The term carbon footprint emanated from the concept of ecological footprint, which was introduced by Rees (1992). Ecological footprint was viewed as a broad concept to determine the impact of humans on the environment. However, ecological footprint could not easily be quantifiable due to it covering the broad aspect of the environment. As such, ecological footprint was broke down into more specific footprints which were measurable, such as carbon footprint, water footprint, among other footprints (Lifset, 2014).

Wiedmann and Minx (2008) were motivated to define carbon footprint given that the term had become widely used without being conventionally defined. They suggested that carbon footprint is a measure of the total amount of carbon dioxide emitted by human activities directly or indirectly or accumulated over the duration of a product's lifetime.

Wiedmann and Minx argue that only carbon dioxide should be considered when measuring carbon footprint and no other greenhouse gases.

However, other academic researchers and practitioners have a different view to the argument presented by Wiedmann and Minx (2008). Čuček et al. (2012) welcomes the inclusion of other greenhouse gases, other than carbon dioxide, provided the gas has a potential to cause global warming and climate change. Defining carbon footprint is difficult as it is rooted in the methodology of its calculation (Peters, 2010). In this regard, Peters (2010) argues that defining the carbon footprint mainly on the basis of carbon dioxide is restrictive. Gases such as nitrous oxide, sulphur dioxide and black carbon also affect climate change.

Wright et al. (2011) also argue that defining the carbon footprint solely on carbon dioxide alone is insufficient. In hindsight, they agree that including all greenhouse gases in the footprint calculation becomes impractical. In this regard, Wright et al. (2011) suggest that carbon footprint be measured based on carbon dioxide and methane as this is relatively uncomplicated.

In all these different opinions of what constitutes a carbon footprint, Wiedmann and Minx (2008) and Wright et al. (2011) share the same view that a 'climate footprint' would be a more encompassing footprint as it would ideally include all greenhouse gases which cause climate change. In addition, Johnson (2008) purports that the differing opinions on what constitutes carbon footprint is a healthy debate as a common understanding is important, especially when carbon footprint needs to be compared across individuals, companies and places of different locations and generations.

Based on these studies, the researcher suggests that carbon footprint refers to the total amount of greenhouse gas emissions caused by human activities either directly or indirectly. In addition, the term greenhouse gas is referring to any of carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, sulphur hexafluoride or perfluorocarbons. Direct emissions are as a result of individual or organizational action, such as fuel combustion and power generation from coal (Pandey et al., 2011). On the other hand, indirect emission results from use of a product or activity whose production generated GHGs such as food and electricity consumption.

2.5.1 Calculating Carbon Footprint

The inclusion of indirect greenhouse gases presents some challenges when calculating the carbon footprint of a product (Pandey et al., 2011). The complexity is found in tracking of the entire carbon footprint involved in the manufacturing of the product. When only direct emissions are used in the estimation, this results in oversimplified carbon footprints. For this reason, Pandey et al. (2011) argues that estimating of carbon footprint for a product should include the GHGs emitted from the moment the product begins to be manufactured.

To measure carbon footprint, life cycle assessment was initially used and this was followed by input-output analysis to estimate footprint at a broader scale (Lifset, 2014). Using input-output analysis allowed the impact of activities on the economy to be measured by considering the output of each sector as an input of another.

Carbon dioxide equivalent (CO2e) is the unit of measure that equates a GHG to a carbon dioxide equivalent (Pandey et al., 2011).

Emission factors: An emission factor is a factor used to estimate greenhouse gas emissions from a unit of measured data (WRI, 2004). The data measured may vary from metric units of electricity units used to litres of fuel consumed. To calculate the CO2 equivalent from an activity the following formula is used:

Carbon dioxide equivalent emitted = emission factor X metric units of activity

Eskom publishes emission factors for electricity each time they change. In 2013, the emission factor for consumption of electricity generated by Eskom was reported as 0.98 kg CO2/kWh. The emission factors for fuel such as petrol and diesel also exist and they can be used to estimate the carbon footprint through combustion of fuel.

Emission factors form a pivotal role in the estimation of carbon footprint. Over the years, the emission factors of electricity generated by Eskom have been varied. In this regard, the more recent the emission factor the more relevant the carbon footprint. For comparison of carbon footprint, between individuals in different places and time, it is important to establish a common set of emission factors.

2.5.2 Impediments to estimating Carbon Footprint

A number of practical challenges in estimating carbon footprint arise partly as a result of the selected methodologies and methods to collect GHG data (Chakraborty & Roy, 2013; Pandey et al., 2011). These challenges are listed below:

- The inability to track all GHG data, as is the case in developing countries, results in the adoption of GHG accounting standards which make inclusion of indirect emissions optional when estimating the carbon footprint (Chakraborty & Roy, 2013). The GHG Protocol is an example of such a standard. This has seen only a few carbon calculators showing the use of indirect emissions (Pandey et al., 2011).
- Lack of information systems to maintain the required environmental data (Chakraborty & Roy, 2013). When disposal of waste is unaccounted, this can result in the carbon footprint from waste to be unobserved.
- The selection of GHGs for a carbon footprint has been a cause of debate (Pandey et al., 2011). Even though GHG standards stipulate six Kyoto GHGs to be included in calculating carbon footprint, some calculators only include carbon dioxide emissions (Chakraborty & Roy, 2013).
- Emission factors for fuel and energy may vary for each country (Kenny & Gray, 2008). Therefore, care must be taken when using the carbon calculators designed for use in specific countries. This can result in understating or overstating the carbon credits required to offset the carbon footprint calculated.
- Kenny and Gray (2008) also suggest that the source data for emission factors should be kept updated for the results obtained to be relevant.
- Given the same inputs, different carbon calculators may yield different estimates (Kenny & Gray, 2008; Padgett et al., 2008). This inconsistency (Kenny & Gray, 2008) and lack of transparency (Padgett et al., 2008) associated with the carbon calculators results in them losing credibility (Pandey et al., 2011) amongst users who wish to understand and clarify the results (Padgett et al., 2008).

2.6 Offsetting Carbon

Carbon offsetting refers to the act of reducing GHG emissions that may be emitted through other activities elsewhere (WBCSD & WRI, 2001). Offsets can be due to voluntary or mandatory obligations by individuals or organizations to meet a specific carbon emission target. They involve investing in projects which ultimately result in the GHG emission reduction. The projects generate emission permits, which can be bought and sold in a carbon market (Bayon et al., 2012). These emission permits are traded in terms of carbon credits, where each credit represents the offset of GHGs equivalent to one ton carbon dioxide equivalent.

Kollmuss et al. (2008) categorizes carbon markets into two main sectors namely compliance market and voluntary carbon market. The compliance market is formed and controlled by nations which belong to a mandatory body. The participating nations trade offsets which are referred to as Certified Emissions Reductions (CERs) or Emissions Reductions Units (ERUs). CERs are generated through Clean Development Mechanism (CDM) projects while ERUs emanate from Joint Implementation (JI) projects (Kollmuss et al., 2008).

The voluntary carbon market operates at a much micro level than the compliance market. Participating entities in this market include businesses, government bodies and individuals (Kollmuss et al., 2008). The offsets which can be purchased in this market are known as Verified or Voluntary Emissions Reductions (VERs). These VERs can be bought by entities that wish to offset their emissions. As an example, individuals can offset their emissions when they pay for their flights.

2.6.1 Voluntary offsetting

Bellassen and Leguet (2007) use the term *voluntary offsetting* to refer to methods used by organizations or individuals who voluntarily use the voluntary carbon market to reduce their GHG emissions.

Traditionally, individuals voluntarily use tree planting as a way to sequester carbon. However, individuals can now voluntarily offset their own emissions through opting to pay the extra cost of offsetting the GHG emission caused by their purchase of goods or services

(Bellassen & Leguet, 2007). This method of offsetting is currently adopted by individuals when they purchase travel packages.

Another way individuals can offset their emissions is through the purchase of a compensatory service from a provider who sells VERs (Bellassen & Leguet, 2007). To start the offsetting process, the service provider would offer to calculate the individual's emission, then the individual would volunteer to purchase the emission reductions and lastly the provider would offset the individual's emission.

Since the purchase of emission reductions is preceded by the calculation of the GHG emission, it is reasonable to expect that such calculations ought to be consistent and accurate in order to result in the purchase of emission reductions representative of the calculated emissions. This expectation is supported by Pandey et al. (2011), who purports that these carbon calculations are not checked and that they lack coherence and transparency.

2.6.2 Carbon offset projects

According to Kollmuss et al. (2008), carbon offset projects can be categorized into five groups, namely; biological sequestration, industrial gas destruction, methane capture, energy efficiency and renewable energy.

1. Biological sequestration. These projects aim to reduce GHG emission from land use and forestry activities. They achieve this by conserving existing forests, planting new forests and improved agricultural practices.
2. Industrial gases. The destruction of GHGs with high global warming potential to reduce GHG emission has received criticism by others suggesting that the gases should not be produced in the first place.
3. Methane capture. Methane can be captured and combusted into carbon dioxide. The latter has lesser global warming potential. Methane can also be converted into another form of energy such as electricity.
4. Energy efficiency. Technology which is energy efficient is not only friendly to the environment, but saves on costs over a period of time. Energy efficient projects include distribution of efficient light bulbs and stoves used for cooking.

5. Renewable energy. These projects include solar, hydro and wind power, solar water heating and use of biomass for energy. Although renewable energy projects may have high set up costs, their operation requires clean energy, which is cheaper than fossil fuel based electricity.

2.6.3 Impediments to forest-based Carbon Offsets

Carbon offset projects relying on forestry suffer from challenges arising from leakage and lack of permanence (Kollmuss et al., 2008). Leakage is unforeseen loss of carbon reductions outside the bounds of the current forestry project. Permanence refers to the timeframe that carbon will remain stored in vegetation taking into consideration that forests cannot last forever.

Due to the susceptibility of forests to destruction, some compensation service providers are no longer interested in offering forestry projects for emission reduction (Bellassen & Leguet, 2007). They rather tend to prefer projects which offer permanent solutions, with no chance of reversal.

This risk of reversal presents a barrier to the use of forest offsets as carbon is released back to the atmosphere due fire and other natural disturbances (Galik & Jackson, 2009). Natural disturbances such as fire, insects, storms, wind and drought are a great threat to forest offsets.

However, better forestry management and practice such as site preparation, wider placing of trees and fertilization can be used to reduce the impact of natural disturbances (Galik & Jackson, 2009). These practices will ensure that the impact of strong wind, fire and insert attack is less destructive.

2.7 Towards the fit of mobile technology

Mobile technologies reduce the ‘digital divide’ between developed and developing countries (Donner, 2008). This is enabled through the provision of affordable mobile devices, to developing countries. Although affordable mobile devices are being produced and sold to developing countries, there are still challenges in network coverage and pricing in some less developed areas (Donner, 2008). In addition, not all social-economic problems can be solved through mobile innovations as there is always the reluctance to adoption until such a time when the technology is socially accepted.

Based on the information system domain posited by Benbasat and Zmud (2003), technology usage influences the impact of technology, which in turn affects its usage. In this regard, if a technology is implemented considering the factors affecting its adoption and usage, that technology may have a desired impact. Therefore, it is important to understand the factors affecting the usage and adoption of a technology to determine the impact inflicted by the technology.

The factors influencing the use and success of mobile technology are embedded in the characteristics of the mobile user, task, technology and socioeconomic context (Sarker & Wells, 2003). User characteristics determining the use and acceptance of mobile phones were identified as demographics such as age, education, computer self-efficacy (Lee et al., 2007) and culture (Sarker & Wells, 2003). It can be argued that the age of the individual can impact if user will adopt the technology based on needs and convenience. Computer self-efficacy is vital in the adoption of newer technology devices by individuals based on their ability to easily understand computer technology. Cultural background can influence the extent of usage of some technological features such as messaging. For example, using mobile messaging in formal settings is limited in cultures that oppose the practice.

Sarker and Wells (2003) suggested that the two important technology characteristics leading to the successful usage of a mobile technology are user interface characteristics and network capabilities. First, the mobile phone should have easy to use user interface, to cater for the less technical users. Second, the network coverage (Gebauer & Ginsburg, 2009) and uptime of the network are characteristics that can test the user's patience and trust in accepting mobile technologies.

In as far as task characteristics is concerned, **t**he volume of communication needed can limit the usage of some mobile features such as messaging (Sarker & Wells, 2003). This limitation can be attributed to the size of the keyboard, which makes it difficult to produce high volumes of text. Therefore, input features as well as form factor features (e.g. size and weight) are important factors in the user evaluation of mobile technology (Gebauer & Ginsburg, 2009).

Carbon calculators are evaluated using measures that make them effective interactive applications; such measures are the appearance and usability of user interface, ability to input relevant data, feedback of results, and adhering to industry standards (Bottrill, 2007). In order for individuals to effectively estimate and offset carbon footprint using these calculators, the application should have a presentable user interface, which allows easy inputting of data and useful feedback provided to the users. This feedback should be easily locatable.

The surrounding socioeconomic context affects the success of mobile technology usage through the effect it has on the individual, task and technology (Sarker & Wells, 2003). The use of some mobile services is affected by the cost of the service offered. Consequently, some members of the society, such as students may not use the service more than they would have liked to if the cost exceeds their budget in the long run. Sarker and Wells (2003) suggest that adoption of mobile devices can be enhanced by social factors such as symbolism, which is a quest to seek self-importance through possession of material things.

This analysis of factors affecting adoption, use and benefit of mobile technology for individuals can be explained by existing theories. The next section reviews theories and results in the development of the research model.

2.8 Theory Review

The present research questions are concerned with the adoption and use of technology that leads to improved individual performance on carbon footprint tasks. Many adoption theories exist. Some of these adoption theories include Theory of reasoned Action (TRA), Theory of Planned Behaviour (TPB), Innovation Diffusion Theory, Social Cognitive Theory and Technology Acceptance Model (TAM) (Kim & Crowston, 2011). Out of these theories, the researcher analysed three theories before developing an appropriate research model. In understudying these theories, the researcher was inspecting which theory is able to harness the fit of a technology to individual tasks in order to explain and predict individual task performance while taking into consideration the individual's characteristics and social-economic context.

2.8.1 Technology Acceptance Model

The *Technology Acceptance Model* (TAM) is a theory to explain and predict the acceptance and adoption of information technology by system users (Davis et al, 1989). This theory was introduced by Davis in 1986 and gives an account for the adoption of a technology based on its perceived usefulness and ease of use by users (Davis et al., 1989). For a technology to be utilized, TAM posits that the technology should be perceived as useful and easy to use.

Figure 2.3 shows the original version of TAM. The following are the six concepts of TAM as illustrated in the diagram.

1. The external variables influence the perceived usefulness, perceived ease of use and the attitude towards using the information system.
2. Perceived usefulness refers to the user belief that system use results in the desired action.
3. Perceived ease of use refers to the user belief that the system will be 'user friendly'.
4. An attitude towards use refers to the user's willingness to use the system.
5. Behavioural intention is a prediction of individual intention based on attitude towards use and perceived usefulness.
6. Actual use refers to the behaviour, predicted using the individual's behavioural intention.

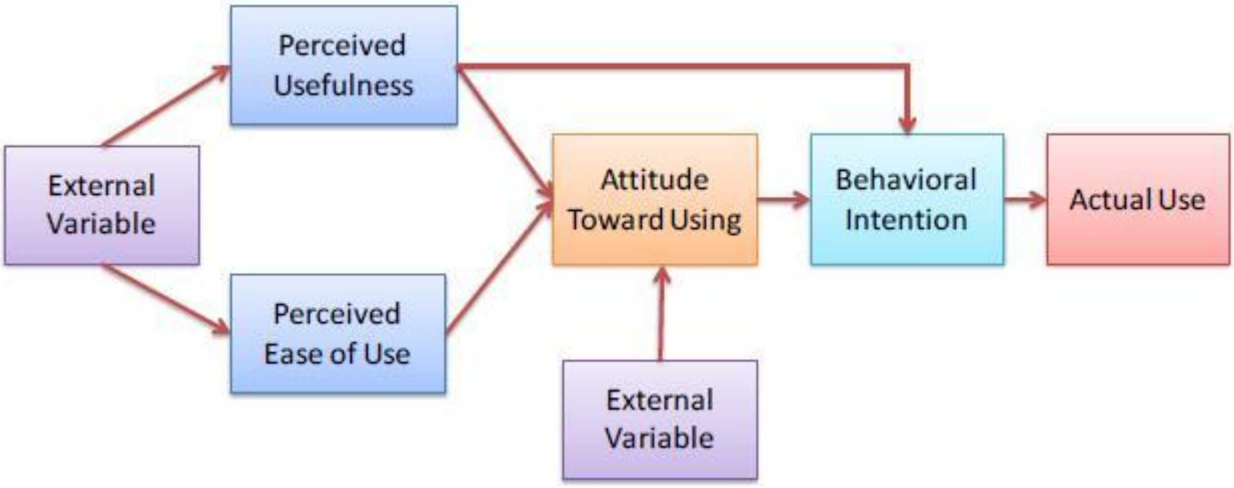

Figure 2.3 Technology Acceptance Model (Davis et al, 1989).

According to the TAM theory, the use of a technology depends on the belief and attitudes of the users towards the technology. However, the theory does not predict the adoption of a technology based on the features of the technology, but rather on how the technology is perceived. TAM has been advanced to later versions such as TAM2 to add the *subjective norm* as well as explicit definitions of the external variables (Legris, 2003). Although TAM is an appropriate theory to predict system use, it sometimes requires integration with other models to increase its prediction potential, especially in cases when actual technology features need to be considered. In this research, the technology characteristics are vital in assessing the fit of the technology to the individual's tasks, of estimating and offsetting carbon footprint.

2.8.2 Task-Technology Fit

Task-technology fit (TTF) theory states that systems positively impact performance and utilization when the technology features are more aligned with the user tasks (Goodhue & Thompson, 1995). Given that TTF is a measure of the alignment between the task and the technology, higher TTF entails higher performance impact on individual tasks. Therefore, better design of systems in relation to user requirements can be argued to yield desired system utilization and performance. This assumption can be tested using the theory of task-technology fit.

Figure 2.4 is a diagram to illustrate the task-technology fit theory. The diagram shows that TTF is affected by the alignment of task characteristics and technology characteristics and that TTF affects system performance and utilization.

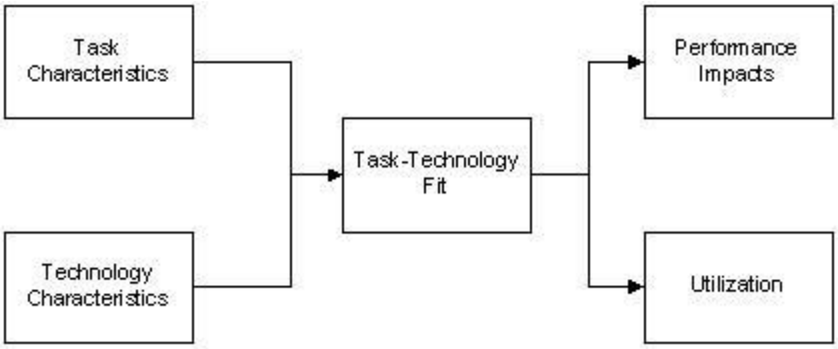

Figure 2.4 Task-Technology Fit (Goodhue & Thompson, 1995).

Technology characteristics refer to the features of the tools used by individuals to conduct their tasks. Examples of these characteristics are the features of computer systems and supporting services.

Task characteristics are the requirements of the actions carried out by individuals.

Utilization is frequency of use of a system to execute a task.

Performance impact relates to the execution of a task, by an individual.

Task-technology fit can be found useful to predict the performance and utilization of a system based on the alignment of the task and technology characteristics. However, TTF does not explicitly use utilization to predict performance and the theory lacks the impact of user involvement and beliefs in predicting performance (Goodhue & Thompson, 1995). This can be shown by the model in Figure 2.4 that the dependent variables (performance impacts and utilization) do not affect each other but are all predicted by task-technology fit. In subsequent research by Goodhue and Thompson (1995) TTF has been combined with theories in beliefs and attitude to posit a model such as the technology-to-performance chain model. Such combination of other theories with TTF has provided more explanatory and predictive power to studies in information systems.

2.8.3 Technology-to-Performance chain

Goodhue and Thompson (1995) developed the *technology-to-performance chain* (TPC) model to strengthen the use of TTF in predicting the impact of technology on individual performance. The TPC model suggests that individual performance can be explained and predicted using a combination of task-technology fit and technology utilization (Goodhue & Thompson, 1995). The resultant performance impact can provide feedback which in turn can affect the technology utilization and fit. Although the model did not manage to prove that TTF leads to utilization it suggested that other factors such as surrounding conditions, beliefs and social norms can predict utilization of a technology.

Figure 2.5 shows the technology-to-performance chain model. The model links TTF theory with theories in attitude and behaviour to predict individual performance. Individual characteristics such as technology experience and user training affect individual performance. After users utilise the system to perform their tasks, they gain experience and attitude towards the system. This feedback determines the future use and individual performance (Goodhue & Thompson, 1995).

Goodhue and Thompson (1995) posited that TTF can be measured through user evaluations of eight factors, namely data quality, locatability, authorization, production timeliness, compatibility, systems reliability, ease of use, and relationship with users. These factors can be analysed in line with performance, utilization and characteristics of tasks, technology and the individual when testing the technology-to-performance chain model.

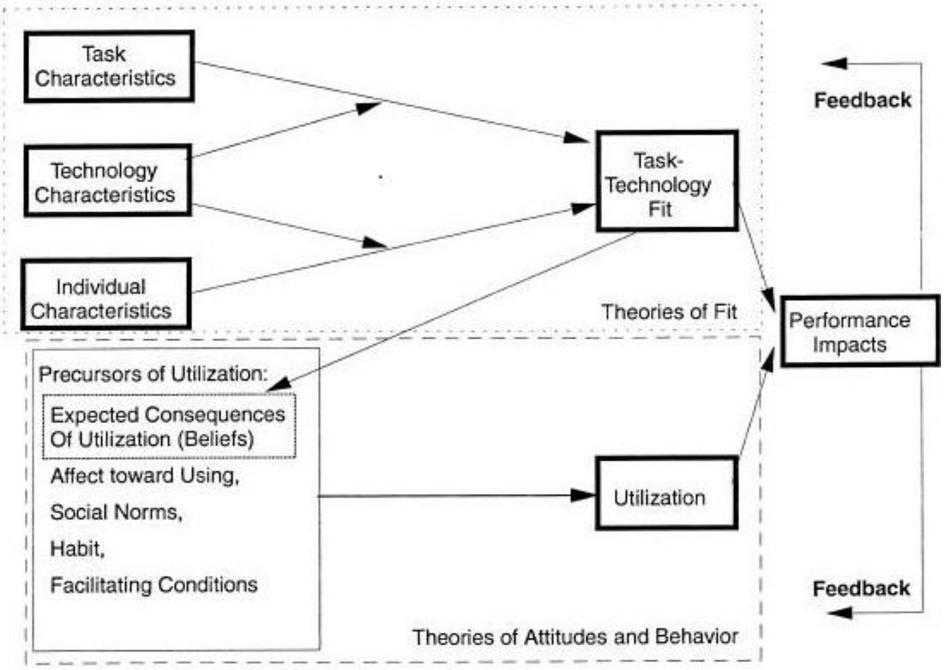

Figure 2.5 Technology-to-performance chain (Goodhue & Thompson, 1995)

2.8.4 Selected Theory

Table 2.3 shows a summary of the nature of theory, constructs and what the three theories can be used to explain and predict. In this summary, TAM uses beliefs and attitudes to explain and predict technology use. TAM theory does not use any technology constructs. While TTF utilizes technology constructs, it does not make use of an individual's belief and attitude as factors affecting task performance and utilization. TPC is shown to utilize both theories of fit (TTF) and theories of attitude and behaviour.

Table 2.3 Summary of Theories Reviewed

Theory	Nature of Theory	What to Explain or Predict	Constructs
TAM	To explain and predict why people use or adopt the technology	Technology use	Beliefs and Attitude
TTF	To explain and predict why people use certain technology for a	Task performance, Technology	Task and Technology characteristics

Theory	Nature of Theory	What to Explain or Predict	Constructs
	specific task	utilization	
TPC	To explain and predict why people use certain technology for a specific task	Task performance	TTF, Beliefs, Social Norms, Attitude, Technology utilization

Based on the research questions, either of TTF or TPC theories can be adopted to answer the questions. Both of these theories seek to explain and predict task performance based on the fit of the technology, on the tasks. However, the TPC model includes theories of belief and behaviour which are crucial in predicting utilization when technology use is voluntary (Goodhue & Thompson, 1995). Whenever voluntary use is concerned, it is vital to consider the beliefs and social norms of the individuals in predicting technology utilization as individuals may opt against technology usage based on their perceptions. This might not be the case when technology use is mandatory.

Given that the present research seeks to determine how the fit of technology influences the performance impacts of mobile carbon footprint calculators for individuals, the TPC model is appropriate to achieve the objectives of the research. In this study, the TPC model has the ability to explain and predict the impact of mobile technology on individual carbon footprint tasks.

Considering that the TPC model is a huge model to be tested in one research study (Goodhue & Thompson, 1995), the present research adapts this model and posits a research model sufficient to meet the research objectives.

2.9 Development of the Research Model

Due to the size of the TPC model, even Goodhue and Thompson (1995) in their initial study did not regress between TTF and the precursors of utilization and deferred this for future studies. To test this relationship, only factors identified in the literature are used. In addition, the present research does not use individual feedback to re-test the fit and utilization as this

would require a longitudinal timeframe. Therefore, a modified version of the technology-to-performance chain model, without feedback, is used as the basis for the research model.
Figure 2.6 shows a decomposed TPC model to which the factors appropriate to this research are applied. In this decomposed model, the user feedback has been omitted.

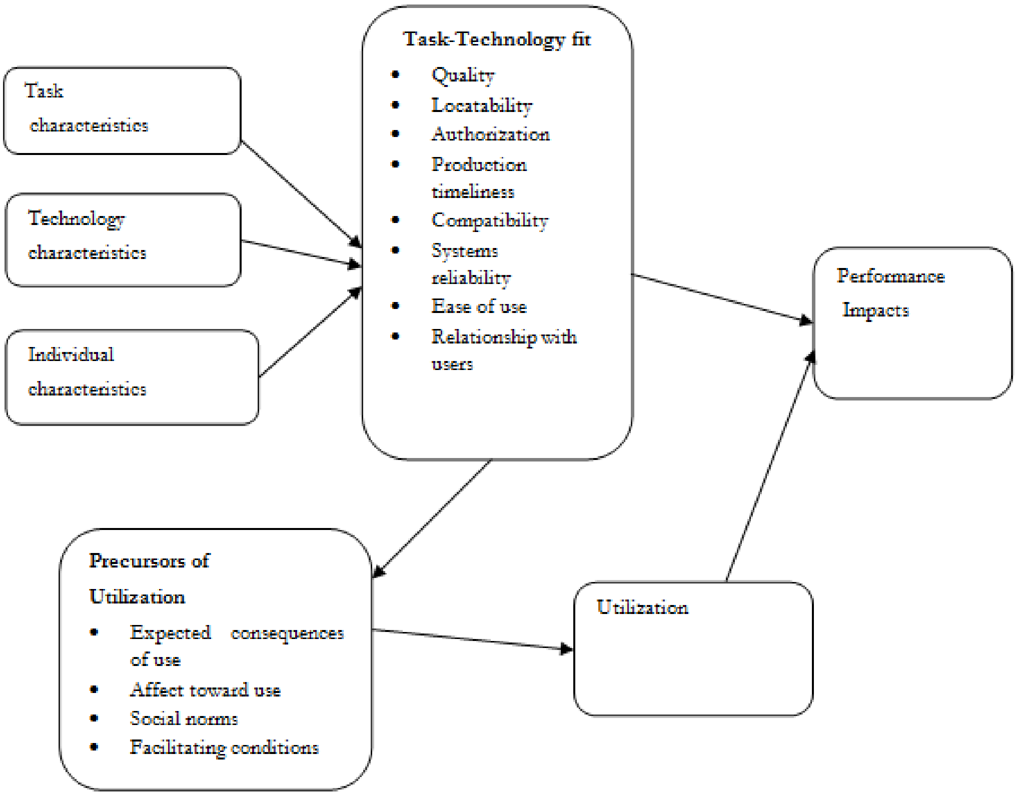

Figure 2.6 Decomposed Technology-to-performance chain.

2.10 Research Model

Figure 2.6 illustrated in the previous section provided a modified version of the Technology-to-Performance Chain model appropriate for the scope of this research. In order to answer the research questions, the lines illustrated in Figure 2.6 are treated as relationships between the constructs and these need further elaboration. To understand these relationships, Figure 2.7 proposes the research model. The constructs identified in the decomposed model have been associated with factors affecting adoption and utilization of mobile technology as revealed by the literature.

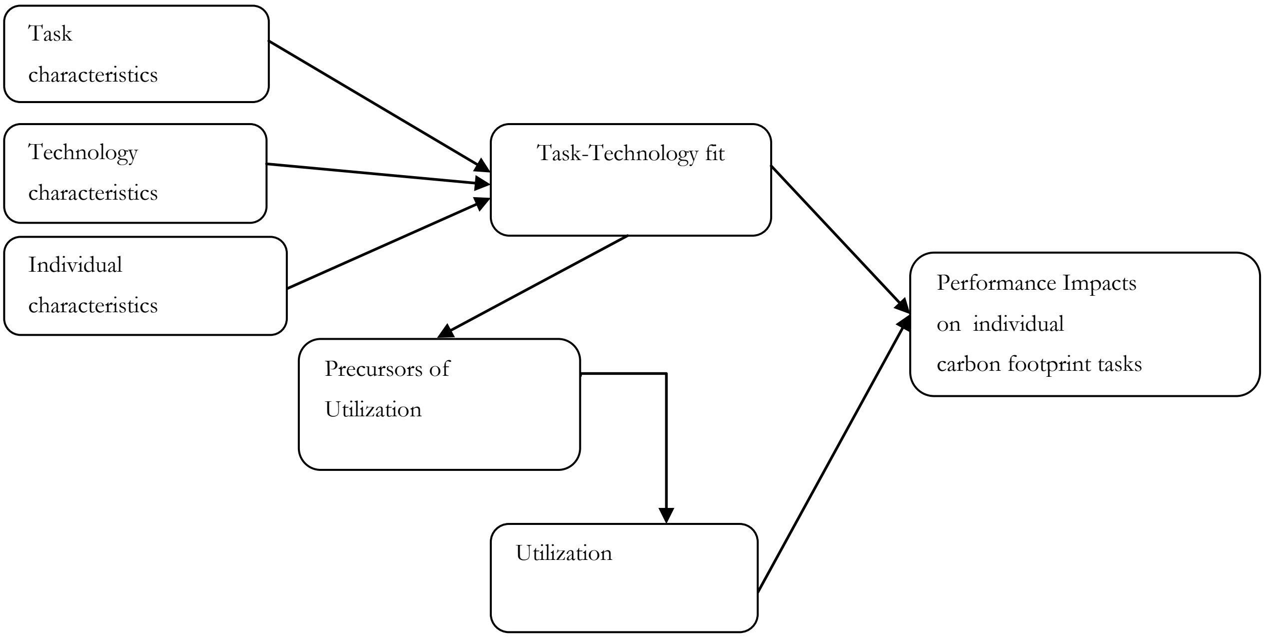

Figure 2.7 Research Model.

The constructs of this research model are defined in the following section.

2.10.1 Definition of Constructs

Task characteristics:

A task is an action undertaken by an individual to perform a piece of work (Goodhue & Thompson, 1995). Task characteristics are the attributes of such individual's actions. These attributes include the activities themselves and opinions possessed by individuals when performing the tasks. Although tools play an important role in accomplishing tasks, their characteristics are dealt with in the *technology characteristics* section. Individuals are faced with different life situations and perceptions when it comes to changing their lifestyle towards more sustainable living.

Nonetheless, (FTFA, 2013) and WWF-SA (2015) advocate that individuals can make sustainable choices such as recycling, reducing energy usage and monitoring transport and energy used in order to determine the impact made on the environment due to carbon emissions. Transport and energy usage have been used as the main sources of carbon emission and therefore used in estimating carbon footprint. The monitoring is perceived, by these conservationists, as necessary to provide awareness required towards 'greener' living. Individuals can also help in reducing the impact of carbon emissions through engaging in projects that reduce the atmospheric carbon content such as tree planting and renewable energy projects in solar and wind energy generation (FTFA, 2013). These carbon reduction initiatives are key activities individuals can participate, in order to offset the carbon footprint.

Therefore, the key task characteristics are estimating carbon footprint and offsetting carbon footprint.

Technology characteristics:

Technology refers to tools used to perform user tasks (Goodhue & Thompson, 1995). In information systems, these tools could be both software and hardware such as computers and mobile devices. Technology characteristics are the features of these tools. A number of web browser tools exist to measure carbon footprint. However, a limited number of individuals in South Africa have access to the internet when compared to the number of individuals with mobile phones. Although some mobile phones have web browsers, some online tools such as Nova Institute (2015) are not scalable to mobile phones. In addition, some tools (such as on the *Greenworks* website) require entering of data into specific applications such as Microsoft Excel. On a mobile platform, such data entry is not supported on most mobile phones prevalent in the present South African market.

There are many technology characteristics in mobile devices, which range from usability, look and feel, storage, security and some are even physical traits (Sarker & Wells, 2003). Changes in technology can affect the adoption of technology as purported through diffusion of technology (Liikanen et al., 2004). The introduction of new technology can have an effect on the adoption of existing technology. Given that the mobile carbon footprint calculator provided by WWF-SA (2015) uses SMS and the presence of mobile network, technology traits required for this tool are considered for the present research. These are network attributes and user interface characteristics. The mobile user interface should be simple to navigate and the mobile network should be available and reliable to support the mobile phone (Sarker & Wells, 2003). Other characteristics related to technology such as ease of use will be discussed in the *task-technology fit* construct section.

Individual characteristics:

These are personal traits and include biographical data such as age and education. Mobile phones considered as 'smart' run mobile operating systems such as Google Android, Apple iOS, Windows Mobile, among others. Considering that these mobile phones are becoming miniature computers, individual characteristics are becoming more vital in the acceptance and use of mobile technology. In this regard, one individual attribute to consider is how well an individual easily learns new computer related technology. This ability is referred as computer self-efficacy (Compeau & Higgins, 1995). In related mobile technology research, education was also found to impact quality ratings in determining the fit of technology to perform user tasks (Lee et al., 2007). In addition, it may be argued that the knowledge on carbon footprint in the general population might be limited. In this case, education might affect the adoption of mobile phones to perform carbon footprint tasks.

Task-Technology fit (TTF):

This refers to the extent to which technology supports the execution of user tasks (Goodhue & Thompson, 1995). TTF is a theory which explains that if a technology is aligned to user tasks, the technology has a better fit and has more utilization and also results in improved user performance. Goodhue and Thompson (1995) posit that this alignment of task and technology can be measured through user evaluations of eight factors which are defined as follows:

Data quality: This refers to the accuracy of the data in terms of correctness, newness and level of detail.

Locatability: This factor refers to whether the meaning of data is easily found.

Authorization: Refers to the ability of an individual to access relevant data on the mobile phone.

Production Timeliness: This is whether the information is provided on time.

Compatibility: This refers to whether the use of the technology is compatible with all the user's tasks.

Systems reliability: Refers to whether the technology is steady and dependable to perform user tasks.

Ease of use: This factor refers to the simplicity and intuitiveness of the technology, for its users.

Relationship with users: Relates to the nature of support an individual receives when they need assistance with customer services or technical support.

Precursors of Utilization:

These are the social factors influencing technology use by individuals and the extent to which it is used (Goodhue & Thompson, 1995). While individual characteristics may determine whether technology is used correctly, the precursors of utilization determine the extent of technology use, based on the individual's beliefs and surrounding conditions. There are many determinants of why technology is used, but the following factors were identified by Goodhue and Thompson (1995) as important:

Expected consequences of use: This refers to the relative advantage of using technology. The perceived usefulness of technology is one of the predictors of technology acceptance (Davis et al., 1989). When technology is considered as useful and is easy to use, that technology is likely to be accepted.

Affect toward use: This refers to the feelings of individuals towards technology use.

Social norms: These refer to the people's cultural perceptions on behaviour. In this study, these norms are people's thoughts on the use of technology. Social norms are important factors to consider when use of technology is voluntary as individuals who might want to use the technology can be influenced by their peers (Staples & Seddon, 2004). An individual's circle of influence, i.e. friends, family and colleagues can influence a person's actions based on what is acceptable in society and what they view as important.

Facilitating conditions: These refer to the technology support the individual receives when assistance is required.

Utilization:

Utilization is the frequency at which technology is used by an individual, to perform a task.

Performance Impacts on individual carbon footprint tasks:

Goodhue and Thompson (1995) refer performance impacts as the completion of a task by an individual. In this study, performance impacts on carbon footprint tasks is the perceived accomplishment of carbon footprint tasks taking into consideration that not all mobile users have used a mobile carbon footprint calculator. This performance is affected by the fit of the technology to the user's tasks (Goodhue & Thompson, 1995). In addition, use of the technology also impacts on the performance achieved by an individual executing the carbon footprint tasks.

2.10.2 Hypotheses

This section gives an account of the research model through proposition of hypotheses, as supported by the literature.

Task characteristics influence user ratings on the adequacy and appropriateness of technology to accomplish user tasks. Goodhue and Thompson (1995) argue that non-routine tasks influence the task-technology fit for user tasks. When users are forced to use systems to achieve an unfamiliar task, they develop attitudes and perceptions towards the systems. The perceptions developed by users have a stronger effect when technology use is voluntary than when it is mandatory. In addition, interdependence of tasks influences TTF (Goodhue & Thompson, 1995). When tasks are dependent of each other, users rate the cognitive fit based on the perceptions of compatibility and system reliability.

Characteristics of the technology influence user ratings on the factors affecting TTF. However, Goodhue and Thompson (1995) suggest that technology characteristics would not influence all the components of task-technology fit. Given that systems that meets user requirements are a step closer to cognitive fit for user tasks, it can be argued that different systems have different cognitive fits to the tasks they serve depending on the number of components of TTF fulfilled. Goodhue and Thompson (1995) found moderate support for technology characteristics as a predictor of task-technology fit.

Goodhue and Thompson (1995) argue that individual traits influence how individuals use technology. As a result, individuals with different characteristics have different cognitive fits in using mobile technology to perform user tasks. This proposition was supported by Lee et al. (2007) when they tested the relationship between individual differences and task-technology fit in accomplishing insurance tasks.

When a technology matches the individual traits and tasks, the technology will have a great fit in accomplishing the individual's tasks. This positive association between TTF and performance has been investigated and supported by previous studies. Goodhue and Thompson (1995) supported this positive association between task-technology fit and performance. Aljukhadar et al. (2014) found support for this hypothesis in their study of website fit for online users. McGill and Klobas (2009) also found support for the relationship between task-technology fit and performance in learning. Therefore the first hypothesis is stated as;

H1: Characteristics of carbon footprint tasks, mobile technology and individuals affect user evaluations of task-technology fit, which in turn affect performance impacts on individual carbon footprint tasks. Hypothesis H1 is supported by the above literature and is further split into the following sub-hypotheses, which have also been motivated in the preceding literature:

- **H1a**: Task characteristics will positively influence task-technology fit
- **H1b**: Mobile technology characteristics will positively influence task-technology fit
- **H1c**: Individual characteristics will positively influence task-technology fit
- **H1d**: Task-technology fit will positively influence performance impacts on individual carbon footprint tasks.

Goodhue and Thompson (1995) argued that task-technology fit is a vital determinant of the beliefs about the usefulness and relative advantage of using a technology. These beliefs about the consequences of using technology form part of the precursors of utilization, presented in the TPC model. Goodhue and Thompson (1995) found support for a positive relationship between TTF and utilization. Consequently, they suggested that the more positive the cognitive fit, the more positive the expected consequences of use and the more the affect toward use or beliefs towards using the technology. Although Goodhue and Thompson (1995) did not test this, Staples and Seddon (2004) found support for this hypothesis in their test of a TPC model for mandatory and voluntary system use.

Theories of attitude and behaviour explain and predict the utilization of technology in the TPC model (Goodhue & Thompson, 1995). Perceived usefulness and ease of use are the predictors of technology acceptance (Davis et al., 1989). These beliefs and attitude, on the technology, impact its utilization as explained in the technology acceptance model. The attitudes towards an action, an individual's subjective norm and perceived behavioural control all have an influence towards behavioural intention which in turn influences behaviour (Arjen, 1991). For an individual to perform a certain action, the individual's attitude towards the action, behavioural control and the surrounding environment (such as social networks and cultural norms) should be favourable. In this research, beliefs (and attitude) on use, social norms and facilitating conditions impact utilization of mobile phones for carbon footprint tasks. The strength of these factors is vital given that the use of the mobile technology to perform carbon footprint tasks is voluntary.

Goodhue and Thompson (1995) purported that more technology utilization is associated with greater performance impact when use of a technology is voluntary. In practice, when technology is frequently used on a voluntary basis, the accomplishment of tasks is achieved effectively and efficiently, by system users, than when the technology is not used. Therefore, it is hypothesized that:

H2: User evaluations on the fit of mobile technology, to perform individual carbon footprint tasks, influence the precursors of utilization, which in turn affect utilization and positively influence performance impacts on individual carbon footprint tasks. Hypothesis H2 is supported by the preceding literature and is decomposed into the following sub-hypotheses, which are also founded in the reviewed literature:

- **H2a**: Task-technology fit will positively influence precursors of mobile technology utilization.

- **H2b**: Precursors of mobile technology utilization will positively influence utilization of mobile phones on carbon footprint tasks.
- **H2c**: Utilization of mobile technology will positively influence performance impacts on individual carbon footprint tasks.
- **H2d:** Individuals with greater mobile phone utilization, in performing their carbon footprint tasks, will achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization.

Chapter 3 : Research Design

The preceding chapter, Literature Review, presented the context of the research in terms of mobile technology, carbon footprint and the setting of the study (i.e. South Africa). As a result of this discussion, the research model was developed and hypotheses of the study were formulated. In this research design chapter, the process used to conduct this research is outlined. To start with, the research philosophy is discussed in terms of the ontological and epistemological notions influencing the research. Thereafter, the purpose, time horizon, approach, strategy and methodology are discussed. This discussion provides a platform for presenting the data collection procedures and analysis techniques for this study.

3.1 Research philosophy

The philosophical stance of a researcher is based on the ontological and epistemological assumptions that influence the research.

3.1.1 Considerations on Ontology

Ontology is the nature of reality (Creswell, 2009; Guba, 1990; Saunders et al., 2009). This reality is whether the researcher views knowledge as existent or constructed. Thus, an ontological view reflects on what exists in the world (Chalmers, 2009). When reality is considered as existent and based on established facts, the researcher adopts a realist view that a single reality exists and can be measured (Lincoln et al., 2011). On the other hand, a relativist view is that reality exists in multiple forms dependent on the researcher and the researched (Guba, 1990). These views present the ontology from which the view of reality for this research was considered.

3.1.1.1 Realist View

Origins of realism can be traced back to 1948 (Chalmers, 2009). Realists claim that facts on what exists are objective (Jenkins, 2010). This posits that there is an objective fact on the existence of matter under study. The question of objectivity is what separates realists from anti-realists.

3.1.1.2 Relativist View

Chalmers (2009) opines that relativism is a form of anti-realism. In this argument, he contends that there is no fact of the matter in explaining the existence of things and that many ontological frameworks exists, further maintaining that some frameworks are more suitable than others depending on the requirement. Relativists maintain that assertions on what exists have an assessment-relative truth-value that is assessable through the principles of the different frameworks (Chalmers, 2009). By this claim, the assessment of the truth values depends on the standards of the context and results in reality that is constructed relative to the assessor and the assessed.

3.1.1.3 Selected Ontology

To answer the present research questions, the researcher used existing theories in technology fit and theories of attitude and behaviour. These existing theories were used to explain cause and effect and support generalizations in technology acceptance, utilization and individual performance. In addition, carbon footprinting has been examined through use of greenhouse gas emission factors, life cycle assessments, carbon tax and other offsetting measures. Given that reality in this research context is based on presence of facts such as emission factors, technology fit and theories of attitude and behaviour, the researcher adopted a **realist** ontological notion.

3.1.2 Considerations on Epistemology

Epistemology is the branch of philosophy which concerns itself with the theory behind knowing (Saunders et al., 2009). This philosophy informs how the researcher knows the reality under study. Creswell (2009) refers epistemology as the knowledge seeking process which lies in the relationship between the researcher and the researched. To acquire knowledge, the researcher can adopt an objective standpoint, which is depended on what can be measured without interacting with the researched (Lincoln et al., 2011). Alternatively, the researcher can adopt a subjective view and also have an opinion about the researched phenomena, in order to construct the reality based on the interaction between the researcher and the researched (Guba, 1990). Epistemology in research can be categorised into positivism, interpretivism, critical inquiry (Orlikowski & Baroudi, 1991) and post positivism (Guba, 1990).

3.1.2.1 Positivism

Positivist epistemology was coined by Auguste Comte (Smith, 1998) initially with the natural sciences and then subsequently in the social sciences (Mack, 2010). The scientific assumptions of a researcher in the natural sciences are adopted by a positivist and applied to a social science research (Smith, 1998). This philosophical stance requires observation of social entities, use of existing theories, development and testing of hypotheses (Saunders et al., 2009). The hypotheses are either verified or rejected, leading to more theory development and testing in further research. Thus, positivist studies are predominantly used for theory testing (Orlikowski & Baroudi, 1991). Theory testing often leads to research that predicts an outcome in the researched phenomena. However, positivist studies are not all about theory testing and prediction. While some positivist studies possess measures that can be quantified and hypotheses that can be tested others are descriptive studies (Orlikowski & Baroudi, 1991). The latter studies are aimed at providing facts as their contribution to the literature. While unscientific studies are based on values, positivist studies thrive on facts (Smith, 1998). Therefore, facts can be considered as the building blocks for social scientific studies.

The researcher cannot change the facts of the matter and bias is eliminated (Guba, 1990). Thus, the researcher does not influence the outcome. Although positivist studies claim to be value-free, the choice that the researcher has on the research and the research objectives imply that an absolute exclusion of choice is not possible (Saunders et al., 2009). The researcher still assumes control of the research by delimiting the scope of the research.

Positivism relies on the existence of cause-effect relationships in the researched phenomena and these are usually investigated in a structured manner (Orlikowski & Baroudi, 1991). This use of structured procedures and techniques ensures reproducibility (Saunders et al., 2009). Through observations, which are quantifiable, the use of statistics for data analysis is enabled (Saunders et al., 2009). Statistical computations, when based on established facts, result in confirmation or rejection of scientific assumptions.

Observation through the human senses fulfils the existence of matter (Smith, 1998). The existence of an object is questioned if none of the senses can observe that object. The observation of objects is the starting point for the development of scientific laws (Smith, 1998). After observation, relationships between entities are investigated with the goal of determining cause and effect – the equivalent of scientific laws.

3.1.2.2 Post positivism

The criticism of positivism gave birth to post positivism (Guba, 1990). By its very nature, post positivism still has a scientific perspective towards research (Creswell, 2003). Post positivists adopt a view that although an objective reality exists, it cannot be perfectly observed as human senses are flawed (Guba, 1990). This calls for researchers to be more critical of their research in light of this imperfection. Post positivists also assume a less stringent form of realism by allowing the critic of their methods from peers and readers (Guba, 1990). This critical review allows for more alignment with other studies in order to achieve objectivity. Thus post positivists believe in several viewpoints rather than a single reality (Creswell, 2003) that is asserted by positivists. Guba (1990) declared himself as a constructivist but his comparison of positivism and post positivism is appropriate to show the salient differences between these approaches. Table 3.1 shows some of the important differences between these approaches.

Table 3.1 Comparison between positivism and post positivism (Guba, 1990).

Positivism	**Post positivism**
Reality is based on facts	Reality is based on imperfect and probabilistic understanding
Findings are a single reality	Findings are probably a single reality
Methods are experimental or manipulative;	Methods are modified experimental or manipulative;

Positivism	Post positivism
Includes verification of hypothesis; Mainly quantitative methods	Involves falsification of hypothesis; May include qualitative methods

3.1.2.3 Interpretivism

Interpretivists critic positivists and believe that social problems cannot easily be generalised as they are quite complicated and unique (Mack, 2010; Saunders et al., 2009). In doing so, interpretivism assumes a relativistic understanding of the researched problem and rejects the prospect of an objective reality underlying positivism (Orlikowski & Baroudi, 1991). Thus, interpretive studies aim to understand the core of a problem, but do not seek to generalize findings from the researched area to the population (Orlikowski & Baroudi, 1991). Instead, researchers produce or inductively build up theory or models (Creswell, 2007) which can be referenced in other settings.

An interpretivist views reality as socially constructed, subjective and existing in multiple forms (Saunders et al., 2009). This requires the researcher to be part of the researched phenomena and provide a personal view on the matter (Orlikowski & Baroudi, 1991). The interpretive inquiry ensures a knowledge gathering process that is culturally derived (Crotty, 1998). This results in interpretations that yield a collective understanding of the society.

The interpretivist has to comprehend the research subjects' world from the viewpoint of the subject (Saunders et al., 2009). To do this, the researcher learns clearly how the participants live their life by asking open ended questions (Creswell, 2007). The contexts in which the participants work and live enable the researcher to understand the cultural and traditional settings of the people (Creswell, 2007). This, in turn, allows the researcher to understand the meanings participants attach to the research context.

Given that interpretivist studies aim to understand phenomena (Mack, 2010), this made interpretivism less appropriate to fulfil the research goal, which seeks to explain and predict the performance impacts on carbon footprint tasks.

3.1.2.4 Critical inquiry

Critical studies seek to understand phenomena in social systems and critique its existence with the purpose of changing the conditions in the society (Orlikowski & Baroudi, 1991). Critical theory approaches deal with empowering people to rise and overcome the restrictions placed on them by social stereotypes (Creswell, 2007). Such stereotyping could be based on gender, race and social class and may lead to oppression. With regards to information systems, critical research explores social issues with regard to the build, usage and impact of information technologies (Myers & Klein, 2011). This allows researchers to challenge existing assumptions in the life cycle of information technology and its users.

Myers and Klein (2011) suggest critical research to comprise of three elements, namely insight, critique and transformation. The insight element provides deeper understanding of the problem. The critique element requires critical theorists to reveal what the situation is meant to be and the justification of why the current social practice is the way it is. This often leads to revealing of the limitations in current social practices (Orlikowski & Baroudi, 1991). For the transformation element, suggestions to improve the social conditions and social theories are considered.

For this research, critical inquiry was not appropriate as this study aims to measure the fit of a mobile approach towards estimating and offsetting carbon footprint, rather than critique and transform the research participants' views or critique the South African community with regards to its history.

3.1.2.5 Selected Epistemology

The epistemological assumptions of this study have been guided by the research questions. These questions seek to (1) explain the fit of a mobile approach to estimate and offset carbon footprint (2) to predict the performance impacts on individual carbon footprint tasks. Given the need to explain and predict social phenomena and the existence of prediction theories and models, the appropriate epistemological assumption of this study was rooted in positivism.

The present research model has been developed from an existing model of technology-to-performance chain model using existing theory in task-technology fit. This model is used to explain causality in task-technology-individual constructs, task-technology fit, technology utilization and individual performance. While some of the constructs have been reduced into simpler elements, other concepts have been operationalized into variables which can be measured quantitatively. This is shown in Table 3.2. The research model in Figure 2.7 also illustrates causal links representing relationships which can be tested. This presentation of the model, as a starting point of the research, shows the adoption of a deductive approach which aims to test the theory presented. The testing of hypotheses produces knowledge (Mack, 2010). Quantitative data are collected to quantify the measures and determine whether the hypotheses postulated are supported by the collected data. A sample of a representative size was selected in order to generalize the theory in the target population.

User ratings on mobile technology were collected and quantified to determine the cognitive fit of technology on carbon footprint tasks. The user ratings are independent of the researcher's presence and reveal how the users view the technology. Additional data on individual's attitude and beliefs was collected without the researcher's values influencing the outcome. Given that the data was collected in a manner that minimizes bias such as through randomly selecting the sample population, and the researcher assuming a distant posture, this shows the externality of the reality to the researcher - a characteristic of positivist studies. Furthermore, the hypotheses formulated in the previous section propose the verification of hypotheses. Confirmation of hypotheses is typical of positivism.

3.2 Research purpose

The main purposes of a research are exploratory, descriptive and explanatory (Saunders et al., 2009). Even though a research purpose could be one of the above mentioned purposes, a study could have at least one purpose (Saunders et al., 2009). For instance, a research can be descriptive and explanatory.

Descriptive research answers questions such as: where, when, what, why and who (Grimes & Schulz, 2002). These questions, provide a background to phenomena (Saunders et al., 2009). For new areas of inquiry, descriptive questions present knowledge necessary to facilitate further investigations. For scientific studies, descriptive studies reveal the characteristics of a phenomenon (Teddlie & Tashakkori, 2009). These attributes are determined through observations.

In social sciences, Stebbins (2001) stress that exploratory research may involve much labour. This work is related to conducting time consuming field work with the field experts or searching the literature (Saunders et al., 2009). In either case, lessons learned are reported. Despite the work required, this sort of work in exploratory studies generates information about new angles of the problem (Teddlie & Tashakkori, 2009). These new insights allow understanding of the problem and answering of the research questions with the knowledge gained (Saunders et al., 2009).

Explanatory research (as with exploratory) builds on descriptive studies (Saunders et al., 2009). The foundation provided is the attributes of the phenomena. However, explanatory studies are aimed at inquiring about cause and effect within phenomena (Teddlie & Tashakkori, 2009). This requires explanatory research to focus on explaining the relationship between variables in a causal or correlational sense (Saunders et al., 2009).

Given the nature of the research questions; they seek to explain the fit of mobile technology for carbon footprint tasks and to predict the technology's impact of the individual tasks. This requires neither a descriptive nor an exploratory research purpose. Therefore, the research purpose that was appropriate for this study was **explanatory**. An explanatory study was more likely to answer the research questions and fulfil the stipulated objectives.

3.3 Time Horizon

The time horizon of a study is the time frame under which the research is conducted (Saunders et al., 2009). This execution of a study in relation to timings can be categorised as either cross-sectional or longitudinal (Janson, 1981; Saunders et al., 2009). Furthermore, the number of times the data are collected from research participants is a distinguishing characteristic between cross-sectional and longitudinal studies. Both cross-sectional and longitudinal studies are classified as observational studies (Mann, 2003). The researcher merely observes the research participants with no interventions.

Cross-sectional studies are observational studies conducted at a single time instance, or short period of time for participating individuals (Levin, 2006; Mann, 2003). A cross-sectional analysis is ordinarily carried out to assess the prevalence of an outcome for a specified population (Levin, 2006). Prevalence is the frequency of cases at a particular time in a population (Mann, 2003). The number of cases is a result of data collected on individual characteristics as well as the outcome at a point in time (Levin, 2006). This provides a snapshot of cross-sectional data.

Although cross sectional data can be acquired within a short period of time (Mann, 2003), the collection of such data at another time does not guarantee similar results to the initial results (Levin, 2006). Mann (2003) suggests that a cross-sectional study can be conducted through the formulation of research questions, sample selection, identification of variables, collection and analysis of data. Furthermore, while many cross-sectional studies are conducted with questionnaires others are done using interviews. Cross-sectional studies are good at estimating prevalence and associations between variables (Levin, 2006). However, they do not distinguish these associations with causal relationships (Mann, 2003). This failure to differentiate or explain is due to the cross-sectional study's design that focuses on data at a specific time instance and not before or after an activity.

Theodorson and Theodorson (1969) cited by Janson (1981) define longitudinal studies as the study of phenomena in successive time intervals. The collection and evaluation of data over a series of timings in longitudinal studies present a useful insight into the change and the factors influencing the change in the individual's life (Schouten & Tager, 1996). The analysis of the factors allows determination of the effectiveness of systems or procedures in the different phases of life. These longitudinal studies also allow the review of trends. A longitudinal method involves measuring the same individuals over successive periods of time (Janson, 1981). Therefore, as long as individuals are measured at least once, the study can be considered as longitudinal regardless of the length of the study. The repeated measurements provide longitudinal data which allows identification of progress and changes in study participants (Fernando & Ravanera, 2000). The results may show stability or growth in individuals and systems.

The nature of a research question can determine whether a phenomenon requires to be researched through a once off measurement or continuously over a longer period of time. Saunders et al. (2009) argue that an academic research can be a longitudinal study provided the research is started on time and the research question requires such a time horizon. Regardless of the time available to this research, a **cross-sectional study was appropriate** as the research questions seek to explain the impact of a mobile phones on individual carbon footprint tasks. Furthermore, the research model has been developed to exclude the impact of individual feedback on the fit of mobile technology and its utilization. This elimination of feedback obliterates the need of a longitudinal study.

3.4 Research Approach

The main reasoning methods are inductive and deductive approaches (Saunders et al., 2009). A research approach that is inductive starts with the gathering of data and ends with the generation of theory (Creswell, 2003). The gathering of data ensures that the study has observations that can then be interpreted (Hayes, 2000). This interpretation of the observations results in the derivation of meaning. In qualitative studies, Creswell (2003) suggests that inductive approach can be conducted through steps such as (1) gathering required data, e.g. through use of open-ended questions or using existing records, (2) analysis of data to form themes or categories, (3) use of themes or categories for identification of patterns, generalizations or theories and (4) developing of theory or generalizations. This process, of deriving theory from data, is more appropriate for a study that seeks to understand a research phenomenon in order to generalise the findings.

Deductive approach is a scientific method involving testing of hypotheses and deducing meaning from the test results (Hayes, 2000). This method of reasoning allows the researcher to find confirmation of the hypotheses (Saunders et al., 2009). The hypotheses are narrowed down from the theory informing the study and the confirmation is based on observed cases. Hayes (2000) suggests that a hypothetico-deductive approach starts with theory formulation, followed by a proposal of hypotheses, then observations are conducted and the hypotheses are tested. The result of hypothesis testing is used to determine whether observations conducted (on the research participants) support or challenge the theory. Support of the theory means that the observations are what the theory predicted while challenging of theory entails that other explanation is required.

The present research adopted the technology-to-performance chain model, developed the research model and proposed hypotheses. Hence, a deductive approach was selected for this study as the researcher showed the initial selection of theory towards confirmation of the initial theory. This is also in line with the ontological notion of this research that there is a single reality that can be tested objectively.

3.5 Research Strategy

Research strategies include experimental, survey, grounded theory and case study. The selection of these strategies is not based on superiority, but on several factors regarding how suitable the strategies are for the study (Saunders et al., 2009). A research strategy is informed through the nature of the research questions (which in turn determine the objectives of the research), the extent of current literature and availability of resources (Saunders et al., 2009). Furthermore, the study's choice of a research strategy is influenced by factors such as the epistemological perspective (positivist, interpretivist, critical, etc.) and the research approach (deductive or inductive) (Gray, 2013). These factors determine the way research is conducted, for example, in a scientific way or socially constructed and also whether the study begins with theory or theory results from the data.

3.5.1 Experimental strategy

Experimental research strategies involve conducting of empirical tests for testing hypotheses under controlled conditions (Guba, 1990). The experiment may result in the hypotheses to be supported or rejected under the conditions of the experiment. With experiments, research participants are randomly allocated to either a control group or an experimental group (David & Sutton, 2004; Gray, 2013). After group allocation, the characteristic to be measured (dependent variable) is observed for both experimental and control groups (David & Sutton, 2004). These observations, at the start of the study, are part of the pre-testing involved in experimental research.

Thereafter, an independent variable is used to manipulate the subjects in the experimental group while the participants in the control group remain unaffected (David & Sutton, 2004; Gray, 2013). This exposure of the subjects to the independent variable allows the researcher to determine its effects on the outcome variable. Following the manipulation or treatment, the characteristic initially measured is observed again in both groups. This constitutes a post-test. Finally, the observations, on both groups, for the pre-test and the post-test are analysed (David & Sutton, 2004).

Although experiments are more appropriate in natural sciences they can also be conducted in the social sciences, but are faced with challenges such as in obtaining demographically similar experimental and control groups from random samples (Gray, 2013). Since the main goal of experimental strategy is to prove the effect of the 'treatment' between the control and the experimental groups, it is vital for these groups to be similar with regards to demographic variables such as gender, age, occupation, etc. This requirement makes conducting true experimental studies more difficult in the real world as the use of random samples makes gathering similar groups a challenge. In light of this challenge, quasi-experimental strategies are often conducted.

Although experimental strategies are scientific, deductive and suit the positivist (Gray, 2013; Guba, 1990), the selection of similar groups at random is a challenge and the introduction of the treatment is also difficult (David & Sutton, 2004). Therefore, the experimental strategy was not considered as appropriate for the present research.

3.5.2 Case study

Case studies seek to describe or explain a case or set of cases (Yin, 2011). The case might be a situation (Yin, 2011), area, organization, an individual (David & Sutton, 2004) or a group of individuals (Benbasat, Goldstein & Mead, 1987). To conduct a case study, a combination of data collection techniques can be employed to collect data (Saunders et al., 2009) and generally field related data are used (Yin, 2011). The varying techniques are important to provide qualitative or quantitative data required for the in-depth study of the case.

A case research strategy can be selected if the research area has limited knowledge (David & Sutton, 2004) and the research seeks to explore the phenomenon (Benbasat et al., 1987). This pursuit of knowledge might result in a longer period to conduct field work and analysis. Also, the intensiveness of case studies identifies grey areas and generates hypotheses (Benbasat et al., 1987). These hypotheses need not be tested by the case study, but future research may find them useful.

Although information for case studies may sometimes originate from experimental studies (Marczyk, DeMatteo, & Festinger, 2005) there is no use of experimental techniques, such as manipulation, in the case study itself (Benbasat et al., 1987). This entails that the researcher may not start the study with a set of independent variables, but rather with just an idea of the phenomenon. Thus a researcher may start the enquiry with a drive to answer the "how" and "why" research questions (Benbasat et al., 1987). These questions seek to acquire a comprehensive aspect of the researched phenomena. This inquiry might need to be unearthed over time.

However, Marczyk et al. (2005) argue that case studies can only describe and are not able to explain the researched phenomena. In addition, they are more susceptible to researcher bias than other strategies. This is because, in order to ensure thoroughness, the interaction between the case and the researcher is more in case studies than with other research strategies. Another disadvantage of case studies is that the small number of participants makes it difficult to infer the results to other similar populations (Marczyk et al., 2005). That is, generalization is less likely with case studies due to the very small sample size. This assumption is disputed by some studies, e.g. Flyvbjerg (2006) which argue that a single case makes it possible to infer to other cases due to the in-depth analysis conducted in that case.

Since the present research adopted a positivist stance, the researcher undertook a research strategy that allowed drawing of generalizations and reduction of bias. The pursuit for generalizations and no research bias made case studies inappropriate for this scientific inquiry.

3.5.3 Grounded theory

Grounded theory is focused on deriving theory that is grounded in the data (Merriam, 2002). This research strategy involves inductive reasoning and allows the derived theory to explain the data it originates from. Studies using grounded theory start with a setting of the real world problem and develop theory from this setting that provides further understanding of the situation (Strauss & Corbin, 1990). Therefore, the generated theory is more applicable to the setting and resembles the practical issue since it emanates from the data.

Studies use grounded theory to build substantive theory (Merriam, 2002). The theory is specific and deals with real-world problems. The constant comparative method is used to analyse data collected for this inductive study (Merriam, 2002). This method is aimed at deriving the theory's elements by continuously comparing new data units with previously collected data. As a result of conducting grounded theory, hypotheses may be suggested (Merriam, 2002). As these are merely suggestions, they are not required to be tested by the study that produces them.

Given that the research approach was deductive, this made grounded theory inappropriate as it involves the use of an inductive approach.

3.5.4 Survey

In the Information Systems (IS) discipline, a survey research is a common research strategy for studies inquiring user involvement (Ives & Olson, 1984). In these surveys, information is collected from the users of the systems in question. Surveys collect information from people that pertain to them or the setting they belong (Forza, 2002). While surveys gather information about individual characteristics or views of the researched phenomena, survey research comprise of surveys aimed towards attaining scientific knowledge (Pinsonneault & Kraemer, 1993). Survey research can be executed with designs that are cross-sectional, repeated cross-sectional and mixed (Visser, Krosnick, & Lavrakas, 2000). Creswell (2003) suggests that further to the existence of cross-sectional designs, surveys can also take the form of longitudinal studies with the use of data collection techniques such as questionnaires or structured interviews. The prevalence of survey strategy, in IS, is partly due to the ability of survey research to fulfil a number of research purposes. Survey research can fulfil research purposes which are exploratory, descriptive and explanatory (Forza, 2002). Thus, a survey research can be an exploratory survey research, a descriptive survey research or an explanatory survey research.

Exploratory survey strategies are carried out, as an entry point, to gain initial understanding of a research area as a foundation for further in-depth survey strategies (Forza, 2002). This exploratory survey is used to find possible responses, from the target population, in order to refine the observed measures (Pinsonneault & Kraemer, 1993). This refinement involves determining the optimal ways to measure concepts in the researched phenomena and uncovering new concepts to be considered. Although exploratory surveys are important as they provide the basis for other survey purposes, Pinsonneault and Kraemer (1993) suggests that exploratory surveys should not be used as the main purpose but rather for the development of concepts for further in-depth research.

Descriptive survey strategies are aimed at providing survey research that describes the spread of the researched phenomenon in the target population (Forza, 2002). This information improves the understanding of the researched area. Descriptive survey research establishes facts rather than testing of relations between variables (Pinsonneault & Kraemer, 1993). Thus the most important goal is to survey research participants to gather evidence on the reality of the research phenomena. The evidence is in the form of the participants' views, attitudes and situations surrounding them.

Explanatory or confirmatory survey strategies involve the conducting of surveys to collect data that can be used to test existing theories or models through proposed hypotheses of the phenomenon (Forza, 2002). Explanatory survey research is therefore aimed at testing relationships between variables which are hypothesized to be causal. Furthermore, prior to designing a survey research, a theoretical framework or model applicable to the research domain is essential (Forza, 2002). This is the model with concepts that require to be measured through the data collected by the surveys. Pinsonneault and Kraemer (1993) suggest that explanatory survey research is appropriate when the research questions seek for an explanation of the existence of a causal relationship and sometimes as well as to why the relationship exists.

The survey strategy is characterized by the gathering of quantitative measures of the phenomenon through the use of pre-defined questions about individuals based on a sample of the target population (Pinsonneault & Kraemer, 1993). This quantitative data obtained from surveys can describe trends or the views of a population by only studying a sample of the population (Creswell, 2003). Such a collection of quantitative data allows statistical analysis, be it descriptive or inferential. Although the survey research strategy is appropriate to answer questions pertaining to "what","how" and "why" in the phenomena's natural setting, the strategy is less appropriate when in-depth understanding of the history and social setting of the phenomena is required (Pinsonneault & Kraemer, 1993). The potential of the survey research to answer a wide range of questions is made possible through the possibility of exploratory, descriptive and explanatory survey researches. However, in-depth analysis of a phenomenon in a natural setting is best achieved through case studies. The survey research strategy is also faced with potential errors which are synonymous with surveys and these include coverage, sampling, nonresponse and measurement error (Visser et al., 2000). These errors may result in insufficient or inaccurate information to be collected from the population, thus compromising the quality of the results and the generalizability of the findings.

Since the survey strategy can be executed with research purposes such as exploratory, descriptive and explanatory, in both cross-sectional and longitudinal designs this strategy provided the researcher with greater flexibility. The possibility of conducting explanatory survey research allowed the researcher to use this strategy to confirm the theory informing the present research. Furthermore, the collection of quantitative data fits the realist stance adopted by the researcher that a single reality exists and can be measured objectively. The use of a sample, which was carefully selected, ensured that the selected sample was representative of the target population and therefore allowed generalizability of the research findings. This generalizability, is characteristic of the researcher's positivist stance.

3.5.5 Selected strategy

The **survey strategy** was the appropriate research strategy based on the nature of the research questions, availability of theory, research philosophy, and research purpose and approach. The research questions seek to obtain an explanation on how the fit of mobile phones influences the performance impacts of mobile carbon footprint calculators for individuals. Furthermore, the research seeks to determine the impact, on carbon footprint tasks, of mobile technology on users when compared to non users of the technology. These questions have directed the research purpose to be explanatory. The adoption of a theoretical model to test the empirical domain of a carbon footprint is consistent with a deductive approach. Also a cross-sectional timeframe was selected and the research philosophy was based on the realist ontology and positivist epistemology. These factors made an explanatory survey research the appropriate research strategy for this study. Hence, a sample was drawn from a target population and data was collected on individual characteristics and their views, in order to facilitate the testing of the research model.

3.6 Methodology

A research methodology outlines the plan for conducting a research and informs the choice of methods to collect and analyse data (Creswell, 2003). The main methodologies are qualitative, quantitative and the mixed methods approach (Saunders et al., 2009). The selection of a methodology is depended on the research questions (Saunders et al., 2009) and the knowledge claims underlying the research (Creswell, 2009; Guba, 1990). Both criteria were considered in selecting the appropriate methodology for this study.

3.6.1 Qualitative

Qualitative research is a study that produces a theoretical explanation of a phenomenon through the analysis of data interpretatively rather than mathematically (Strauss & Corbin, 1990). The theory is developed through interpreting data acquired through different participants and researchers, to discover emerging notions and relations. This does not rule out quantification completely as responses may need to be at least counted as in census data.

However, the majority of the analysis involves interpretation rather than statistical computations.

Qualitative research is often conducted when the research problem requires understanding of what the participants think and do and there is limited understanding (Strauss & Corbin, 1990). Thus, in ideal cases, the nature of phenomena determines whether qualitative inquiries are required in order to develop theories to further the understanding of the practical issue. In other cases, Strauss and Corbin (1990) suggest that preference to qualitative research is sometimes informed by the choice of the researcher based on the researcher's background and experience in the qualitative field. Some researchers tend to have studied more qualitative inquiries and tend to prefer these studies due to their own inclination. In view of preference, qualitative research is conducted through beliefs based in interpretivism/constructivism (Creswell, 2007). Ontologically, when researchers study participants in qualitative research, the purpose is to report on the different realities as viewed by the participants, researchers and the readers. The researcher conducting a qualitative study maintains a close distance to the research participant (Creswell, 2007). This ensures that the researcher gets immediate information from as close to its source as possible. Creswell (2007) suggests that an inductive research approach is prevalent in qualitative studies. This inductive approach suits generation of theory to explain the participants' situation.

Yin (2011) characterise qualitative research with five features, which are; (1) qualitative research allows studying the lives of participants in their natural environment (2) representing the values and meaning of phenomena as viewed by the participants (3) includes the conditions in which the participants live (4) building new concepts to explain social behaviour (5) ensure credibility by using various sources of information to reach conclusions. These features ensure that participants are free to express their views without being restricted to the responses they provide as well as the setting of the environment. New concepts are often aided through procedures such as coding (Strauss & Corbin, 1990), which include categorization of data.

Strategies for qualitative inquiry include action research, case studies, ethnography, grounded theory, and phenomenology studies (Yin, 2011). This list is not exhaustive, as there are many more strategies available for qualitative researchers.

3.6.2 Quantitative

Use of quantitative studies, as with qualitative studies, depends on the research purpose (Cohen et al., 2007). Quantitative studies are by no means better or worse than qualitative but are appropriate if they fit the study (answer the research questions). In addition, the quantitative methodology is more appropriate for the post-positivist (Creswell, 2003) and positivist (Cohen et al., 2007; Creswell, 2003). These knowledge claims primarily use realist and objectivist notions to develop knowledge (e.g. through causal models, reductionism and hypotheses testing), use experimental and survey strategies, and collect numeric data using predetermined instruments.

Creswell (2003) suggests that quantitative studies tend to embrace deductive approaches as they start with a theory which needs to be tested or advanced. To make use of a theoretical framework/model, variables showing relationships in the model are identified and research hypotheses are presented. Quantitative variables vary in size (Marczyk et al., 2005). For example, reporting on the number of times a system fails can be recorded in a quantitative variable. Variables often used in quantitative studies include independent (input) and dependent (outcome) variables (Cohen et al., 2007). The dependent variable is thus affected or caused by the independent variable either in part or in full. The need to expose the relationship between these variables is often one of the purposes of conducting a quantitative study.

Quantitative studies are often conducted through the use of experimental and survey research strategies (Creswell, 2003). Although experiments are the original scientific strategies for quantitative research, they are faced with criticism with the way they control the environment and this has led to quasi-experimental strategies to be employed (David & Sutton, 2004).

Numeric data are collected using closed-ended and predetermined questions on a research instrument or test (Creswell, 2003). This data could be such as ratings, performance scores or test scores. An important aspect in quantitative studies is to ensure reliability of the research instrument. Reliability is crucial in order to determine the consistency of the data collection instrument (Cohen et al., 2007). A test for reliability can be conducted statistically using Cronbach's alpha. This test is often conducted before the data are analysed.

After any issues relating to reliability are resolved, the numeric data are analysed using statistics. To aid the analysis, computer software such as Statistical Package for Social Sciences (SPSS) and even Microsoft Excel can be used to perform statistical analysis (Cohen et al., 2007). This software can carry out rudimentary calculations to complex statistical computations. Numerical analysis in quantitative studies involves handling variables, use of appropriate data scales, and handling of distribution dependent or distribution free data analysis, computing descriptive and inferential statistics (Cohen et al., 2007).

On the scales of data, namely nominal, ordinal, interval and ratio scale (Cohen et al., 2007), nominal and ordinal scales are categorized as nonmetric while interval and ratio scales are metric. Although the metric scales are quantitative in nature (Marczyk et al., 2005), the nonmetric scales are also useful in quantitative studies as descriptive statistics can be derived from these scales of measurement.

Distribution of quantitative data determines whether parametric or non-parametric statistical analysis is used (Wagner et al., 2012). Parametric data assume a normal data distribution while non-parametric data make no assumptions on the data distribution (Ghasemi & Zahediasl, 2012). Thus, selection of statistical tests depends on the assumptions made on the data. An experimental research strategy is the main source of parametric data while questionnaires and survey strategies tend to produce more non-parametric data than parametric (Cohen et al., 2007).

Descriptive statistics offer reporting of the quantitative data collected (Cohen et al., 2007). These include as median, mean, mode and standard deviation. They merely describe the data and no inferences are extracted from them. To infer and predict using quantitative data, inferential statistics are used (Cohen et al., 2007). The examples of inferential statistics include t-tests and analysis of variance. These allow for testing of hypothesis together with other data analysis techniques such as regression and structural equation modelling. Following hypothesis testing, results are discussed and conclusions are drawn.

3.6.3 Mixed methods

Mixed method methodology refers to the use of data collection techniques and data analysis procedures from both quantitative and qualitative methodologies in the same research (Saunders et al., 2009). The data collection instruments may include both open and closed-ended questions, resulting in narrative, nonmetric and numeric data (Creswell, 2003). In mixed methods, this data can be analysed using text analysis and statistical analysis.

In addition, it is possible for numeric data to be qualitised (transformed into a narrative) (Saunders et al., 2009). This 'qualitisation' enables metric data to be analysed qualitatively. On the other end, qualitative data may be quantitised (transformed to numerical data) (Saunders et al., 2009). This 'quantitisation' enables nonmetric data to be analysed with quantitative data analysis procedures. Qualitisation and quantitisation gives the advantages gained from both methodologies and the freedom to choose which methods and procedures best suit the study (Creswell, 2003). However, their weaknesses are also perpetuated.

The adoption of mixed methods is informed through pragmatic reasoning, which is pluralistic and problem-centered (Creswell, 2003). The pragmatist philosophy is that the research questions best inform the ontological and epistemological views adopted by the researcher and when the questions lean to neither positivist nor interpretivist, this confirms the possibility of working with variations of ontology and epistemology in the same study (Saunders et al., 2009). In practice, this entails the use of both qualitative and quantitative methods in a single study. Furthermore, the study adopting a pragmatic stance assumes perspectives of both observed and multiple realities as well as subjectivism.

3.6.4 Selected Methodology

This study was conducted for an explanatory research purpose, to investigate the effect of mobile technology in the estimation and offsetting of carbon footprint for individuals. To meet this purpose, the researcher adopted an existing model from the Information Systems domain in order to solve a problem in the field of carbon footprint. This resulted in the acceptance of a deductive approach for testing relationships in the hypothesised model. With survey research as the appropriate strategy to collect information on individuals and also to examine the relationships in the collected data, the methodology selected as appropriate for this study was **quantitative**. The selection of a quantitative methodology suits the positivist philosophical stance adopted for this study. Furthermore, quantitative studies can be conducted with a survey strategy as they aid the collection of quantitative data (Creswell, 2003). In addition, the statistical analysis available within quantitative studies paves way for testing of the hypothesized model.

3.7 Data Variables

The selection of a quantitative research methodology requires that the collected data are numeric. This quantitative data are used to assess the relationships between mobile technology, carbon footprint tasks, individual characteristics, fit of technology to the tasks, individual attitudes, technology utilization and performance impacts on carbon footprint tasks. These concepts were measured by expressing items in the research's survey instrument i.e. the questionnaire. This entails operationalization of concepts.

Operationalization is a process that defines constructs into measurable items (Saunders et al., 2009). This produces variables that can be quantified and helps to measure abstract constructs (Marczyk et al., 2005). This study is interested in operationalizing what the constructs of the research model are and how they can each be measured. For example, Goodhue and Thompson (1995) identified the factors affecting task-technology fit and these factors were operationalized through participant evaluations on estimating and offsetting carbon footprint tasks using mobile phones.

The literature identified the independent and dependent variables summarised in Table 3.2, with relevance to the research objectives and constructs in the research model.

Table 3.2 Research Objectives, Constructs and Variables

Research Objective	Constructs	Variables
To measure the relation between characteristics of carbon footprint tasks, mobile technology and individuals with the fit of mobile phones to perform carbon footprint tasks.	Task characteristics (Carbon footprint tasks), Technology characteristics (Mobile), Individual characteristics, Task-technology fit	Independent variables: Carbon footprint estimate, Carbon offset, User Interface, Mobile Network, Education, Computer Self-Efficacy Dependent variables: Quality, Locatability, Authorization, Production timeliness, Compatibility, Systems reliability, Ease of use, Relationship with users
To measure the relation between fit of mobile phones with performance impacts on individual carbon footprint tasks.	Task-technology fit, Performance impacts on individual carbon footprint tasks.	Independent variables: Quality, Locatability, Authorization, Production timeliness, Compatibility, Systems reliability, Ease of use, Relationship with users, Dependent variable: Performance impacts on individual carbon footprint tasks
To measure the relation between fit of mobile phones on carbon footprint tasks and the beliefs and attitude towards technology use.	Task-technology fit, Expected consequences of use, Affect toward use	Independent variables: Quality, Locatability, Authorization, Production timeliness, Compatibility, Systems reliability, Ease of use, Relationship with users Dependent variables: Perceived Usefulness, Voluntariness
To determine the impact of beliefs and surrounding conditions	Expected consequences of use,	Independent variables: Perceived Usefulness, Voluntariness, Technology Support

Research Objective	Constructs	Variables
on utilization of mobile phones in performing carbon footprint tasks.	Affect toward use, Social norms, Facilitating conditions, Utilization	Dependent variables: Frequency of Use
To measure the relation between mobile phone utilization and performance impacts on individual carbon footprint tasks.	Utilization, Performance impacts on individual carbon footprint tasks	Independent variable: Frequency of Use Dependent variables: Performance impacts on individual carbon footprint tasks

3.8 Instrument Design

For survey research, instrument design is concerned with designing the means to collect research data i.e. designing the questionnaire. Instrument choice is influenced by the methodology selected (Cohen et al., 2007). In this case, selection of quantitative methodology requires instruments that can capture quantitative data. Thus, a quantitative data collection technique such as questionnaires in the form of structured interviews was selected to collect the research data. For this study, the questionnaire measures the variables shown in Table 3.2. These variables provide measurements for the constructs of the research model.

Identifying a unit of analysis is essential in informing the level at which the data are collected and analysed (Forza, 2002). The choice of the unit of analysis influences instrument design, methods of data collection and selection of the sample. The unit of analysis for this study is the individual level. For this level, the research instrument was designed to collect data on individual’s attitudes, beliefs and demographics that allowed answering of the research questions.

When developing a survey instrument, a study should consider measurement items that already exist (Forza, 2002). This use of existing measures, for related variables, ensures that the questions are worded and scaled appropriately. Given that a number of measurement items exist to measure the user rating of mobile technology, the researcher adopted existing survey questions. Thus, the instrument was based on the work of (Brown et al., 2003; Davis, 1989; Goodhue & Thompson, 1995; Lee et al., 2007; McGill & Klobas, 2009; Moore and Benbasat, 1991; Sarker and Wells, 2003; Seddon and Kiew, 1996; Staples and Seddon, 2004; Taylor and Todd, 1995; Wilson, 2001). The selection of items from these sources was argued to yield appropriate measures and reduce measurement error for the present research.

The design of a questionnaire should also consider the nature of the questions (open-ended or closed-ended), response options and the order of the questions (Visser et al., 2000). While open-ended questions allow subjects to provide answers in their own words (Saunders et al., 2009), this requires a coding scheme to be developed for each question and multiple coders to reach the established coding agreement (Visser et al., 2000). In closed-ended questions, subjects choose responses from pre-determined set of options provided by the researcher (Saunders et al., 2009). These eliminate the need for coding and therefore are less time consuming when compared to open-ended questions (Visser et al., 2000). Although it is possible for a questionnaire to have a mixture of open-ended and closed-ended questions (Saunders et al., 2009), the present research designed a questionnaire with **closed-ended questions** only. Even though the selection of closed-ended questions reduces the options for the responded, the options provided are self-coded and allow for quicker data analysis.

Opinion data are often collected using rating questions (Saunders et al., 2009). Given user ratings on mobile technology was expected, rating questions were used. In addition, category questions were designed to obtain the respondents biographical data. Since rating questions were designed, the **Likert-style rating scale** shown in Table 3.3 was adopted. This selected scale has five points to allow for a neutral point to be selected by the respondents. The questions are designed to check for agreement, frequency and likelihood.

Table 3.3 Likert Scale (Saunders et al., 2009).

Rating Type	**1**	**2**	**3**	**4**	**5**
Agreement	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Frequency	Never	Rarely	About half the time or Sometimes	Frequently	Always
Likelihood	Not at all	Slightly	Moderately	Very	Extremely

Level of quality is rated from *Poor* to *Excellent* (Vagias, 2006) with ratings, namely; Poor (1), Fair (2), Good (3), Very Good (4) and Excellent (5).

For the education variable, the respondent was asked to complete the highest education level reached. For standardization with other scales, the education levels were ranked and allocated rankings from High school (1) to Post graduate (5) as; *High school (1)*, *Grade 12 (2)*, *Tertiary (3)*, *Degree (4)*, *Postgraduate (5).*

3.8.1 Development of Survey Instrument

The survey instrument was developed through the use of existing constructs and survey instrument items. Most of the items have already been validated by prior research. Only a few items were developed based on practice in the context of carbon footprint. Table 3.4 shows the constructs and items adapted from prior research. The items for task characteristics were based on practice in carbon footprinting i.e. estimating and offsetting of carbon footprint.

Table 3.4 Adapted constructs and survey items

Construct	**Item**	**Source**
Task characteristics	CFE1: I monitor my energy usage or transport costs CFE2: Estimating my average energy consumption daily or monthly increases my awareness towards using less energy CFO1: Tree planting increases my awareness towards resource conservation.	Developed based on practice as raised by the need to calculate carbon footprint (WWF-SA, 2015) and

Construct	Item	Source
	CFO2: Taking part in renewable energy activities (such as solar and wind energy) increases my awareness towards energy conservation. CFO3: I am likely to contribute towards tree planting activities in the near future CFO4: I am likely to contribute towards renewable energy activities (such as in generation of solar and wind energy) in the near future	offsetting carbon footprint through planting trees (FTFA, 2013).
Technology characteristics	TEC1: I would use the mobile phone to perform my carbon footprint tasks if the network coverage is sufficient. TEC2: I would use the mobile phone to perform my carbon footprint tasks if the phone is always responsive with little or no network downtime. TEC3: I would use the mobile phone to perform my carbon footprint tasks if the user interface is simple to use. TEC4: I would use the mobile phone to monitor carbon footprint if the device keeps update with technology advancements.	(Sarker & Wells, 2003)
Individual characteristics	IND1: I would use the mobile phone to monitor carbon footprint if l could learn the process easily. IND2: Mark the highest education level reached	(Brown et al., 2003; Lee et al., 2007)
Task technology fit Factor 1 – Quality	TTF1: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if the information provided is accurate	(McGill & Klobas, 2009)
Task technology fit Factor 2 - Locatability	TTF2: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if the meaning of data are easy to find out	(Goodhue & Thompson, 1995)
Task technology fit Factor 3 - Authorization	TTF3: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if I have access to data to allow me to achieve my tasks	(Goodhue & Thompson, 1995)
Task technology fit Factor 4 –	TTF4: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if I get the information I need on time	(McGill & Klobas, 2009)

Construct	Item	Source
Production Timeliness		
Task technology fit Factor 5 – Compatibility	TTF5: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if using the mobile system is compatible with all aspects of my tasks.	(Moore & Benbasat, 1991)
Task technology fit Factor 6 – Systems reliability	TTF6: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if the calculator is not subject to unexpected errors	(Goodhue & Thompson, 1995)
Task technology fit Factor 7 – Relationship with users	TTF7: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if user technical support is available when I need it.	(Goodhue & Thompson, 1995)
Task technology fit Factor 8 – Ease of use	TTF8: The mobile carbon footprint calculator would be fit for my carbon footprint tasks if the calculator is easy to use.	(McGill & Klobas, 2009; Moore & Benbasat, 1991)
Expected consequences of use – perceived usefulness	POU1: The mobile carbon footprint calculator would enable me to accomplish my tasks more quickly.	(Davis, 1989)
Affect toward use - Voluntariness	POU3: I am not forced to use the mobile carbon footprint calculator.	(Moore & Benbasat, 1991)
Social norms	POU4: People close to me would think it is important to monitor my carbon footprint using this mobile carbon footprint calculator.	(Taylor & Todd, 1995)
Facilitating conditions	POU5: I would use the mobile carbon footprint calculator if there is sufficient support from service providers.	(Brown et al., 2003; Staples

Construct	Item	Source
		& Seddon, 2004)
Utilization	UTI1: I use a carbon footprint calculator to calculate energy usage or transport costs UTI2: I would use the carbon footprint calculator to calculate energy usage or transport costs in the future	Developed based on frequency of use.
Performance impacts on individual carbon footprint tasks	PEF1: How do you rate your performance on monitoring transport and energy usage? PEF2: I would monitor my energy usage effectively if I used a mobile carbon footprint calculator PEF3: I would monitor my transport usage effectively if I used a mobile carbon footprint calculator PEF4: How would you rate the mobile carbon footprint calculator in carrying out your carbon footprint tasks?	(Seddon & Kiew, 1996).

Table 3.4 shows instrument items that were refined following a pilot survey explained in section 3.11. This pilot study was conducted with five individuals and correspondence with the pilot participants resulted in the refinement of the questionnaire. The final questionnaire is shown in ***Appendix B***. In this questionnaire, the questions have been aligned with the constructs of the research model. A few items were developed for this research based on the literature reviewed (See Table 3.4). The Likert scales illustrated in Table 3.3 have also been inserted in this appendix. The questionnaire is divided into seven sections (Section A – Section G).

Section A has questions to collect biographical data and has been adapted from Brown et al. (2003). The data collected is on gender, age group, education, employment status and possession of a mobile phone for each individual survey participant.

Section B captures data concerning familiarity of respondent with carbon footprint tasks based on the need to calculate the carbon footprint (WWF-SA, 2015) and offsetting carbon footprint through planting trees (FTFA, 2013) or engaging in projects towards renewable energy. The questions seek to find agreement, frequency and likelihood of respondents in performing carbon footprint tasks.

Section C asks questions on the characteristics of mobile phones and the respondent based on the work of (Lee et al., 2007; Sarker & Wells, 2003). There are many characteristics of mobile technology. For instance Baharuddin et al. (2013) reviewed nine empirical studies to determine a number of usability dimensions for mobile technology. However, only the appropriate traits such as user interface, network and technology advancements have been considered.

Section D is based on the eight factors affecting task-technology fit (Goodhue & Thompson, 1995) and instrument items adapted based on the work of (Goodhue & Thompson, 1995; McGill & Klobas, 2009; Moore & Benbasat, 1991). The section probes for the respondents' ratings on these factors affecting task-technology fit.

Section E is concerned with questions about the factors leading to utilization of technology (Goodhue & Thompson, 1995). These factors have been reduced to perceived usefulness, voluntariness, social norms and facilitating conditions. The questionnaire items have been adapted from (Brown et al., 2003; Davis, 1989; Moore & Benbasat, 1991; Staples and Seddon, 2004; Taylor & Todd, 1995).

Section F consists of questions regarding utilization of the mobile carbon footprint calculators. These questions were developed for this research based on the conservation organization's argument that measuring of carbon footprint is the initial step towards reducing carbon footprint (WWF-SA, 2015).

Section G provides questions for measuring individual performance on carbon footprint tasks. These questions were developed for this research based on Seddon and Kiew (1996).

3.8.2 Validity of Survey Instrument

Survey instruments need to be validated prior to their distribution for data collection (Straub, 1989). This validation ensures that the instruments capture the data that is required by the research. Instrument validation resolves problems that arise in measuring of research variables (Straub, 1989). This can be improved through pre-tests and pilot tests.

3.8.2.1 Content Validity

Content validity is the determination of how representative the instrument items are in measuring the constructs they intend to measure (Lynn, 1986). Content validity is vital in the assessment of research instruments (Haynes, Richard & Kubany, 1995; Yaghmaei, 2003) as it builds the field under study with measures that are accurate (Straub, 1989). This enables future research to adapt already validated instrument items and in turn contribute to the body of knowledge. Therefore, content validity particularly becomes more important when new measures are created (Rubio, Berg-Weger, Tebb, Lee & Rauch, 2003) as this imminently requires validation to avoid the use of flawed measures.

In order to establish content validity, experts in the field of research are used to rate research instruments (Grant & Davis, 1997). For this study, four specialists in the subject area were requested to rate the items in the questionnaire. These specialists included environmentalists and mobile application developers and these experts were based in Cape Town. The selection of these reviewers was thus based on their professional experience in the related fields i.e. the environment and software development for mobile phones.

The criterion for rating the items was based on a dichotomous scale of appropriateness. This resulted in a rating with a value of either “appropriate” or “not appropriate” for each measurement item. The rater feedback was valuable in assessing the extent to which the survey items measured the intended dimensions. As a result, appropriate items were retained while inappropriate items were either refined or discarded. Content validity is necessary, but it is by no means sufficient on its own (Sireci, 1998). Additional validity of the constructs is required. However, content validity provides the base from which additional validity can be built upon. Further validity, such as construct validity is discussed in section 3.14.2.2 and assessed in section 4.5.3.

3.9 Target Population

The target population or population is the complete group of entities (e.g. individuals, organizations, plants or other things) with subjects to be investigated (Forza, 2002). A survey is applied to a population that has characteristics to answer the research questions. In addition, this is the population to which the result of the survey applies (Kitchenham & Pfleeger, 2002). This target population should be a representation of all its elements, to allow a sample to be extracted from it.

The literature has identified South Africa as having the greatest greenhouse gas per capita in Africa. Also revealed is the high usage of mobile phones by individuals in the region. These population attributes present a platform to extract data from individuals who ideally possess mobile phones and their everyday activities have an impact on their carbon footprint. Given the greater need to travel to places of interest (e.g. entertainment areas, shopping malls and work) in urban areas relative to rural settlements, there is increased use of private and public transport as well as energy (in the form of electricity) in urban areas. Therefore, the target population for this study is the entire group of individuals living in urban areas, in South Africa, that possess mobile phones, make use of electricity and travel frequently from one point to the other.

To consider an urban area with a variety of transport options as offered by road, rail, air and water, the geography of the main urban areas of South Africa was considered. In addition to geography, data from the census of 2011 in South Africa was used to determine which urban areas had better coverage for electricity and ownership of private vehicles. Although the data used were specific to households, this information was sufficient to inform an urban area with elements characterising the research participants. The data on the population, as of the census of 211 is summarised in Table 3.5 with regards to electricity and ownership of private vehicles per household.

Table 3.5 Population in Major South African Urban Areas

Area	**Population**	**Coverage of Electricity (%)**	**Possession of Private vehicles (%)**
Johannesburg	4 434 827	90.8	38.2
Cape Town	3 740 026	94.0	45.8
Ethekwini	3 442 361	89.9	32.6

This data (Table 3.5) showed that most "urban" people reside in the urban areas of Johannesburg, followed by Cape Town then Ethekwini. However, of the three areas, there are more households with electricity and in possession of more private cars in Cape Town than in Johannesburg and Ethekwini. Furthermore, Cape Town offers most tourist resorts than the rest of South Africa and is thus a tourist attraction. In light of these features, the urban area with the target population is Cape Town.

3.10 Sampling

A sample is a subset of a target population (Forza, 2002). In a sample, only some elements of the population are represented. Kitchenham & Pfleeger (2002) argue that the key concern in drawing a sample is to ensure that the sample is representative of the target population from which it is drawn. Representativeness offers the researcher the ability to generalize the results of the study to the target population.

Considering a possession of mobile phones in South Africa to be 34 mobile phones per 100 individuals (Vodafone, 2007) and an urban area of Cape Town with a 94% coverage in electricity, this presents a target population of 1 195 312 (3740026 X (34/100) X (94/100)). Within a student's budget, this is a prohibitive number of subjects to collect data from. Collecting data from the entire target population can indeed be expensive, both in cost and time (Forza, 2002). However, this difficulty can be overcome by sampling (Saunders et al., 2009). Sampling is the process of identifying an adequate subset of subjects from the target population (Forza, 2002). In view of this, the study considered the selection of a subset of individuals living in the urban area of Cape Town that possessed mobile phones, made use of electricity and travelled frequently from one point to the other.

Sampling techniques can be categorized into probabilistic and non-probabilistic sampling. The sampling technique selected can be influenced by the needs of data analysis techniques such as the use of inferential statistics (Saunders et al., 2009). In this regard, experimental research and explanatory survey researches often aim to make inferences to the target population. Since this study undertakes an explanatory survey research and there exists the need to conduct inferential statistics, a probability sampling technique was found appropriate. Every element of the target population has a chance of being selected in a probabilistic sample (Kitchenham & Pfleeger, 2002). This feature of probability sample ensures that samples are unbiased and representative of the target population.

There are various techniques of conducting probability sampling. These techniques include random sampling or simple random, stratified random, systematic and cluster (Kitchenham & Pfleeger, 2002; Saunders et al., 2009).

Considering the high availability of mobile phones in individuals of the South African public and the coverage of electricity in the urban area of Cape Town, there is a non-zero probability of an individual in the target population being included in the sample of this study. Therefore, the appropriate probabilistic sampling technique selected was random sampling. The selection of this sampling technique eliminates bias and enables generalization of survey results, obtained from the sample, to the target population.

One challenge affecting random sample is the size of the sample. Exceptionally small or even large samples can generate results that inaccurately depict the relationship between variables (Marczyk et al., 2005). These misleading results tend to influence the data analysis. To obtain a scientifically calculated sample size, the study considered the target population (1 195 312), error margin (5%), confidence level (90%) and response distribution (50%). These figures were provided to the Raosoft's sample size calculator and the estimated sample size computed was 271.

In summary, the random selection of 271 subjects from Cape Town was argued to provide a chance of selecting an individual in possession of a mobile phone, make use of electricity and use either private or public transport. This sample captured individuals whose ratings, on mobile phones to estimate and offset carbon footprint, were invaluable to fulfil the objectives of the present research.

3.11 Pilot Study

The survey instrument needs to be tested before distribution to the final research participants (Cohen et al., 2007). This test is required to ensure that the instrument accurately presents the instrument items and collects the data that the researcher intends. In order to test the actual survey instrument, a pilot study was conducted. This initial test of the instrument served to check the ease of comprehension of the questions, identify inappropriate questions, check presentation and evaluate the time taken to complete the questionnaire (Cohen et al., 2007). As a result of the pilot study, any modifications identified were made. This produced a questionnaire which was more relevant and valid for the investigated phenomenon.

An easily comprehensible questionnaire makes it simpler for the subject to provide responses as well as increasing the chance for relevant responses to be provided (Visser et al., 2000). This is argued to reduce survey errors such as measurement and nonresponse errors. These errors, reduce generalizability and ways to resolve the errors should be discovered during pilot testing (Forza, 2002). For purposes which require no generalization of findings, nonprobability sampling can be conducted as it is less complex and inexpensive (Saunders et al., 2009). For this research pilot study, nonprobability sampling was used.

Nonprobability sampling techniques include snowball, purposive, dimensional, convenience, quota (Cohen et al., 2007) and self-selection sampling (Saunders et al., 2009). The selected sampling technique for this pilot study was self-selection sampling. A sample of five individuals who wished to be included in the pilot survey was used. The data collected from the responding subjects were analysed, redundant items were deleted, items were numbered and the layout of the questionnaire was revised. This pilot study was useful in ensuring that the questionnaire was appropriate and ready for distribution.

3.12 Data Collection Procedure

To collect data using surveys, questionnaires need to be administered to the sample. Distributing of questionnaires to respondents can be achieved in a number of ways, such as internet, phone, face to face and through the post (Cohen et al., 2007). Depending on the method used, the researcher might be present or absent. Administering of questionnaires can be categorised based on two modes, namely interview mode and self-administration mode (Bowling, 2005). While interviewer-administered questionnaires are conducted and recorded by an interviewer or researcher, self-administered questionnaires are completed by the subject (Saunders et al., 2009). Self-administered questionnaires include hand delivery and collection, postal and online questionnaires whereas interview based questionnaires are structured interviews and telephone based (Saunders et al., 2009).

Response rate and cost are some of the factors normally used for selecting means for administering questionnaires (Marczyk et al., 2005). Interviewer-based questionnaires are known to yield high response rates (Saunders et al., 2009) and are thus selected when response rate is the major goal (Marczyk et al., 2005). On the other end, self-administered questionnaires are used when cost is a concern.

The researcher understands the limitations of self-administered questionnaires and thus considered using structured-interviews. Although the use of structured-interviews is faced with its own challenges such as the need to travel and perform other administrative work, the research accepts the benefit of high response rates the structured-interviews provide. Also, in structured interviews, the interviewer ensures that the respondent fully understands the survey items.

The traditional pen and paper interview method (Bowling, 2005) was used to conduct the structured interviews and this data collection was aided by trained interviewers or "field workers". The paper-based responses were returned to the researcher and captured into Microsoft Excel. This captured data were then validated for missing values and unusual data combinations, at a case by case basis.

3.12.1 Sites for data collection

The data collection sites for this study were informed by the target population proposed in section 3.9. Given that the target population is based in the City of Cape Town, the sites are derived from this city. At the heart of this city is the Cape Town Central Business District (CBD), which is easily accessed by rail and road (through either private or public transport). Table 3.6 shows sites selected for data collection in the Cape Town CBD. The nature of the sites discussed provides some context to the reader with regards to the sites where data are collected.

Table 3.6 Survey sites

Site Name	**Nature of Site**
Cape Town Train Station	The Cape Town Station is situated at the junction of Adderley Street and Strand Street in the CBD of Cape Town (Turner, 2016). It is the central connection point for public transport such as commuter taxis, long distance buses, short and long distance trains.
Cape Town's Company Garden	The Company Gardens is situated in Queen Victoria Street and attracts visitors both local and foreign due to its vast features (Richmond & Corne, 2012). Features include a pond, restaurant, lawn and benches.
Cape Town's Grand Parade	The Cape Town's Grand Parade is a large open area situated on the northwest of the Castle of Good Hope (McCrea & Pinchuck, 2015). It was historically used by residents for trading and currently turns into a flea market on selected days.
Cape Town Church Square	The Church Square in Cape Town CBD is an open area at the junction of Bureau Street and Parliament Street. This Church Square is near the Slave Lodge, which was historically built to house slaves (McCrea & Pinchuck, 2015). The Cape Town Church Square was thus an area near the Slave Tree where slaves were auctioned (Richmond & Corne, 2012). This area attracts visitors, has resting benches and sometimes hosts events from time to time.

3.13 Multivariate Data Analysis

The aforementioned sections (section 3.7 and 3.8) show that the present research has multivariate data. This data requires data analysis techniques with the ability to analyse such multivariate data.

Multivariate analysis is the analysis of several variables (measurements) made on each observation (e.g. individual or other sampling unit) in one or more samples (Rencher, 2003). The goal of multivariate analysis rests in assessing the meaning of multivariate data using fewer dimensions. To achieve this goal, multivariate analysis is generally concerned with offering descriptive and inferential statistics by simultaneous analysis of the multivariate data (Rencher, 2003). While the linear combination of measurements is of interest in descriptive statistics, inferential statistics would involve testing the multivariate measurements simultaneously using the same significance level (Rencher, 2003). Several methods exist to perform multivariate analysis.

Some multivariate methods include principle component analysis (PCA), factor analysis (FA), cluster analysis (CA), linear discriminant analysis (LDA), multiple linear regression (MLR), principle component regression (PCR) and partial least squares regression (PLS-R) (Esbensen, Guyot, Westad, and Houmoller, 2002). Multivariate methods based on variance and covariance in multivariate data are multivariate analysis of variance (MANOVA) (Rencher, 2003) and multivariate analysis of covariance (MANCOVA) (Weinfurt, 1995) respectively.

Chin (1998) refers to multivariate methods such as PCA, FA or MLR as 1st generation multivariate techniques. The 2nd generation multivariate methods extended the first and thus provide greater benefits. An example of a second generation multivariate method is structural equation modeling (SEM) (Chin, 1998). This will be discussed in the next section.

3.13.1 Structural Equation Modeling

Structural equation modeling is a multivariate data analysis technique integrating features of multiple regression and factor analysis to simultaneously estimate interrelated relationships among multiple independent and dependent variables (Gefen, Straub & Boudreau, 2000). The use of SEM, in research, usually follows a positivist stance (Urbach & Ahlemann, 2010). As a recap from section 3.1, this stance assumes the existence of a human independent, objective world which is characterisable and quantifiable and uses a scientific process to explain the researched phenomenon. In this case, the use of SEM would be fulfilling part of the scientific process suggested.

In SEM, the researcher makes use of latent variables to theorise assumptions on a phenomenon. These latent variables are unobservable but are made complete by use of observed variables, which are measurable. This combination of latent variables and observable variables completes the structural equation model, which comprises of the structural model and the measurement model (Gefen et al., 2000). The researcher does not intervene in the phenomenon under test, but is concerned with whether the causal links between the latent variables are rejected or not rejected. Therefore, SEM allows the interplay between theory and practice through the structural equation model, which is composed of the theoretical assumptions and empirical data (Urbach & Ahlemann, 2010). This use of theory, in analysis, is one of the benefits of SEM over 1st generation multivariate techniques.

In addition, SEM based approaches allow the researcher to model measurement errors in observed variables and also statistically test theoretical and measurement assumptions against empirical data (Chin, 1998). This is achieved through confirmatory analysis. Unlike in the 1st generation techniques, SEM techniques also provide useful information about how the data support the research model (Gefen et al., 2000). This allows the theoretical model to be analysed in a more rigorous manner.

Due to the several benefits offered by SEM techniques over the 1st generation multivariate techniques, the present research selected structural equation modeling for multivariate data analysis. Although SEM techniques utilise some 1st generation methods such as FA, exploratory factor analysis is conducted initially to examine the patterns in the measured variables. The FA conducted during SEM is used to confirm the hypothesised patterns in the variables. Two main approaches to SEM are covariance-based SEM and partial least squares-based SEM (Gefen et al., 2000; Henseler, Ringle and Sinkovics, 2009). Of the two, the first SEM-based analysis was the covariance-based SEM (Garson, 2016; Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). An additional approach, partial least squares SEM, was later developed to cater for an alternative objective under different assumptions. These approaches will be compared in the next section.

3.13.1.1 CB-SEM and PLS-SEM

Covariance-based structural equation modeling (CB-SEM) uses a covariance based approach that utilises a maximum likelihood function to minimize the difference between the sample covariance and that predicted by the theoretical model (Urbach & Ahlemann, 2010). Due to the application of a maximum likelihood function, the observed variables are required to be normal distributed (Urbach & Ahlemann, 2010).

Partial least squares SEM (PLS-SEM) is a technique which maximizes the explained variance in a structural equation model's dependent variable based on the least squares estimation (Henseler et al., 2009). This structural modeling technique thrives with low theory and high complexity of latent variables to predict causal relationships (Gefen et al., 2000). This makes PLS-SEM more suited for theory building and prediction.

Table 3.7 shows a comparison between CB-SEM and PLS-SEM as raised by Chin (1998).

Table 3.7 Comparison of CB-SEM and PLS-SEM (Chin, 1998)

Covariance-based SEM	**Partial Least Squares-based SEM**
Requires larger sample size	Minimal demand on measurement scales (e.g. measures can be ordinal) and sample size
More appropriate for theory testing	Theory development and prediction
Factor-based covariance-fitting approach	Component based approach
Normal distribution is assumed	No assumption of data distribution on variables
Independence of observations	No assumption that observations are independently distributed
Parameter-oriented	Prediction-oriented
Constructs are indeterminate	Constructs are determinate
All indicators are treated in a reflective manner	Indicators can be reflective or formative

The selection of the data analysis technique should be based on the objective of the research and whether the assumptions on the measurement variables and sample have been met (Gefen et al., 2000). In view of this, PLS-SEM was selected as the structural equation modeling technique based on the predictive-nature objective of the research. In hindsight, the ordinal variables used as measurements of the survey instrument are likely to yield a distribution which is not normally distributed. However, the PLS-SEM algorithm can work with non-normal data (Chin, 1998; Gefen et al., 2000; Hair, Sarstedt, Hopkins & Kuppelwieser, 2014) as all variables are normalised during the initial computations of the algorithm (Cassel, Hackl & Westlund, 1999; Urbach & Ahlemann, 2010).

The following section shows the construction of the structural equation model for PLS-SEM.

3.13.1.2 PLS Model Construction

Chin (1998) describes the path models in PLS to consist of three sets of relations. First, the path models have relationships between the latent variables. Second, there are relationships between the latent variables and the observed variables. These first two relationships are represented as inner and outer models and these are set up based on theory (Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). Third, there are weight values which are used to estimate the case values for the latent variables.

Latent variables are considered as either exogenous or endogenous (Hair et al., 2014). Exogenous variables act as independent variables and do not have other latent variables causing them, whereas endogenous variables are explained by other variables. Although endogenous variables can be mostly regarded as dependent variables, they can be placed between two latent variables (Hair et al., 2014); in which case they act as independent variables.

3.13.1.2.1 Inner Model

A model that presents the relationships among latent variables is referred to as the inner model or structural model (Chin, 1998). When setting up a path model for PLS-SEM, no circular relationships between latent variables are allowed (Hair et al., 2014). The present research used existing theory modelled in the technology-to-performance chain model to set up the inner model. Hence none of the relationships between the latent variables were circular. Figure 3.1 shows the relationship between the latent variables. The exogenous and endogenous variables have been marked for illustration purposes.

The structural relationships of the latent variables are based on the research model, which was adopted from the technology-to-performance chain model.

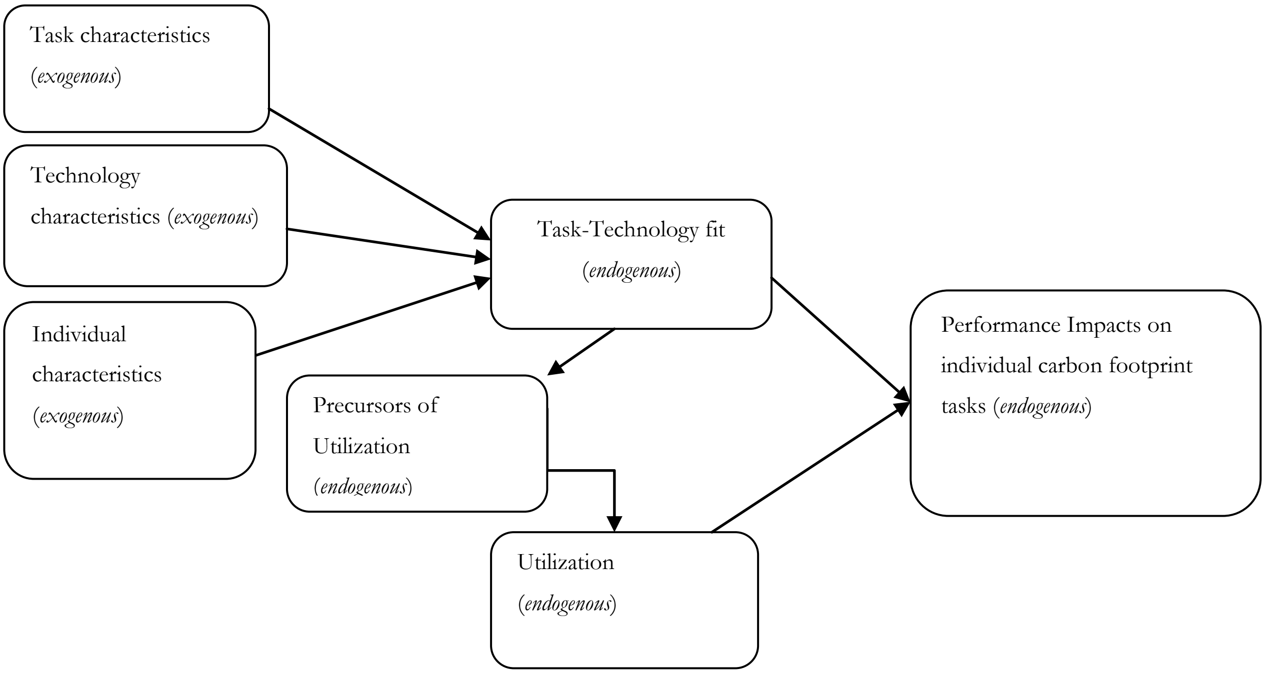

Figure 3.1 Inner Model

3.13.1.2.2 Outer Model

A model which defines how each block of indicators relates to its latent variable is referred to as the outer model or measurement model (Chin, 1998). The validity and reliability of the outer model are crucial if the hypothesized relationships in the inner model are to be valued (Hair et al., 2014). To design an outer model which is valid and reliable, a choice between a reflective or formative outer model is vital. Chin (1998) distinguishes between PLS models based on the relationships between indicators and latent variables. Table 3.8, which follow, distinguish between PLS models based on types of indicators.

Table 3.8 Types of PLS Outer Models

Mode A	**Mode B**
Reflective indicators only	Formative indicators only
Indicators measure the same underlying latent variable, i.e. highly correlated	Indicators not assumed to be correlated/measure the same underlying phenomenon
Latent variable gives rise to its observed variables.	Indicators are the cause of the latent variable. Latent variable is the effect.
Objective is explanation/prediction of observed measures	Objective is to account for the unobserved variance rather than the observed indicators
To determine appropriateness of indicators, loadings between latent variable and indicators are inspected.	The appropriateness of the indicators is interpreted using the weights
Arrows in a path model point away from the latent variable	Arrows in path model point towards the latent variable
A change in the underlying latent variable results in a similar change in all indicators	A change in the underlying latent variable does not result in a similar change in all indicators
Indicators only represent possible items in the latent variable's domain (Hair et al., 2014).	Indicators represent the entire domain of the latent variable (Hair et al., 2014).

A **Mode C** PLS model has both reflective and formative indicators (Chin, 1998). In this case, the arrow scheme uses both reflective and formative indicators.

Coltman, Devinney, Midgley & Venaik (2008) discussed a framework which reflects on theoretical and empirical considerations in designing and validating a measurement model. The theoretical considerations are based on the nature of the latent variable, direction of causality and the characteristics of the indicators. Coltman et al. (2008) suggest empirical considerations to be based on inter-item correlations, item's relationships with construct antecedents and consequences and measurement error and collinearity.

The theory, technology-to-performance chain model, informing the present research has been tested using PLS-SEM by previous researchers. A reflective measurement model was used by Staples and Seddon (2004) in testing the technology-to-performance chain model for mandatory and voluntary use of technology. McGill and Klobas (2009) also used a reflective outer model when testing the technology-to-performance chain model while assessing the impact of a learning management system for students. This entails that a reflective model is an appropriate outer model type for testing the technology-to-performance chain model. Therefore, the measurement model for this research is reflective as such an outer model has already been validated by previous research.

Figure 3.2 shows the reflective outer model for this research, as informed by existing theory and the instrument design.

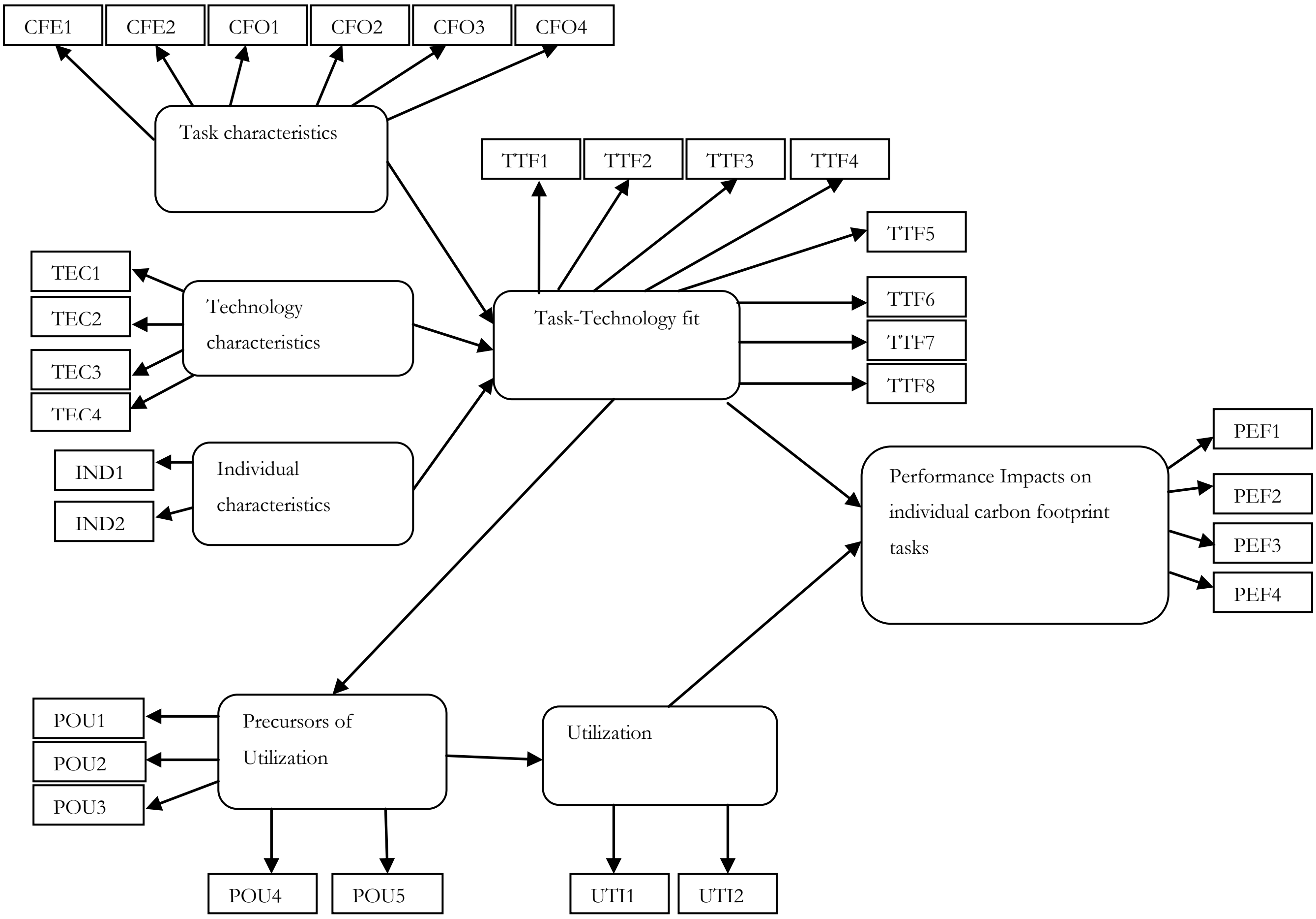

Figure 3.2 Reflective Outer Model

3.14 Data Analysis Techniques

Quantitative data analysis is conducted to determine whether the proposed hypotheses are supported. There is several software can be used for data analysis. This software includes IBM SPSS, Statistica, Orange, SAS University Edition, among others. Of these various statistical software packages and programs, the present research used two packages. First, IBM's SPSS version 23 was used for computing descriptive statistics, factor analysis, bivariate statistics and checking data distribution. Second, SmartPLS version 3 was selected to apply PLS-SEM analysis on both the measurement and structural model.

The following sections will describe the actions used to analyse the collected data:

3.14.1 Data transformation and screening

3.14.1.1 Transformation

Upon inputting the survey responses into Microsoft Excel, some questionnaire responses (namely education levels and performance related measures) were transformed. The transformation ensured uniformity in the responses, as the items were to be analysed in conjunction with other scales. An additional variable, "utilization grouping variable" was derived from the data based on the frequency of use measures.

3.14.1.2 Missing data analysis

Responses need to be inspected for missing values and resolved. Frane (1976) presents assumptions, in multivariate analysis, which need to be met for handling missing data using regression techniques. These assumptions include: none excesses of missing data, data missing at random intervals and missing data to be highly correlated with other variables. Failure to meet any of these assumptions leads to unsatisfactory results when handling missing data.

Other than replacing missing data, another procedure used to handle missing data is through deletion of cases with missing values (Frane, 1976). However, this has its own assumptions which need to be met such as number of respondents with missing data, which needs to be small and random appearance of the missing values (Frane, 1976; Tabachnick et al., 2001). Deletion of cases is both available in SPSS and SmartPLS packages.

3.14.1.3 Detecting outliers

An outlier is a case with an extreme value on one variable or an unusual grouping of scores on sets of variables (Tabachnick et al., 2001). These univariate or multivariate outliers distort statistics and need to be identified and resolved. The reason behind these extreme values could be a result of erroneous data entry or a foreign process unrelated to the source of the other data values.

Stevens (1984) suggests that cases with outlier values may be deleted if there is chance that the responses could have arisen from a population different from the source of the rest of the data. Otherwise, the researcher may analyse two scenarios; one with the influence of the outlying cases and the other with cases deleted. Univariate outliers can be detected through the use of z scores or graphical methods such as histograms and box plots (Hodge and Austin, 2004). Z scores unexpectedly greater than other standardised scores are used to identify univariate outliers. For very large samples, z scores could be in excess of 3.29 (Tabachnick et al., 2001). However, the cutover threshold for this research was set at 3. That is, any standardised z score above 3 was treated as an outlier.

To detect multivariate outliers, the Mahalanobis distance statistic can be used (Tabachnick et al., 2001). In software packages such as SPSS, each group of variables is run separately and the screening process is iterative to the point when deletion is no longer required.

3.14.2 Test for Reliability and Validity

The evaluation of the measurement model is assessed through the testing of reliability and validity of the constructs. The subsequent sections discuss factor analysis, construct validity and internal consistency reliability.

3.14.2.1 Factor analysis

Prior to determining the validity of the constructs and reliability of measurement items, factor analysis is conducted to reveal and understand relationships and patterns from the data (Child, 2006). Essentially, variables can be regrouped into smaller sets based on their shared variance. The main techniques are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Yong & Pearce, 2013).

EFA explores the data and test predictions in order to reveal complex patterns while CFA uses path models, to represent variables and factors, in order to confirm hypotheses (Child, 2006). EFA is employed to determine the suitable number of factors and to decide which observed measures are logical indicators for the latent variables (Brown, 2015). The choice of indicators to keep depends on whether the factor loadings are above the threshold specified in the research.

Unlike EFA which is exploratory, CFA requires the researcher to specify the exact number of factors and the direction of the relation between the indicators and the factors (Brown, 2015). This requires a stronger theoretical framework to support the hypothesized factor model.

For this study both EFA and CFA were used. EFA was conducted to initially explore relationships and factors using SPSS. Thereafter, CFA was carried out using PLS-SEM prior to further validity and reliability tests.

3.14.2.2 Construct validity

Construct validity is examined by testing discriminant and convergent validity.

Discriminant validity ensures that the correlations of variables within a construct are examined in relation to correlation with variables in other constructs. This validity is assessed through examining the Fornell-Larcker criterion, crossloadings (Farrell, 2010) and the Heterotrait-Monotrait Ratio (Henseler et al., 2015). Each of these techniques has different criteria to evaluate discriminant validity. These techniques will be discussed later.

Convergent validity is another test for construct validity that involves assessing the extent to which associated items are related to the same construct. Convergent validity requires that the average variance extracted (AVE) be greater than or equal to 0.50 (Bagozzi & Yi, 1988).

3.14.2.3 Internal consistency reliability

The correlation between items in a construct is used to determine whether a construct shows construct reliability. The one most used criterion for reliability is the use of Cronbach's alpha; with values greater than 0.70 as acceptable (Nunnally, 1978). Another, perhaps less stringent measure is the use of composite reliability; with values greater than 0.70 also acceptable (Bagozzi & Yi, 1988; Hair et al., 2011). The purpose of this reliability test is to ensure that constructs are represented by items that are correlated.

3.14.3 Computing descriptive statistics

The profile of the respondents was presented using frequencies in tables and graphs. This respondent's profile covered age groups, gender, level of education and employment status. Responses to the survey questions were described through measures of central tendency, that is mean, median and mode. In addition, variability was measured by the standard deviation and also tabulated for variables. The difference between the demographic groups was also assessed.

The consistency of parameters can be assessed by comparing these parameters across different groups using statistical tests (Bagozzi & Yi, 1988). The present research explored whether the causal relationships between variables were similar across the demographic groups or there could be other moderating effects that these different groups might present. Several approaches to multiple group (multi-group) analysis have been proposed and there have been more methods that require distribution assumptions to be met than distribution free methods (Henseler, 2007). With this in mind, Henseler (2007) proposed a distribution free approach that utilizes results of a bootstrap to test difference between groups.

Partial least squares multi-group analysis (PLS-MGA) is a non-parametric approach to multi-group analysis that compares PLS statistical estimates between data groups (Henseler, 2012). This approach is implemented by Ringle, Wende & Becker (2015) in SmartPLS 3. The present research is interested in the comparison of statistical differences, on such PLS estimates as path coefficients, among different demographic groups. Therefore, to compare the different demographic groups, PLS-MGA was used.

3.14.4 Test for Normality

One of the reasons informing the choice between parametric and non-parametric statistical tests is the distribution of the data in the population (Kim, 2013; Wagner et al., 2012). The graph plotted for a normal distribution is bell-shaped, symmetrical and asymptotic (Wagner et al., 2012). However, for a non-normal distribution, the graph could be skewed and/or kurtotic.

Parametric tests are conducted when data are normally distributed (Ghasemi & Zahediasl, 2012) and non-prarametric tests when the assumptions of normality are not met. For example, to test the difference between groups a parametric statistical test that can be used is a T-test while a Mann-Whitney U test is a non-parametric statistical test which can be used (Wagner et al., 2012). Since many statistical procedures assume normal distribution, data transformations can be applied to improve the normality of variables (Kim, 2013; Osborne, 2005). This can assist the research to utilise parametric tests without the risk of committing type I or type II errors. For this study, no normalization transformations were conducted but the appropriate statistical procedure was applied based on the distribution of the data.

Normality can be tested using raw data plots, probability plots and regression tests (Thode, 2002). Some common raw data plots are histograms, stem-and-leaf plots and box plots. Probability plots include quantile-quantile (Q-Q) plots and percent-percent (P-P) plots. Regression tests are more objective than the graphical representation of raw data and include the Shapiro-Wilk test (Thode, 2002). In addition, kurtosis and skewness can be used to assess normality (Rencher, 2003).

Skewness measures the asymmetry of a variable's distribution (Kim, 2013). Symmetric distribution is characterized by a skew value of zero. While symmetry characterizes the normal distribution, non-symmetry is either positively skewed or negatively skewed and could be characteristic of non-normal distribution. Kurtosis refers to the peakedness or flatness of a distribution in relation to a normal distribution (Saunders et al., 2009). A positive kurtosis value results in a pointed or peaked (leptokurtic) distribution whilst a negative kurtosis value results in a flat or a platykurtic distribution (Saunders et al., 2009). Kurtosis and skewness were used for the preliminary assessment of normality followed by the more objective regression tests.

3.14.5 Correlation analysis

Correlation analysis establishes whether a relationship exists between variables as well as the nature of the relationship, in terms of direction and size (Cohen et al., 2007; Saunders et al., 2009). Correlation is an association between two variables (Marczyk et al., 2005). When a relationship exists between variables, this association can either entail a variation in the same direction (positive correlation) or a variation in different directions (negative correlation) (Marczyk et al., 2005). Correlation is simply a relationship and does not mean that one variable causes the other. However, the existence of such a relationship is important for further investigations.

A correlation coefficient is used as a measure of correlation. Correlations are often calculated using either Spearman rank order ("Spearman") or Pearson product moment correlation ("Pearson"). Spearman is appropriate for ordinal data while Pearson is appropriate for data that is in intervals or ratios (Cohen et al., 2007). The use of the Spearman with ordinal data implies that this method does not make any assumptions on the data distribution as ordinal data may not be normally distributed. Metric data, such as ratio and interval data are likely to produce normally distributed data and this makes Pearson an appropriate correlation method.

In this study, correlation analysis was used to evaluate the existence of relationships between variables as well as their direction and strength.

3.14.6 Evaluating Inner Model

The evaluation of the inner model is assessed through administering PLS-SEM. First, the fit of the inner model was assessed. Measures to assess model fit include the coefficient of determination (R^2), adjusted R^2 and Normed Fit Index (NFI). Second, the predictive relevance of the model was examined. The Stone-Gleisser's Q^2 value provides a way of assessing whether a model is relevant in predicting underlying endogenous variables (Chin, 1998). Q^2 values greater than zero show predictive relevance while values less than zero show lack of predictive relevance for the endogenous variable (Chin, 1998).

3.14.7 Testing of hypotheses

The diagram in Figure 3.3 shows the hypotheses tested in the inner model. These hypotheses are H1abcd and H2abc. This hypothesised model shows the relationship between variables which cannot be observed. The task-technology fit is providing a causal link between the characteristics (of technology, tasks and individual) and performance impacts on individual carbon footprint tasks. Also, precursors of utilization are mediating between task-technology fit and utilization.

In addition, utilization is providing another causal link between the precursors of utilization and performance impacts on individual carbon footprint tasks. These unobserved variables such as utilization were measured through use of observed variables such as frequency of use, as presented by the measurement model.

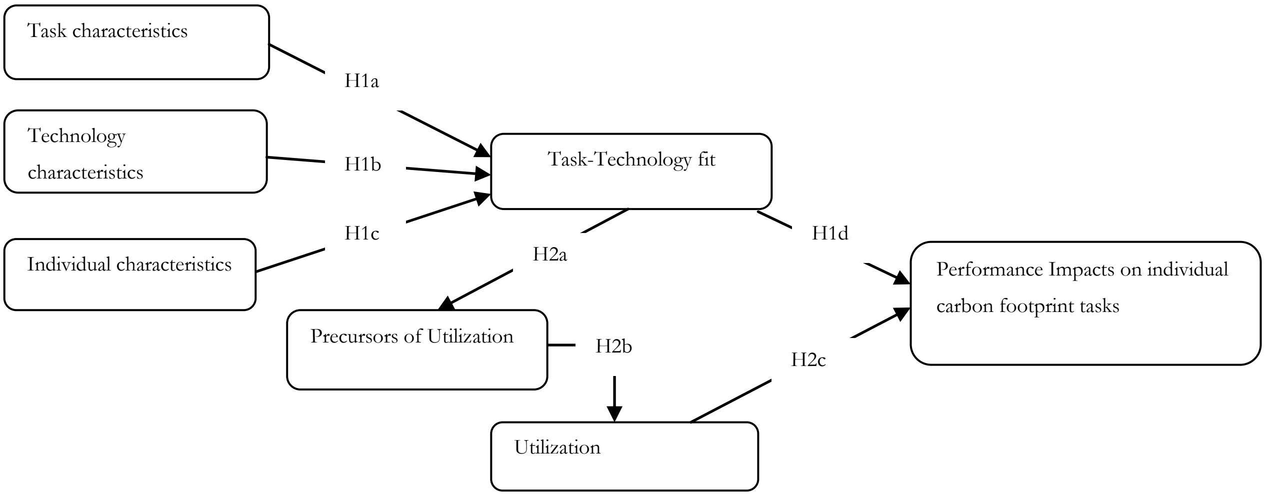

Figure 3.3 Hypothesised paths in Inner Model

This structural model posed a complex model to be tested. A model of this nature called for data analysis techniques that could handle a hypothesised model with observed and latent variables.

Structural equation modeling (SEM) allows assessing of complicated models through easier mapping of hypothesised causal models (Schumacker & Lomax, 2004). Through its use of path and confirmatory factor analysis models, SEM allows the modeling of the natural sequence of causation to resemble the hypothesised theoretical model, which can contain observed and latent variables. One assumption for using SEM is its requirement for a large sample size, depended on the size of the model (Tanaka, 1987). The size of the model is with reference to the number of latent variables and observed variables. With more variables, the sample size is expected to be large.

The partial least squares (PLS) approach to structural equation modeling suites complex models with large numbers of observed and latent variables that have a causal relationship (Chin, 1998). In addition, the PLS approach to SEM (PLS-SEM) is suitable even when data are not normally distributed and the sample size requirement is not met (Chin, 1998). As an approach to SEM, this technique also addresses measurement error (Schumacker & Lomax, 2004). PLS-SEM addresses reliability in measurement instruments and this cannot be said of the traditional regression models. Therefore, PLS-SEM was considered appropriate to test the hypothesized structural equation model.

PLS-SEM can be conducted through the use of computer software. There are many PLS software packages. Some common ones are SmartPLS, PLS-Graph and WarpPLS (Garson, 2016). The present research made use of SmartPLS 3.0. This software fulfils the requirements of SEM such as the ability to determine the direct and indirect effects of latent variables. SmartPLS 3.0 is graphical and thus allows the easy modeling of complex causal models and produces output, which facilitates the assessment of reliability, validity and model fit.

3.15 Ethical Issues

The dilemma of ethics is not only limited to qualitative studies, but also applicable to quantitative research (Guillemin & Gillam, 2004). A survey was conducted to collect data on individual's attitudes, beliefs and ratings on mobile phones in performing carbon footprint tasks. For the purposes of the dissertation, random individuals were selected from the general public to provide the required data.

Doing survey research in the general population requires certain ethical principles to be considered (Fowler, 2013). These principles require respondents to be informed about, the research (researching organization, research purpose, confidentiality and assurance on participation). This information was fully communicated to the respondents using the cover letter.

Respondents should also feel protected if they accept or decline participation in the survey (Fowler, 2013). In the present research, the survey did not request the name or contact details for the respondent. This ensured anonymity of respondents. In addition, no data on race and minors was collected.

Acquiring respondent's consent and maintaining confidentiality is vital in survey research (Kelley, Clark, Brown & Sitzia, 2003). The respondents were asked for their consent before participating in the survey. This participation was also on a voluntary basis. Given that respondents should be communicated in a language that is easily understandable (American Psychological Association, 2002), simple English language was used to communicate with the respondents.

American Psychological Association (2002) also suggests that research of this nature attains institutional approval before the survey is conducted. The proposal for this research, its questionnaire and cover letter were provided to the Ethics Committee of the University of Cape Town to acquire ethics approval. The questionnaire and cover letter are presented in the appendix section.

Chapter 4 : Data Analysis and Results

As a recap from the research design chapter, a survey was the selected research strategy. This was deemed appropriate to acquire data by sampling the target population of individuals living in urban areas that use electricity, have a mobile phone and use transport for mobility. A survey research consists of the data collection technique that uses a set of questions to gather data about respondent's profiles, perceptions and preferences (Bhattacherjee, 2012; Privitera, 2013). The questions designed in this research were all closed-ended items with Likert scales. A pilot study was conducted by providing five colleagues with the questionnaires. These pilot questionnaires were returned and their feedback was used to clarify some questions on the questionnaire. Thereafter, the questionnaires were distributed in order to start the survey.

This chapter presents survey responses and analysis of missing and outlier data. Further, in this analysis the researcher conducts data transformations, checks reliability and validity of the constructs.

In addition, this chapter presents the results of the study through descriptive statistics, difference between demographic groups, normality testing, correlation analysis, evaluation of the inner model and hypothesis testing.

4.1 Survey and Responses

A survey was conducted in the city centre of Cape Town at four busy places, namely the open area at the Cape Town Train Station, Cape Town 's Company Garden, Cape Town 's Grand Parade and at Cape Town Church Square. This survey was carried out by five individuals (field workers) trained by the researcher. A structured interview was the main data collection technique. The researcher's cover letter was available to participants who wished to know more details about the research and the researcher. In some cases, the field worker would hand out the questionnaire to an individual willing to participate. The participant would be informed to return at the field workers' data collection stand. Some participants would return whilst others would not. No follow ups on the issued questionnaires were made. This was in line with the research's ethics commitment.

The response rate is the number of participants who actually complete a survey out of all the invited survey takers (Privitera, 2013). Participants do not complete a survey mainly because they do not wish to (Baruch, 1999) and at times find justification not to. This results in un-returned questionnaires or returned but with missing data. This, nonreponse bias (Yu and Cooper, 1983), affects generalizability (Bhattacherjee, 2012) as the reasons the non-participants did not respond remain unknown.

The various survey administering methods (Dillman, 1978; Greenlaw & Brown-Welty, 2009; Sibbald, Addington-Hall, Brenneman & Freeling, 1994), which exist, offer different advantages but their response rates also differ (Baruch, 1999). For instance, mail administered questionnaires need more attention to increase their low response rates (Bhattacherjee, 2012) while in-person surveys offer high response rates but are time consuming (Privitera, 2013). That highlighted, Baruch and Holtom (2008) have reviewed minimal response rates to range from 50% to 80%. Since structured interviews are associated with high response rates (Saunders et al., 2009), this led to their deployment.

Of the 372 questionnaires distributed, 276 were returned. The returned questionnaires represents a response rate of 74.19% (276/372 * 100). The response rate for the present research is within the prevalent response rates for mobile technology related surveys within a South African context (Maduku, 2013; Radder, Pietersen, Wang & Han, 2010; Shambare & Rugimbana, 2012). With regards to sample sizes for PLS path models, the sample size should be at least ten times the largest number of causal paths directed at a particular latent variable (Barclay, Higgins & Thompson, 1995). Therefore, the acquired sample data meets the suggested minimal sample size for PLS-SEM.

The following sections will now show cleansing of the returned questionnaires with regards to missing data and identification of outliers.

4.2 Missing Data

Missing data can arise when no survey data are collected from the unit under analysis (total nonresponse), some unit of analysis is excluded from the sampling frame (noncoverage) and respondent incompletely or inconsistently answers some items (item nonresponse) (Brick & Kalton, 1996). This missing data misrepresents the sampled population (Schafer & Graham, 2002) and can cause problems in analysing the survey.

There are several methods to resolve missing data. Vast studies on handling missing data include: (Allison, 2003; Enders, 2010; Graham, 2012; Little & Schenker, 1995; Royston, 2005) and others revealing the limitations of the various methods include: (Allison, 2001; Pigott, 2001; Graham, Cumsille & Elek-Fisk, 2003). However, mitigation of the problems caused by missing data are embedded in better survey design (Brick & Kalton, 1996). To this end, the present research has considered the research participants such that they are representative of a wide range of mobile phone users who use transport and electricity in urban areas. The data collection technique has been selected such that the respondent understands the questions presented. However, as respondents are not forced to complete a survey, incomplete surveys are inevitable.

Four of the returned questionnaires were incompletely captured. These incomplete questionnaires were missing responses from the Section D (task technology fit) and Section G (performance impacts on carbon footprint tasks) of the questionnaire. As a recall from the previous chapter, missing data can be resolved with relevance to the extent of the missing values.

Discarding incomplete responses can be an efficient method only when small portions of the sample are missing data (Schafer & Graham, 2002). Missing values can also be assigned data by imputation methods (Raghunathan, 2004). While ignoring a missing case presents nonresponse bias (Brick & Kalton, 1996), assigning missing values can also result in biased results in the relationships between variables (Kalton, 1983). Since each method of resolving missing data has its own limitations and complexity, the most appropriate method is one that has the least bias.

Given that the number of questionnaires with missing values is four; this is argued to be a small number of cases unlikely to influence the findings of this research if the cases were rejected. If a few cases are missing data and appear at random, deletion of the cases can be a viable option (Tabachnick et al., 2001). Therefore, the four cases with missing data were removed from the 276 returned questionnaires. This case deletion left a remainder of 272 (276 minus 4) compete cases.

The next section evaluates the completed cases for outliers.

4.3 Detecting Outliers

An outlier is an unusual observation in the sample data (Hodge & Austin, 2004). These anomalies in observations contaminate the data and need to be identified and removed before data analysis can be conducted. PLS-SEM results, like results from other statistical procedures, are deformed by the existence of outliers (Garson, 2016). Outliers exist in both univariate (Bamnett & Lewis, 1994; Osborne & Waters, 2002) and multivariate (Hadi, 1992; Penny, 1996) data. A univariate outlier is an unusual value for one variable while a multivariate outlier is an unusual value on a combination of variables (Tabachnick et al., 2001). The presence of outliers in these forms requires this study to detect both univariate and multivariate outliers.

As established in the previous chapter, univariate outliers will be detected using z-scores. A univariate outlier would be identified as a case with a z-score value greater than three. Standardised z-scores were computed using SPSS 23 for all measurement items. Six cases had at least one variable with a standardised z-score greater than the cutoff value of three. These variables belonged to task characteristics, individual characteristics, task technology fit and the utilization variables. Since univariate outliers may be deleted (Stevens, 1984), these six cases were excluded from the sample. This resulted in 266 (272 - 6) cases with no univariate outliers as well as no missing values. Next, the remaining sample was analysed for multivariate outliers.

In multivariate data, Hodge and Austin (2004) recommend using the Mahalanobis distance to show which group of items stands out from the rest of the cases. The Mahalanobis distance traverses the entire sample data to evaluate correlations between variables (Hodge & Austin, 2004). As a result, a distance for the case based on the set of predictor variables is computed relative to the centroid of all cases (Stevens, 1984). The computed distance is further analysed whether it may belong to an outlying case, especially when the measure is large.

The Mahalanobis distance was computed for each group of independent variables using the linear regression function of SPSS version 23. This resulted in seven variables for Mahalanobis distance (i.e. MAH_1, MAH_2… MAH_7). The Mahalanobis distance values need to be compared against a chi-squared distribution with the same degrees of freedom as the number of predictor/independent variables for each set of variables (Tabachnick et al., 2001). This is required as the value alone will not show if the set of variables, for a case, is indeed an outlier.

Seven transformations, one for each saved Mahalanobis measure, were computed in SPSS to produce probability values needed to evaluate if cases are outliers. The SIG.CHISQ function was used to calculate the cumulative probability that a value from the chi-square distribution, with degrees of freedom equal to the number of independent variables would be greater than the Mahalanobis measure. If the cumulative probability is less than 0.001, the case is a multivariate outlier (Tabachnick et al., 2001). This criterion for detecting multivariate outliers was used for this study (i.e. Mahalanobis distance at cumulative probability < 0.001).

As a result of this outlier assessment, four cases were detected as multivariate outliers. Two cases were identified with cumulative probabilities less that the cutoff value (0.001) for the variables measuring task technology fit. The other two cases had their individual characteristics with cumulative probabilities less than 0.001 for the Mahalanobis distance.

Stevens (1984) purports that influential outliers have a Cook's distance greater than 1 and need to be examined carefully before exclusion. Hence, Cook's distance was computed using the linear regression function of SPSS. The results for the seven sets of predictor variables yielded Cook's distance less than 1 for the cases tagged as multivariate outliers. Therefore, the multivariate outliers were not influential.

Given that these four multivariate outliers were non-influential, they were deleted from the sample. This resulted in 262 (266 - 4) cases in the sample with no outliers (univariate and multivariate) and no missing data.

4.4 Data Transformations

Transformations were computed using SPSS version 23. These transformations are discussed below.

Utilization group variable

A utilization group variable was computed based on the utilization of mobile phones. A median, of the utilization variables (UTI1 and UTI2) was used. The saved variable had values either 1 or 2; where 1 represented a group with a median less than 3 ("low mobile phone utilization") or 2 represented a median greater than 3 ("high mobile phone utilization").

Performance indicators

Measurement items capturing performance were made consistent with the rest of the performance indicators. To be precise, this refers to items, namely PEF1 and PEF4 that had ratings ranging from "Poor" to "Excellent". These ratings were recorded using ranked values from 1 to 5. Other transformations such as the computation of an overall performance score could only be conducted after reliability and validity checks as some indicators could be dropped.

Education Level

Another variable to measure individual characteristics, "IND2", was computed based on the highest education level of a respondent. The respondent selected their level from the possible values of high school to post-graduate. This data was used to produce the new variable with ranked values from 1 to 5 such that the values represented 1 (high school), 2 (grade 12), 3 (tertiary), 4 (degree) and 5 (post graduate).

4.5 Reliability and Validity

4.5.1 Preliminary Interpretation

This section shows how data were interpreted prior to checking for reliability and validity of the constructs. SPSS was used to analyse the data in order to determine if factors could be extracted from the data. The descriptive options selected for dimension reduction were correlation matrix, coefficients, significant levels, Determinant, Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity.

Correlations greater than r=0.90 highlight that the data may have issues of multicollinearity (Yong & Pearce, 2013). The correlation matrix did not show any variable with a correlation coefficient greater than r=0.90, with another variable. In addition, a Determinant score greater than 0.00001 indicates the absence of multicollinearity (Yong & Pearce, 2013). In the present research, the preliminary Determinant score was 3.56E-006, indicating the absence of multicollinearity.

Table 4.1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.726
Bartlett's Test of Sphericity	Approx. Chi-Square	3134.477
	df	465
	Sig.	.000

The results of the Bartlett's Test of Sphericity (significant level of $p < 0.001$) show that the variables have relationships amongst them since the significant level p is less than 0.05.

The KMO calculated (0.726) is above the suggested minimum of 0.50. This suggests that the sample size (262) is adequate for factors to be extracted and that the relationships amongst the variables have patterns.

The results of the tests for the Determinant, KMO and the Bartlett's Test of Sphericity all pass pre-requisites for factor analysis to be conducted. Next, exploratory factor analysis (EFA) was conducted and is presented in the following section.

4.5.2 Factor Analysis

Factor analysis is a multivariate technique aimed at reducing the number of observable variables, which are linearly related, to a few random variables (factors) that are unobservable (Rencher, 2003). In this research, factor analysis was conducted to: (1) understand the constructs used to give an account for the intercorrelations among the measurement variables; (2) to reveal the number and nature of constructs that explain the intercorrelations among variables under study (Comrey & Lee, 2013). Data for the measurement models has been collected and factor analysis is undertaken to discover if the correlations between the measurement variables is due to some underlying factors. The researcher uses extraction of underlying factors to quantify the number of these factors and their nature.

4.5.2.1 Exploratory Factor Analysis

Exploratory factor analysis (EFA) is aimed at revealing any constructs that cause the observed variables to vary with other observed variables (Osborne & Costello, 2005). EFA is conducted through a selection of observed variables, the choice of a factor extraction method and rotation method and interpreting the rotated factor matrix (Comrey & Lee, 2013). The Interpretation also involves determining the number of factors to be extracted, retained and the nature of the factors.

In this research, EFA was run twice. First, a preliminary run was used to identify how the items were loading and whether there were any correlations between the measurement items. Second, a final run was necessary as some items had to be discarded, and the final factor loadings had to be identified. In both cases, the number of factors extracted and retained was consistent.

Preliminary Factor analysis

Table 4.2 shows a factor matrix as a result of the initial factor analysis in SPSS. The extraction method used was Principal Axis Factoring. In total, seven factors were extracted. From this initial run, four items, namely *CFE1, TEC4, TTF1* and *TTF5* were observed to have the lowest factor loadings (i.e. < 0.4) on all factors extracted.

Table 4.2 Initial Rotated Factor Matrix

	SPSS version 23 Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization.						
	Factor						
	1	2	3	4	5	6	7
CFE1	.165	**.108**	-.061	-.006	.074	.329	.078
CFE2	.008	**.796**	-.060	.001	.038	.081	-.072
CFO1	-.038	**.704**	-.014	-.041	.111	.044	-.022
CFO2	-.017	**.816**	.016	-.021	-.007	.067	-.004
CFO3	.022	**.679**	-.052	.071	-.086	-.022	.149
CFO4	-.001	**.776**	-.001	-.026	-.139	-.032	.095
TEC1	.080	-.005	.034	.055	**.605**	.023	.029
TEC2	-.048	-.015	.081	.091	**.903**	.050	.044
TEC3	.087	-.046	-.054	.101	**.687**	.131	.000
TEC4	.127	.170	.010	.069	**-.023**	.184	.044
IND1	.184	-.020	.210	-.039	.102	**.771**	-.015
IND2	.212	-.018	.306	-.016	.085	**.810**	-.045
TTF1	**.328**	-.029	.114	.057	.015	.009	.077
TTF2	**.659**	-.010	.129	-.012	-.007	.108	.123
TTF3	**.690**	-.092	.006	.111	.048	.130	-.022
TTF4	**.644**	.068	.010	.027	.038	.033	.054
TTF5	**.437**	.103	-.021	.030	.038	.105	-.036
TTF6	**.639**	-.018	-.013	.128	.031	.035	-.033
TTF7	**.582**	-.017	.013	.190	.059	.111	.002
TTF8	**.686**	-.015	.058	.085	-.044	.137	-.088
POU1	.222	-.020	.080	**.563**	.027	-.072	-.009
POU2	.167	.011	.041	**.601**	.089	.068	.124
POU3	.090	-.087	-.044	**.724**	.137	-.071	.071
POU4	.056	.090	.014	**.639**	-.026	-.031	-.006
POU5	.022	.001	-.001	**.560**	.058	.096	.150
UTI1	-.012	.112	-.061	.123	-.007	.114	**.687**
UTI2	.069	.013	.066	.154	.074	-.052	**.666**
PEF1	.033	-.016	**.711**	-.047	.118	.108	.043
PEF2	.044	-.045	**.789**	-.071	-.054	.127	.005
PEF3	.138	-.020	**.687**	.067	-.087	.012	-.053
PEF4	.024	-.016	**.717**	.136	.080	.057	.016

Item loadings less than 0.32 are viewed as undesirable for exploratory factor analysis (Yong & Pearce, 2013). For this research, a cutoff of 0.40 was used to validate meaningful factor loadings, only for EFA. In light of this, the loading of item TTF5 (.437) was on the border line of the cutoff threshold (0.4), when rounded to one decimal place. As a result of the preliminary factor analysis, items *CFE1, TEC4, TTF1* and *TTF5* were discarded due to their lower factor loadings. All the other items loaded above the cutoff level of 0.4 and were thus retained.

Final Factor analysis

A final run of exploratory factor analysis was conducted in SPSS. The Table 4.3 below shows the options used.

Table 4.3 Options for running final Factor Analysis

Criteria	Selected Value
Extraction method	Principal axis factoring
Rotation method	Varimax
Minimum eigenvalue	1
Analysis option	Correlation matrix
Maximum Iteration for convergence	25
Discarded Items	CFE1, TEC4, TTF1 and TTF5

Correlation Matrix

A correlation matrix shows the relationship between ranked measurement variables; with the value in each cell a correlation coefficient (Saunders et al., 2009). Since the correlation coefficient is likely to be either a negative or positive value, the importance of the value can entail a weak or a strong relationship.

Table 4.4 shows a correlation matrix produced by running factor analysis. The correlation between authorization (TTF3) and ease of use (TTF8) is 0.655. The magnitude of this correlation coefficient is large such that TT3 and TTF8 maybe related or overlap in what they measure. This correlation coefficient shows that there is a strong positive relationship between the authorization and the ease of use of mobile carbon footprint calculators. As with the preliminary factor analysis, this correlation matrix shows all correlation coefficients are less than 0.90. In addition, the determinant of the correlation matrix was 1.423E-5. A determinant above 0.00001 indicates the absence of multicollinearity (Yong & Pearce, 2013). Since the determinant of this correlation matrix (i.e. 1.423E-5) is greater than 0.00001 there is no indication of multicollinearity.

Table 4.4 Correlation Matrix of Measurement variables

	CFE2	CFO1	CFO2	CFO3	CFO4	TEC1	TEC2	TEC3	IND1	IND2	TTF2	TTF3	TTF4	TTF6	TTF7	TTF8	POU1	POU2	POU3	POU4	POU5	UTI1	UTI2	PEF1	PEF2	PEF3	PEF4
CFE2	1.000	.723	.652	.452	.512	-.004	.000	-.016	.013	.033	-.037	-.058	.093	-.010	-.006	.017	.014	.029	-.062	.046	-.033	.097	-.045	-.026	-.100	-.041	-.027
CFO1	.723	1.000	.545	.433	.440	.049	.072	.035	.023	.022	-.016	-.044	.035	-.065	-.061	-.026	-.051	-.054	-.075	.085	-.039	.067	.029	.023	-.061	-.067	.009
CFO2	.652	.545	1.000	.508	.693	.031	.000	-.070	.025	.049	-.002	-.114	.020	.018	-.042	-.012	-.029	-.002	-.112	.064	.015	.089	-.008	-.006	.003	-.009	-.026
CFO3	.452	.433	.508	1.000	.707	-.052	-.074	-.055	-.025	-.062	.006	-.067	.071	.024	.062	-.025	-.008	.068	-.012	.113	.085	.152	.119	-.062	-.060	-.047	-.051
CFO4	.512	.440	.693	.707	1.000	-.097	-.112	-.113	-.035	-.057	.024	-.072	.013	-.070	-.023	.001	-.049	.011	-.080	.019	-.023	.119	.035	-.069	-.039	.007	-.016
TEC1	-.004	.049	.031	-.052	-.097	1.000	.575	.405	.104	.096	.099	.049	.039	.074	.099	.045	.082	.128	.180	.023	-.020	.009	.101	.071	.004	.021	.055
TEC2	.000	.072	.000	-.074	-.112	.575	1.000	.638	.146	.155	-.028	.039	.008	-.003	.050	-.052	.080	.121	.160	.037	.136	.035	.113	.137	.015	-.001	.120
TEC3	-.016	.035	-.070	-.055	-.113	.405	.638	1.000	.168	.129	.036	.148	.108	.089	.140	.039	.041	.148	.157	.022	.183	.013	.028	.093	-.065	-.117	.079
IND1	.013	.023	.025	-.025	-.035	.104	.146	.168	1.000	.762	.256	.215	.137	.145	.193	.226	-.026	.070	-.061	-.027	.049	.037	-.018	.201	.250	.181	.241
IND2	.033	.022	.049	-.062	-.057	.096	.155	.129	.762	1.000	.273	.238	.174	.190	.200	.257	.028	.111	-.042	-.022	.031	.032	-.026	.312	.357	.235	.267
TTF2	-.037	-.016	-.002	.006	.024	.099	-.028	.036	.256	.273	1.000	.417	.428	.382	.316	.455	.155	.163	.062	.012	.009	.050	.113	.100	.095	.198	.108
TTF3	-.058	-.044	-.114	-.067	-.072	.049	.039	.148	.215	.238	.417	1.000	.449	.380	.473	.655	.153	.146	.144	.126	.149	-.028	.090	.057	.037	.108	.066
TTF4	.093	.035	.020	.071	.013	.039	.008	.108	.137	.174	.428	.449	1.000	.464	.326	.394	.161	.153	.091	.050	.025	.074	.087	.045	.052	.114	.011
TTF6	-.010	-.065	.018	.024	-.070	.074	-.003	.089	.145	.190	.382	.380	.464	1.000	.525	.375	.225	.174	.139	.127	.070	-.029	.071	.012	.029	.054	.038
TTF7	-.006	-.061	-.042	.062	-.023	.099	.050	.140	.193	.200	.316	.473	.326	.525	1.000	.454	.222	.214	.135	.120	.202	.071	.034	.048	.029	.083	.108
TTF8	.017	-.026	-.012	-.025	.001	.045	-.052	.039	.226	.257	.455	.655	.394	.375	.454	1.000	.236	.169	.110	.044	.042	-.043	-.009	.060	.091	.184	.050
POU1	.014	-.051	-.029	-.008	-.049	.082	.080	.041	-.026	.028	.155	.153	.161	.225	.222	.236	1.000	.467	.472	.353	.198	.043	.126	.027	.022	.114	.130
POU2	.029	-.054	-.002	.068	.011	.128	.121	.148	.070	.111	.163	.146	.153	.174	.214	.169	.467	1.000	.540	.289	.324	.178	.163	.046	.023	.050	.104
POU3	-.062	-.075	-.112	-.012	-.080	.180	.160	.157	-.061	-.042	.062	.144	.091	.139	.135	.110	.472	.540	1.000	.420	.366	.120	.167	-.055	-.120	.052	.061
POU4	.046	.085	.064	.113	.019	.023	.037	.022	-.027	-.022	.012	.126	.050	.127	.120	.044	.353	.289	.420	1.000	.524	.046	.138	-.052	-.048	.090	.097
POU5	-.033	-.039	.015	.085	-.023	-.020	.136	.183	.049	.031	.009	.149	.025	.070	.202	.042	.198	.324	.366	.524	1.000	.206	.162	.013	-.008	-.002	.123
UTI1	.097	.067	.089	.152	.119	.009	.035	.013	.037	.032	.050	-.028	.074	-.029	.071	-.043	.043	.178	.120	.046	.206	1.000	.485	.002	-.032	-.058	-.029
UTI2	-.045	.029	-.008	.119	.035	.101	.113	.028	-.018	-.026	.113	.090	.087	.071	.034	-.009	.126	.163	.167	.138	.162	.485	1.000	.063	.031	.005	.113
PEF1	-.026	.023	-.006	-.062	-.069	.071	.137	.093	.201	.312	.100	.057	.045	.012	.048	.060	.027	.046	-.055	-.052	.013	.002	.063	1.000	.611	.436	.570
PEF2	-.100	-.061	.003	-.060	-.039	.004	.015	-.065	.250	.357	.095	.037	.052	.029	.029	.091	.022	.023	-.120	-.048	-.008	-.032	.031	.611	1.000	.581	.514
PEF3	-.041	-.067	-.009	-.047	.007	.021	-.001	-.117	.181	.235	.198	.108	.114	.054	.083	.184	.114	.050	.052	.090	-.002	-.058	.005	.436	.581	1.000	.496
PEF4	-.027	.009	-.026	-.051	-.016	.055	.120	.079	.241	.267	.108	.066	.011	.038	.108	.050	.130	.104	.061	.097	.123	-.029	.113	.570	.514	.496	1.000

Determining Number of Factors to Retain

There are a number of methods to determine the number of factors to retain as a result of exploratory factor analysis (Courtney & Gordon, 2013). SPSS allows for application of some methods such as Kaiser's criterion and the Scree test (Yong & Pearce, 2013) to determine the number of factors to extract during factor analysis. Studies such as: (Hayton, Allen & Scarpello, 2004; O'connor, 2000; Zwick & Velicer, 1986) have suggested newer methods such as parallel analysis that aims at reducing sampling error by using a population correlation matrix. However, the major statistical packages such as SPSS still need to play catch-up to include these modern functions (Courtney & Gordon, 2013). As such, additional programs have been developed separately to fill this gap.

Knowing the appropriate method to estimate the number of factors to retain prevents the researcher from making incorrect conclusions about factors to report on (Courtney & Gordon, 2013). The present research makes use of the methods readily available in SPSS to inform factors to be retained. These methods include the use of the scree plot (for performing the Scree test), and use of the "Total Variance Explained" output (to apply the Kaiser's criterion on).

Kaiser's criterion

Kaiser (1960) purported that a factor with an eigenvalue greater than one should be retained. In order to use this criterion, exploratory factor analysis was run using a minimum eigenvalue set to one. Table 4.5 below shows the truncated output of the extracted and rotated eigenvalues. From factor number eight onwards, the eigenvalues are less than the cutoff of one and the variance in their eigenvalues is not extracted. The factor which has the most variance explained is factor number one while factor number seven has the least variance explained. Of the significant factors, the first seven factors account for 64.50% of the total variance.

Table 4.5 Trimmed Total Variance Explained Results

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.286	15.875	15.875	3.805	14.094	14.094	2.907	10.766	10.766
2	3.340	12.370	28.245	2.929	10.847	24.941	2.777	10.287	21.053
3	2.813	10.418	38.663	2.375	8.795	33.736	2.285	8.464	29.517
4	2.358	8.733	47.396	1.900	7.038	40.774	2.093	7.753	37.270
5	2.012	7.451	54.847	1.577	5.840	46.614	1.804	6.680	43.950
6	1.394	5.162	60.009	.919	3.404	50.019	1.419	5.255	49.205
7	1.212	4.489	64.498	.825	3.054	53.073	1.044	3.867	53.073
8	.994	3.682	68.180						
9	.820	3.036	71.216						
10	.775	2.869	74.084						

Some studies (Cliff, 1988; O'connor, 2000; Ledesma & Valero-Mora, 2007) argue that the Kaiser's "eigenvalue greater than one" rule overestimates the number of factors to be retained. These studies offer different approaches to determine the number of factors to be retained. In light of this, the present study, double checks the number of factors to retain using another criterion i.e. the Scree test.

Scree test

The number of factors to retain can be determined by the Scree test (Cattell, 1966). In a scree plot, eigenvalues are plotted against the factor numbers. A Scree test involves inspecting the plot for a break point where the curve begins to level out (Osborne & Costello, 2005). The factors plotted above the break point, excluding the factor on the break-point, are the factors to be preserved (Osborne & Costello, 2005).

Figure 4.1 shows the eigenvalues plotted against the extracted factors. From factor number eight onwards, the slope of the graph changes slightly meaning that each successive factor accounts for less and less on the total variance. Therefore, excluding the point where the break begins, i.e. at factor eight, the number of factors to retain based on the Scree plot is seven.

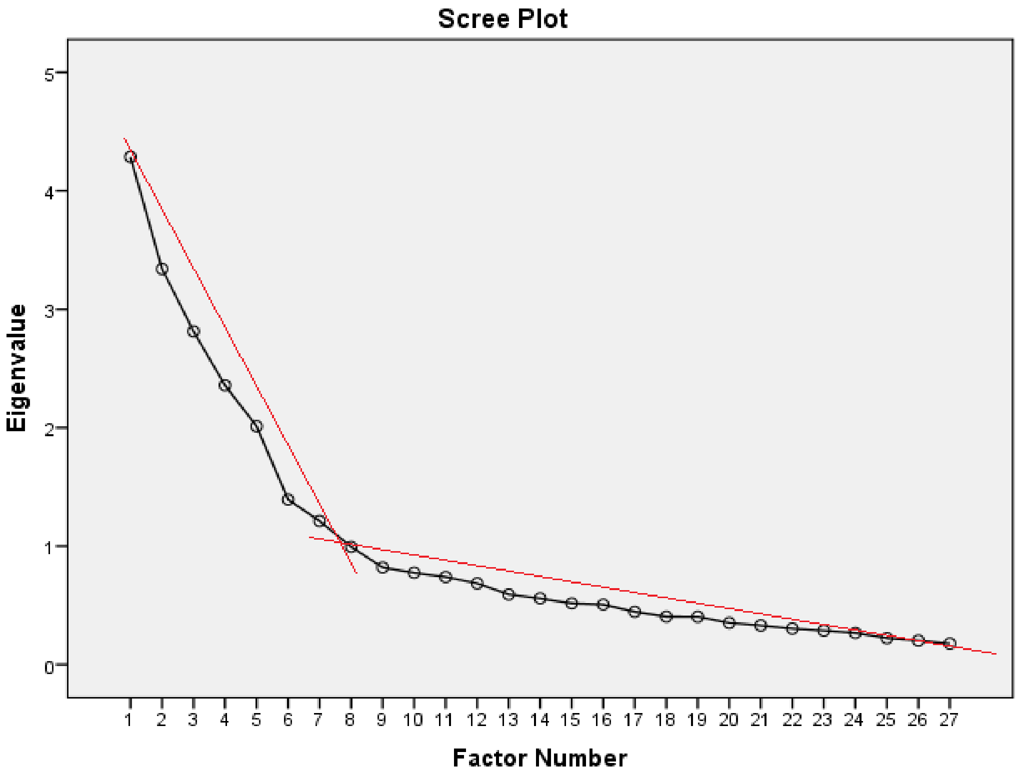

Figure 4.1 Scree Plot

Based on the total variance explained on the rotated eigenvalues and the scree plot, the number of significant factors in the data is seven.

Table 4.6 below shows the factor loadings, as correlations between the observed variables and the factors, after rotation with the Verimax method.

Table 4.6 Rotated Factor Matrix

	SPSS version 23 Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. **Factor**						
	1	2	3	4	5	6	7
CFE2	**.791**	.011	-.047	.002	.038	.028	-.060
CFO1	**.711**	-.037	-.014	-.037	.110	.023	-.019
CFO2	**.816**	-.026	.016	-.015	-.008	.041	-.006
CFO3	**.678**	.022	-.051	.074	-.090	-.040	.159
CFO4	**.778**	-.007	-.006	-.022	-.140	-.044	.090
TEC1	-.005	.072	.039	.056	**.604**	.005	.024
TEC2	-.009	-.054	.069	.090	**.907**	.065	.047
TEC3	-.044	.086	-.048	.098	**.686**	.102	.007
IND1	.007	.206	.179	-.032	.109	**.817**	.008
IND2	.008	.243	.285	-.015	.099	**.787**	-.014
TTF2	.000	**.602**	.116	.009	-.003	.114	.089
TTF3	-.084	**.716**	.019	.105	.056	.084	-.014
TTF4	.065	**.624**	.027	.030	.039	.008	.076
TTF6	-.016	**.619**	-.006	.131	.031	.032	-.009
TTF7	-.013	**.598**	.019	.182	.067	.083	.023
TTF8	-.004	**.731**	.068	.075	-.033	.086	-.095
POU1	-.024	.228	.084	**.559**	.032	-.086	-.013
POU2	.010	.177	.043	**.596**	.096	.044	.124
POU3	-.090	.093	-.041	**.723**	.139	-.086	.061
POU4	.083	.029	.011	**.649**	-.030	-.013	.003
POU5	-.001	.018	-.001	**.563**	.057	.083	.155
UTI1	.108	-.005	-.054	.117	-.005	.069	**.708**
UTI2	.010	.067	.069	.153	.073	-.073	**.655**
PEF1	-.019	.025	**.728**	-.047	.121	.097	.046
PEF2	-.048	.034	**.798**	-.071	-.054	.143	.015
PEF3	-.019	.137	**.683**	.069	-.086	.032	-.061
PEF4	-.012	.018	**.698**	.137	.078	.105	.022

4.5.2.2 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a multivariate technique that assesses the patterns and inter-correlations between observed measures and their underlying latent variables in a structural equation model (Brown, 2015). In essence, CFA deals with the measurement models of a structural equation model.

CFA, as with EFA, is based on the common factor model which states that each indicator/observed measure is a linear function of a unique factor (Brown, 2015). For a reflective outer model, which is the researcher's selected model type, this entails that an observed measure is influenced by the underlying latent variable and all indicators on the same factor would be inter-correlated.

Following exploratory factor analysis conducted in the previous sections using SPSS 23, the path model is constructed in SmartPLS 3.0. First, the hypothesized inner model is designed using the 7 factors revealed in the previous section. Second, the retained measurement items are added to form the outer models in a reflective manner. Lastly, a PLS algorithm is run and outer loading results are inspected. Indicator loadings above 0.70 show indicator reliability (Hair et al., 2011). Hence, a threshold of 0.70 was used to inspect the output and a few runs were conducted until all remaining indicators were above this threshold.

The meaning of a latent variable measured by reflective indicators is unchanged even when some indicators are omitted (Hair et al., 2014). This stability of a factor in the face of omitted items is due to the interchangeability and the high correlation between reflective items. Therefore the omission of observed measures with lower loadings is argued to preserve the relationships between the latent variables in the hypothesized research model. Figure 4.2 shows the setup of outer model (as well as the inner model) in SmartPLS 3.0. The latent variables are the blue circles and the yellow rectangles are the measurement items which measure the observed variables.

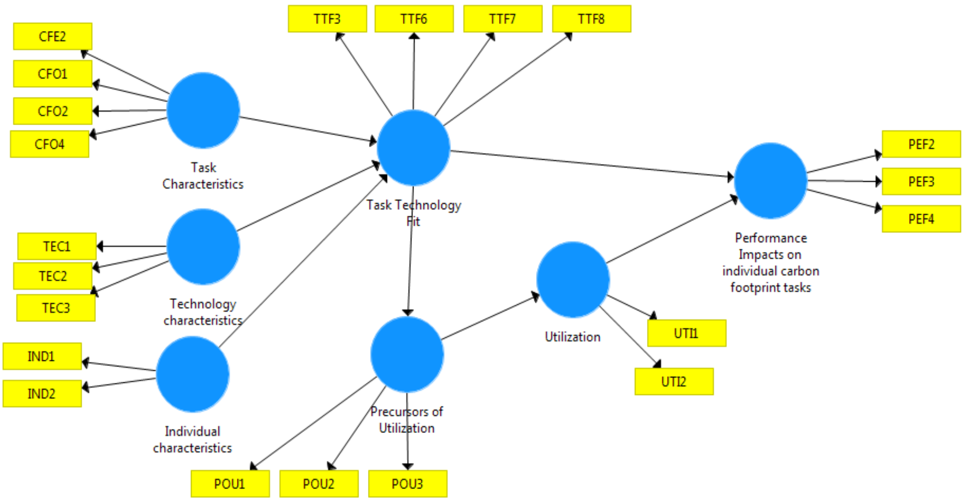

Figure 4.2 Path Model in SmartPLS 3.0

Table 4.7 shows the options used for the PLS algorithm and bootstrapping.

Table 4.7 PLS algorithm and bootstrapping Settings

PLS Algorithm Settings	
Data metric	Mean 0, Var 1
Initial Weights	1.0
Max. number of iterations	300
Stop criterion	7
Weighting scheme	Path
Bootstrapping Settings	
Complexity	Complete Bootstrapping
Confidence interval method	Bias-Corrected and Accelerated (BCa) Bootstrap
Parallel processing	Yes
Samples	5000
Significance level	0.05
Test type	Two Tailed

The PLS algorithm was run a few times, each time requiring assessing the results of the outer loadings. Table 4.8 shows the final outer loadings of the reflective indicators i.e. with magnitudes above the specified threshold (0.70).

Table 4.8 Final Outer Loadings

	SmartPLS version 3 PLS Algorithm Calculation : Outer Loadings **Factor**						
	1	2	3	4	5	6	7
CFE2	**0.807**						
CFO1	**0.828**						
CFO2	**0.868**						
CFO4	**0.810**						
IND1						**0.931**	
IND2						**0.946**	
PEF2			**0.775**				
PEF3			**0.905**				
PEF4			**0.777**				
POU1				**0.801**			
POU2				**0.839**			
POU3				**0.798**			
TEC1					**0.753**		
TEC2					**0.750**		
TEC3					**0.906**		
TTF3		**0.810**					
TTF6		**0.709**					
TTF7		**0.789**					
TTF8		**0.809**					
UTI1							**0.814**
UTI2							**0.903**

This confirmatory run ensures that the observed variables are appropriate measurements of the latent variables represented in the hypothesized inner model. After obtaining the items with the appropriate outer loadings, these loadings were tested for statistical significance.

Statistical Significance of Outer Loadings

The significance of the outer loadings can be determined through running of the bootstrapping procedure. Bootstrapping samples were set to 5000 and a two-tailed test on a significance level of 0.05 was used. The statistical results on the outer loadings were computed and the mean, standard deviation, T-values and P-values are presented in Table 4.9.

Table 4.9 Statistical Significance of Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
CFE2 <- Task Characteristics	0.807	0.716	0.273	2.954	0.003
CFO1 <- Task Characteristics	0.828	0.712	0.263	3.149	0.002
CFO2 <- Task Characteristics	0.868	0.743	0.254	3.420	0.001
CFO4 <- Task Characteristics	0.810	0.680	0.278	2.919	0.004
IND1 <- Individual characteristics	0.931	0.930	0.014	65.558	0.000
IND2 <- Individual characteristics	0.946	0.946	0.011	83.846	0.000
PEF2 <- Performance Impacts on individual carbon footprint tasks	0.775	0.738	0.166	4.666	0.000
PEF3 <- Performance Impacts on individual carbon footprint tasks	0.905	0.839	0.171	5.296	0.000
PEF4 <- Performance Impacts on individual carbon footprint tasks	0.777	0.742	0.214	3.630	0.000
POU1 <- Precursors of Utilization	0.801	0.797	0.046	17.365	0.000
POU2 <- Precursors of Utilization	0.839	0.836	0.036	23.414	0.000
POU3 <- Precursors of Utilization	0.798	0.795	0.040	19.751	0.000
TEC1 <- Technology characteristics	0.753	0.669	0.240	3.136	0.002
TEC2 <- Technology characteristics	0.750	0.652	0.268	2.802	0.005
TEC3 <- Technology characteristics	0.906	0.803	0.235	3.848	0.000
TTF3 <- Task Technology Fit	0.810	0.807	0.038	21.044	0.000
TTF6 <- Task Technology Fit	0.709	0.708	0.053	13.266	0.000
TTF7 <- Task Technology Fit	0.789	0.787	0.039	20.156	0.000
TTF8 <- Task Technology Fit	0.809	0.806	0.038	21.380	0.000
UTI1 <- Utilization	0.814	0.783	0.154	5.270	0.000
UTI2 <- Utilization	0.903	0.881	0.132	6.827	0.000

P-values less than a significance level of 0.05 are regarded as significant while p-values greater than 0.05 are not statistically significant. The table above shows that all outer loadings were statistically significant at the 0.01 significance level. Based on the T statistics, the loadings on the individual characteristics variable had the greatest significance, followed by loadings on task-technology fit and the precursors of utilization. The least significant outer loadings are on the variables for task characteristics, technology characteristics, utilization and performance impacts on carbon footprint tasks.

Using these confirmed indicators, the outer model was further evaluated for validity and reliability.

4.5.3 Construct Validity

4.5.3.1 Discriminant Validity

The discriminant validity of a model is the extent to which constructs, within the model, differ from each other (Roldán & Sánchez-Franco, 2012). To establish the discriminant validity, the variables within a construct should correlate more strongly with each other and less strongly with variables in another construct. Discriminant validity can be established through the Fornell-Larcker Criterion and through the examination of crossloadings (Farrell, 2010). In cases when discriminant validity cannot be reliably established, the Heterotrait-Monotrait Ratio of correlations can be used (Henseler et al., 2015). Although, the cross loadings can be obtained from the CFA output in SPSS, the present research uses a different tool which can test all three criteria of establishing discriminant validity. Discriminant validity was assessed through the use of the SmartPLS 3 program, which is the work of Ringle et al. (2015).

Fornell-Larcker Criterion

For a structural model to be suitable for theory testing or prediction, the square root of the average variance extracted (AVE) must be greater than the correlation of the construct with all other constructs (Fornell & Larcker, 1981).

In Table 4.10, the diagonal figures, in bold, are the square root of the shared variance between the constructs and their measurement items i.e. average variance extracted (AVE). The non-diagonal figures are the correlations among the constructs. When the diagonal figures are greater than the non-diagonal figures, discriminant validity is established. This is the Fornell-Larcker Criterion to test discriminant validity.

Table 4.10 Fornell-Larcker Criterion

	Individual characteristics (IND)	**Performance Impacts on individual carbon footprint tasks (PERF)**	**Precursors of Utilization (PRE-U)**	**Task Characteristics (TASK)**	**Task Technology Fit (TTF)**	**Technology characteristics (TECH)**	**Utilization (UTI)**
IND	**0.938**						
PERF	0.310	**0.821**					
PRE-U	0.026	0.090	**0.813**				
TASK	0.009	-0.036	-0.063	**0.829**			
TTF	0.287	0.127	0.274	-0.061	**0.780**		
TECH	0.164	-0.022	0.174	-0.035	0.130	**0.806**	
UTI	0.002	0.008	0.193	0.064	0.034	0.054	**0.860**

It is observed that the figures in bold (square root of AVE) are greater than the off-diagonal figures (correlations). Therefore, all seven constructs pass the discriminant validity assessment.

Crossloadings

A measurement model with crossloadings is a model when one or more of its items load at 0.32 or higher on two or more factors (Osborne & Costello, 2005). If an observed measure loads higher with other factors than the one it is intended to measure, it may become unclear which factor it is reflecting (Chin, 1998). Osborne and Costello (2005) suggests that a researcher may remove a crossloading item if there are other items which load at 0.50 or higher on a factor.

Out of 21 measurement items, 19 items loaded above 0.32 on a single factor. Two items may seem to be crossloaded. First, "IND2" item loaded at 0.946 with its factor (individual characteristics) but also loaded at 0.323 with another factor (performance impacts on individual carbon footprint tasks). Second, "PEF2" item loaded at 0.775 with its own factor (performance impacts on individual carbon footprint tasks) but also loaded at 0.327 with another factor (individual characteristics).

Table 4.11 Crossloadings

	Individual characteristics	Performance Impacts on individual carbon footprint tasks	Precursors of Utilization	Task Characteristics	Task Technology Fit	Technology characteristics	Utilization
CFE2	0.025	-0.058	-0.003	0.807	-0.018	-0.013	0.018
CFO1	0.024	-0.051	-0.072	0.828	-0.062	0.050	0.052
CFO2	0.040	-0.014	-0.053	0.868	-0.049	-0.034	0.038
CFO4	-0.050	-0.011	-0.044	0.810	-0.050	-0.127	0.082
IND1	0.931	0.254	-0.001	0.008	0.252	0.170	0.006
IND2	0.946	0.323	0.047	0.010	0.284	0.141	-0.002
PEF2	0.327	0.775	-0.023	-0.049	0.061	-0.042	0.005
PEF3	0.223	0.905	0.089	-0.033	0.141	-0.072	-0.025
PEF4	0.272	0.777	0.124	-0.014	0.085	0.085	0.061
POU1	0.003	0.119	0.801	-0.046	0.268	0.069	0.105
POU2	0.098	0.072	0.839	-0.016	0.225	0.166	0.196
POU3	-0.054	0.022	0.798	-0.103	0.168	0.197	0.170
TEC1	0.107	0.033	0.156	-0.003	0.085	0.753	0.072
TEC2	0.161	0.047	0.145	-0.008	0.011	0.750	0.092
TEC3	0.157	-0.056	0.140	-0.049	0.133	0.906	0.025
TTF3	0.242	0.096	0.182	-0.087	0.810	0.126	0.046
TTF6	0.180	0.052	0.223	-0.046	0.709	0.094	0.033
TTF7	0.209	0.094	0.238	-0.048	0.789	0.143	0.058
TTF8	0.258	0.147	0.215	-0.012	0.809	0.044	-0.027
UTI1	0.037	-0.052	0.141	0.109	-0.008	0.015	0.814
UTI2	-0.024	0.051	0.186	0.016	0.057	0.070	0.903

The potential crossloadings observed are not more than 0.01 from the cutoff of the 0.32 threshold. It is expected that each group of indicators loads, higher for its respective latent variable than loading on other latent variables (Chin, 1998). In this case, the items in question loaded highest on the factors they were associated with. Therefore, the "IND2" and "PEF2" items do not correlate more strongly with factors other than their own. Due to these crossloadings being of a smaller magnitude, the researcher has decided to keep these items and argue that there are no crossloading. Thus the discriminant validity is established.

Heterotrait-Monotrait Ratio (HTMT)

Henseler et al. (2015) argue that both the Fornell-Larcker criterion and crossloading are weak when it comes to assessing the lack of discriminant validity in variance-based structural equation modeling (PLS-SEM). They propose a newer criterion namely the “Heterotrait-Monotrait Ratio” (HTMT) of correlations based on the multitrait-multimethod matrix (MTMM).

Given that K_i and K_j are indicators, the HTMT for the ij^{th} constructs is the average of the heterotrait-heteromethod correlations divided by the average of the monotrait-heteromethod correlations (Henseler et al., 2015). This calculation of HTMT is represented by the following formula in Figure 4.3:

$$\mathrm{HTMT}_{ij} = \frac{1}{K_i K_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j} r_{ig,jh} \div \left(\frac{2}{K_i(K_i-1)}\cdot\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,ih}\cdot\frac{2}{K_j(K_j-1)}\cdot\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg,jh}\right)^{\frac{1}{2}}.$$

Figure 4.3 Heterotrait-Monotrait Ratio Formula

Heterotrait-heteromethod correlations are correlations of indicators across constructs measuring different phenomena. The monotrait-heteromethod correlations refer to the correlations of indicators measuring the same construct.

The lack of discriminant validity is indicated by HTMT values above 0.85 (Kline, 2011). Table 4.12 shows the MTMM matrix for the seven constructs of the hypothesised model.

Table 4.12 Heterotrait-heteromethod

	Individual characteristics (IND)	**Performance Impacts on individual carbon footprint tasks (PERF)**	**Precursors of Utilization (PRE-U)**	**Task Characteristics (TASK)**	**Task Technology Fit (TTF)**	**Technology characteristics (TECH)**	**Utilization (UTI)**
IND							
PERF	0.401						
PRE-U	0.092	0.147					
TASK	0.048	0.060	0.088				
TTF	0.345	0.145	0.355	0.075			
TECH	0.208	0.099	0.236	0.088	0.136		
UTI	0.046	0.088	0.271	0.114	0.098	0.097	

In the present study, all HTMT values are below the 0.85 threshold. Therefore discriminant validity has been established using the .85 threshold.

4.5.3.2 Convergent Validity

Convergent validity is the degree to which associated items are related to the same construct. The average variance extracted (AVE) can be calculated and examined in order to assess the convergent validity (Hair et al., 2011). AVE greater than 0.50 are considered acceptable (Bagozzi & Yi, 1988). The Table 4.13 shows the AVE for all constructs in the outer model.

Table 4.13 Average Variance Extracted

	Average Variance Extracted (AVE)
Individual characteristics	0.881
Performance Impacts on individual carbon footprint tasks	0.674
Precursors of Utilization	0.661
Task Characteristics	0.687
Task Technology Fit	0.609
Technology characteristics	0.650
Utilization	0.739

The AVE for all constructs is above the threshold of 0.50. That is, each construct explains more than half of its item's variance. This meets the threshold set for convergent validity.

Given that both discriminant and convergent validity has been established, the measurement model can be argued to have met construct validity.

4.5.4 Internal Consistency Reliability

In order to evaluate whether the items belong to one dimension, an alpha is calculated by considering the correlations between the items and also taking into account the number of items within the construct (Cronbach, 1951). Due to the way the alpha is calculated, this coefficient increases as the number of items in the construct is increased. This is provided the correlations between items remains more or less constant. Nunnally (1978) suggests that

Cronbach's alpha greater than 0.70 is acceptable in indicating whether indicators for constructs display construct reliability.

Although Cronbach's alpha has been used as a measure of construct reliability, other studies (Garson, 2016; Hair et al., 2012) argue that Cronbach's alpha may underestimate reliability. Hair et al. (2012) suggest that composite reliability should be preferred over Cronbach's alpha. The cutoff threshold for composite reliability is similar to that set for Cronbach's alpha (Garson, 2016). Hence, an adequate measure of composite reliability is an estimate greater than or equal to 0.70 (Bagozzi & Yi, 1988; Garson, 2016; Hair et al., 2011).

Table 4.14 shows the measures to assess internal consistency reliability. Individual and task characteristics have the highest estimates while the utilization construct has the least.

Table 4.14 Measures of Internal Consistency Reliability

	Cronbach's Alpha	**Composite Reliability**
Individual characteristics	0.865	0.937
Performance Impacts on individual carbon footprint tasks	0.772	0.861
Precursors of Utilization	0.745	0.854
Task Characteristics	0.854	0.898
Task Technology Fit	0.785	0.861
Technology characteristics	0.778	0.847
Utilization	0.653	0.849

The underestimate of reliability, by Cronbach's Alpha, can be seen as every alpha is less than the composite reliability for all the constructs. Using a cutoff threshold of .70, the results of composite reliability show measures greater than the 0.70 threshold. Therefore, the measurement model can be considered to be reliable.

4.5.5 Final Outer Model

The outer model consists of the instrument items used to measure the latent variables of the inner model. Figure 4.4 shows the final outer model with the factor loadings of the indicators and AVE of the constructs. Of notable absence are indicators CFE1, TEC4 and TTF (1, 5) which were discarded as a result of exploratory factor analysis. Furthermore, confirmatory factor analysis resulted in the elimination of items CFE3, PEF1, POU (4, 5) and TTF (1, 2 and 4). These items will not be used to measure the model.

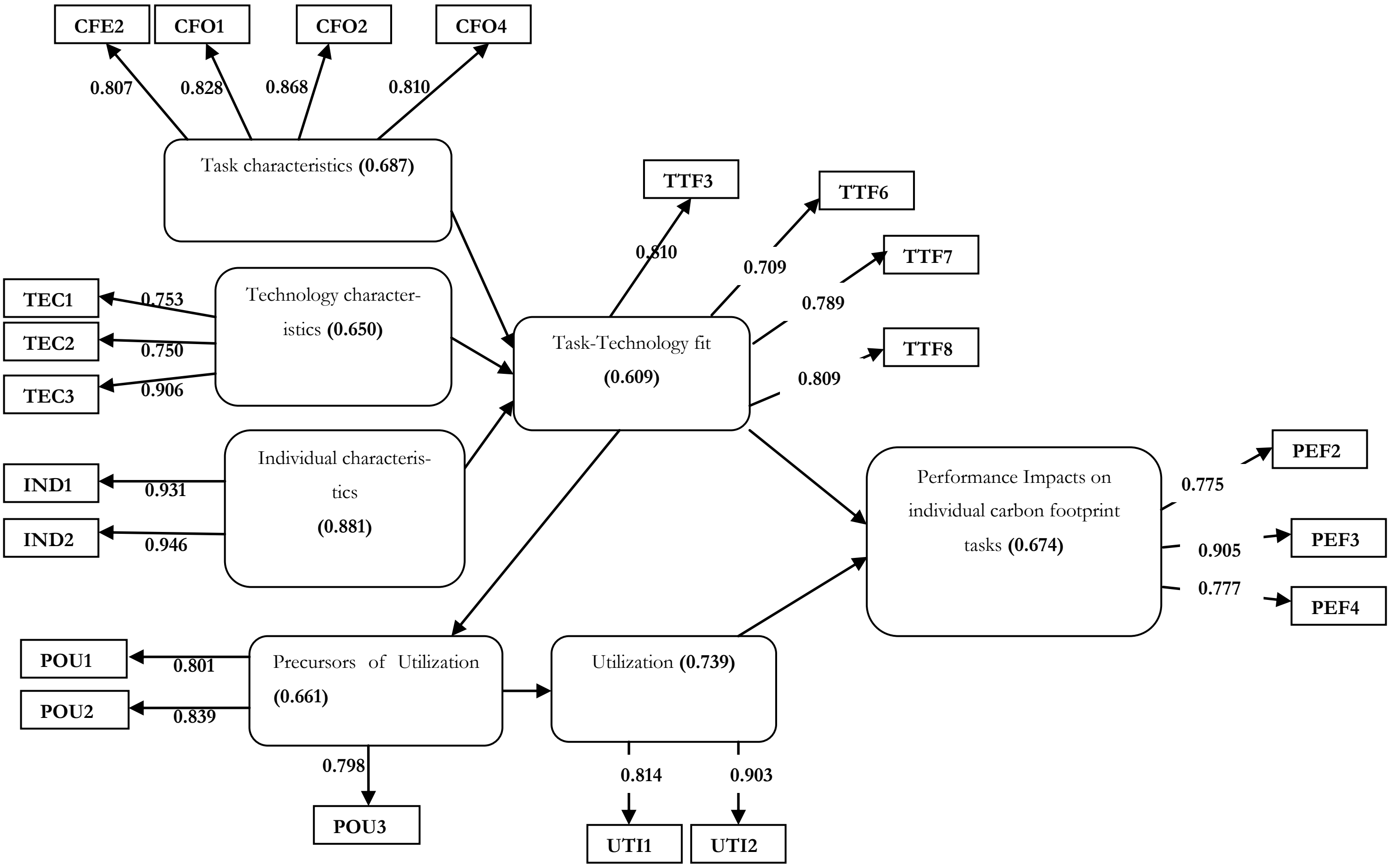

Figure 4.4 Final Outer Model

4.6 Descriptive Statistics

Having conducted reliability and validity tests in the previous chapter, the data were now analysed. Microsoft Excel package was used to calculate rudimentary frequencies and statistics. SmartPLS 3.0 was used to perform statistical tests for differences between groups resulting from demographic factors.

4.6.1 Demographic factors

This section describes the respondents based on their demographic factors. Variables such as gender, age, education and profession are personal attributes which can influence use of information systems by individuals (Zmud, 1979). Many survey based research on individuals have used at least one of these demographic variables to describe their sampling units. The following sections will present the demographic dimensions captured for the participants.

4.6.1.1 Gender

Out of the 262 usable responses in the sample, there were more female respondents (53%) than male (47%).

Table 4.15 Gender

Gender	Count	Percentage (%)
Male	124	47
Female	138	53
Total	**262**	100

Many studies, such as: (Agarwal & Prasad, 1999; Hur et al., 2014; Lee et al., 2007; Nysveen, Pedersen & Thorbjørnsen, 2005; Wang & Wang, 2010; Zmud, 1979) have investigated the moderating effects of gender on technology adoption or success of technology innovations. Their investigations revealed varying findings. Of interest is Venkatesh and Morris (2000)'s finding that males are driven to use technology based on its perceived usefulness whilst females were more influenced by ease of use. This argument is interesting for this current study because ease of use (TTF8) is a variable measuring task-technology fit while perceived usefulness

(POU2) is a measurement for the precursors of mobile technology utilization. Hence, two propositions require testing.

First, there is a need to test whether the effects of task-technology fit on the precursors of mobile technology utilization are stronger for females than males. Second, there is a need to test whether the effects of precursors of mobile technology utilization on utilization are stronger in males than females. The analysis is performed using a multi-group analysis based on the male and female groups and results are presented in the section 4.6.1.1.

4.6.1.2 Age of Respondents

The data collected reflected five age categories. The majority of the respondents were within the 26-35 age-group. Overall, there were fewer respondents above 46 years old. Collecting data about participant's age allows such investigations as whether age can have an effect on relationships between constructs.

Age has a moderating effect on attitude; which influence technology use (Brown, Dennis & Venkatesh, 2010; Hur et al., 2014; Venkatesh et al., 2003; Zmud, 1979). This moderation is sometimes combined with other individual characteristics such as gender.

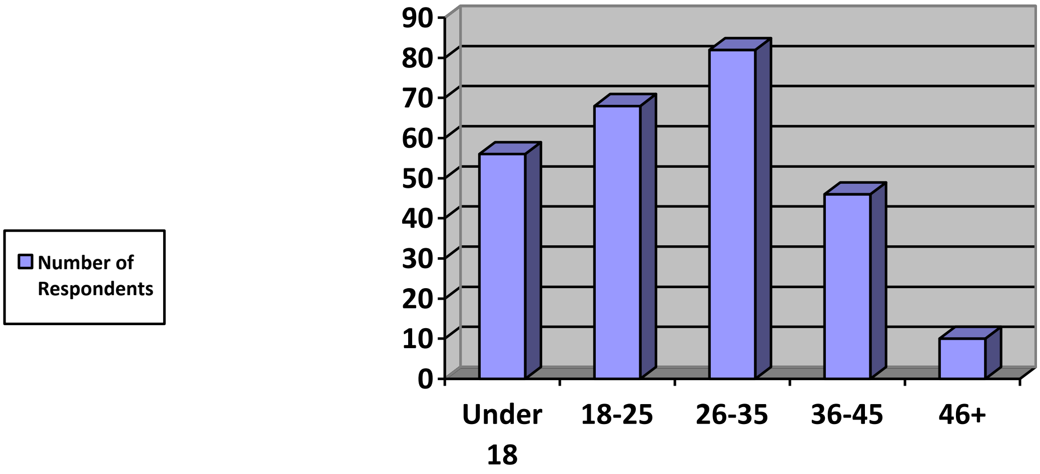

Figure 4.5 Age of Respondents

A statistical test to determine whether the pre-defined age groups had significant differences in the parameter estimates of the hypothesized model was conducted. The results are presented section 4.6.1.2.

4.6.1.3 Employment Status of Respondent

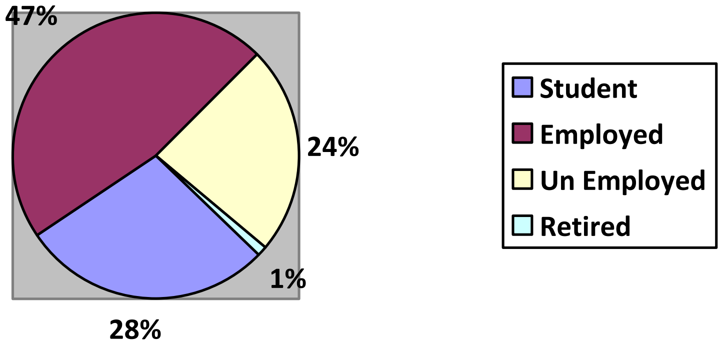

Figure 4.6 Employment Status of Respondent

Of the 262 individuals, the majority of the respondents (proportion of 47%) were employed, followed by 28% of students and 24% representing the unemployed. A mere 1% responded as retired.

Schleife (2006) suggests that technology usage is affected by the employment status of an individual especially when the usage is mandatory. In the present study, the mobile technology usage is voluntary. However, there is still merit in assessing whether there is a difference between the occupation groups.

A statistical test to determine whether the occupation groups had significant differences in the parameter estimates of the hypothesized model was conducted. The results are presented in the section 4.6.1.3.

4.6.1.4 Highest Education Level for Respondents

The respondents were also asked to complete the highest education level they reached. The survey results showed that more than half of the sample had high school as their highest educational level. Only 0.4% completed a post graduate degree.

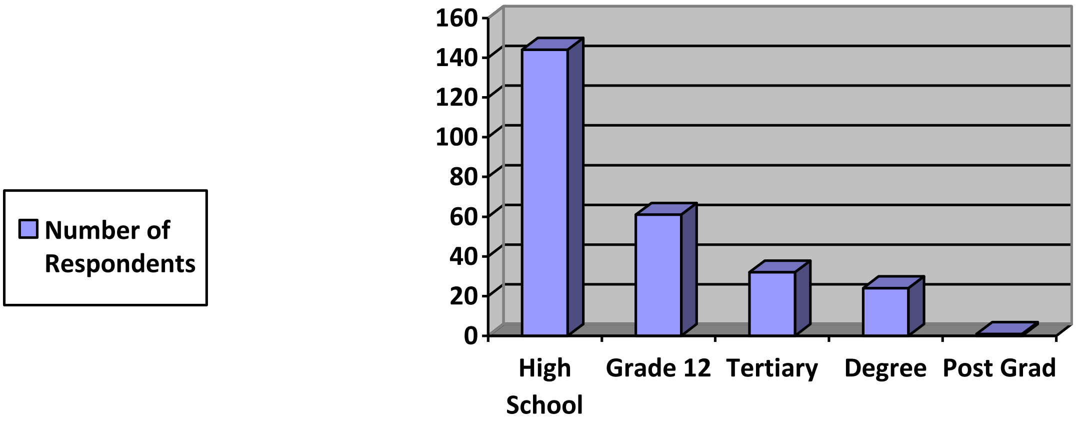

Figure 4.7 Highest Education Level

Zmud (1979) argued that individuals with more education possess greater attitudes towards the use of information systems. In addition, individuals with greater optimistic beliefs about the value of technology are more receptive to new technology advancement (Agarwal & Prasad, 1999). The present research also tests whether there is a difference between the education groups in estimating and offsetting carbon footprint in South Africa using mobile phones.

A statistical test was conducted to determine whether the education groups have significant differences in the parameter estimates of the hypothesized model. The results are presented in section 4.6.1.4.

4.6.1.5 Demographic Summary on Respondents

Table 4.16 below shows the summary of the biographic characteristics of the respondents. The number of male and female respondents is almost similar while the majority of respondents are employed and attended high school. All of the respondents had access to a mobile phone.

Table 4.16 Summary of Respondents

Respondent's	characteristic	Number of Respondents	Percentage (%)
Gender	Male	124	47.3
	Female	138	52.7
Age	Under 18	56	21.4
	18-25	68	26.0
	26-35	82	31.3
	36-45	46	17.6
	46+	10	3.8
Employment Status	Student	74	28.2
	Employed	123	46.9
	Un Employed	62	23.7
	Retired	3	1.1
Highest Education Level	High sch	144	55.0
	Grade 12	61	23.3
	Tertiary	32	12.2
	Degree	24	9.2
	Post grad	1	0.4

4.6.2 Difference between Participant Groups

As a recall from the design chapter, multi-group analysis enables the researcher to test whether groups in a sample have significant differences in their statistical estimates such as path coefficients and outer loadings (Ringle, Wende & Becker, 2015). A multi-group analysis (PLS-MGA) is conducted in SmartPLS using bootstrapping samples set at 5000, significance level of 0.05 and a two-tailed test type. The PLS-MGA test for significance between groups is significant if p-value for the comparison of a statistical estimate between groups is less than 0.05 (Garson, 2016).

The loadings and path coefficients are assessed for the constructs: individual characteristics (IND), technology characteristics (TEC), task characteristics (TAS), task technology fit (TTF), precursors of utilization (POU), utilization (UTI) and performance Impacts on individual carbon footprint tasks (PERF).

4.6.2.1 Gender Groups

Given that the number of female and male respondents in this study is more or less the same, this section now addresses whether the research model shows differences in the cause-effect relationships between the male and female groups.

Table 4.17 below shows the bootstrapping results for the PLS multi-group analysis. The p-values for the path coefficients between the constructs are shown.

Table 4.17 Difference between path coefficients for gender groups

	Path Coefficients-diff (Gender(M) - Gender(F))	**p-Value(Gender(M) vs Gender(F))**
IND -> TTF	0.150	0.053
POU -> UTI	0.173	0.898
TAS-> TTF	0.118	0.645
TTF -> PERF	0.065	0.408
TTF -> POU	0.006	0.512
TEC -> TTF	0.141	0.830
UTI -> PERF	0.007	0.515

The p-value for the path IND -> TTF can be argued to be approximately 0.05 when rounded to two decimal places. Since this p-value is equal to the significance threshold (0.05), there is a statistical significant difference between the male and female groups in the prediction of task technology fit using the individual characteristics. Further statistical test on the path coefficients was conducted to clarify the meaning of this difference.

Table 4.18 shows the results of the test for significance of the path coefficients for path IND -> TTF across the two gender groups.

Table 4.18 Statistical significance of difference between path coefficients for gender groups

	Path Coefficients Original (Gender(F))	**Path Coefficients Original (Gender(M))**	**t-Values (Gender(F))**	**t-Values (Gender(M))**	**p-Values (Gender(F))**	**p-Values (Gender(M))**
IND -> TTF	0.213	0.363	3.118	5.598	0.002	0.000

Although the p-values are both less than the significance threshold (0.05) for both gender groups, the t-value for males (5.598) is greater than the t-value for female (3.118). Therefore, the effects of individual characteristics on task technology fit are stronger in males than females.

While there was statistically significant difference between the gender groups for path IND -> TTF, the other paths did not show differences between the gender groups.

4.6.2.2 Age Groups

The age of an individual might have an effect on their attitude towards use of mobile technology (Sarker & Wells, 2003). This attitude might result in a choice between the conveniences of mobility or any effort (e.g. cost and time) involved in the acquisition or use.

Since Zmud (1979) argued that younger individuals might possess greater positive attitudes towards the use of information systems, the researcher assessed whether the survey data portrayed any difference between the younger and older age groups. To perform this assessment, a statistical test using PLS-MGA was used to compare the 18-25 and the 36-35 age groups. The results are presented in Table 4.19.

Table 4.19 Difference between path coefficients for age groups

	Path Coefficients-diff (Age(18-25) - Age(36-45))	p-Value(Age(18-25) vs Age(36-45))
IND -> TTF	0.060	0.390
POU -> UTI	0.576	0.031
TAS-> TTF	0.139	0.394
TTF -> PERF	0.043	0.435
TTF -> POU	0.163	0.308
TEC -> TTF	0.730	0.017
UTI -> PERF	0.002	0.468

Two paths, namely POU -> UTI and TEC -> TTF have p-values less that the significance threshold (0.05). The other paths show p-values greater than the significance level and therefore reveal that the paths are not statistically different between the age groups in question. On the other hand, the p-values of path POU -> UTI and TEC -> TTF show that the difference between the 18-25 and the 36-35 age groups is statistically significant. A further statistical test was conducted to reveal which age group showed a stronger effect in these paths.

Table 4.20 shows the results of a statistical test on the significance of the path coefficients for the paths POU -> UTI and TEC -> TTF for these age groups.

Table 4.20 Statistical Significance of difference between path coefficients for age groups

	Path Coefficients Original (Age(18-25))	**Path Coefficients Original (Age(36-45))**	**t-Values (Age(18-25))**	**t-Values (Age(36-45))**	**p-Values (Age(18-25))**	**p-Values (Age(36-45))**
POU -> UTI	0.330	-0.247	2.250	0.818	0.025	0.413
TEC -> TTF	0.274	-0.456	2.699	1.096	0.007	0.273

The p-values for the 18-25 age group are less than the significance level (0.05) while the p-values for the 36-45 age group are greater that the significance threshold. This implies that, for paths POU -> UTI and TEC -> TTF the causal links are not only supported, but are stronger for the 18-25 age groups.

4.6.2.3 Occupational Groups

Two multi-group analysis were computed for the occupation categories, namely the *employed*, *unemployed* and *student* groups. The *retired* group had too few respondents to be included in the group comparisons. The comparisons presented are *employed* group vs *student* group and *employed* group vs *unemployed* group.

Table 4.21 Difference between path coefficients for occupational groups

	Path Coefficients-diff (EMPLOYED - STUDENT)	**Path Coefficients-diff (EMPLOYED - UNEMPLOYED)**	**p-Value (EMPLOYED vs STUDENT)**	**p-Value (EMPLOYED vs UNEMPLOYED)**
IND -> TTF	0.168	0.242	0.897	0.827
POU -> UTI	0.179	0.129	0.878	0.721
TAS-> TTF	0.043	0.61	0.557	0.248
TTF -> PERF	0.266	0.080	0.087	0.629
TTF -> POU	0.288	0.455	0.067	0.021
TEC -> TTF	0.063	0.428	0.439	0.131
UTI -> PERF	0.133	0.287	0.723	0.888

The PLS-MGA on comparison of the employed group versus the unemployed group yielded a p-value less than the significance threshold (0.05) for the path TTF -> POU. Therefore, there is a statistically significant difference between the employed and unemployed groups for this relationship.

An assessment of the significance of this path is presented in the Table 4.22. The p-value for testing significance of employed participant's path TTF -> POU is less than the significance level (0.05) while the corresponding p-value for the unemployed is greater than the significance level threshold. This entails that the hypothesized path TTF -> POU is supported only when employed respondents are considered.

Table 4.22 Statistical Significance of difference between path coefficients for occupational groups

	Path Coefficients Original (EMPLOYED)	Path Coefficients Original (UNEMPLOYED)	t-Values (EMPLOYED)	t-Values (UNEMPLOYED)	p-Values (EMPLOYED)	p-Values (UNEMPLOYED)
TTF -> POU	0.311	-0.144	3.269	0.545	0.001	0.586

4.6.2.4 Groups based on Education Level

PLS-MGA could not be run on the pre-defined groups based on the respondent's highest education level. SmartPLS 3 suggested to increase the sample size in the pre-defined groups or to identify indicators to be removed from the outer model. The removal of indicators was not pursued as this would have resulted in a different outer model. Acquiring more data was not viable either. Consequently, the researcher used the functionality available in SmartPLS to modify the pre-defined groups. This alteration resulted in two groups, namely **Group A** (High School and Grade 12) and **Group B** (Tertiary and Degree). The postgraduate respondent was unavailable, in SmartPLS, for selection as the number of respondents was too small.

Table 4.23 shows the results of the multi-group analysis of the two groups, Group A and Group B.

Table 4.23 Difference between path coefficients for education levels

	Path Coefficients-diff (EducationLevel(Group A - EducationLevel(Group B))	**p-Value (EducationLevel(Group A) vs EducationLevel(Group B))**
IND -> TTF	0.055	0.511
POU -> UTI	0.345	0.086
TAS-> TTF	0.088	0.290
TTF -> PERF	0.024	0.545
TTF -> POU	0.045	0.700
TEC -> TTF	0.040	0.553
UTI -> PERF	0.040	0.428

Since none of the p-values were less than the significance level (0.05), there was no statistically significant difference in the path coefficients as a result of the differing education groups. Hence, no further statistical tests were conducted on these groups.

4.6.3 Descriptive Data in Variables

Table 4.24 shows the descriptive data of variables whose items were measured on a five point Likert scale. The measures of central tendency (mean, median and mode), variability (standard deviation) and distribution (skewness and kurtosis) were calculated using SPSS.

Table 4.24 Descriptive Statistics

	N									
	Valid	Missing	Mean	Median	Mode	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
CFE2	262	0	3.64	4.00	4	.555	-1.256	.150	.613	.300
CFO1	262	0	3.69	4.00	4	.538	-1.569	.150	1.553	.300
CFO2	262	0	3.50	4.00	4	.566	-.591	.150	-.668	.300
CFO4	262	0	3.63	4.00	4	.551	-1.135	.150	.298	.300
TEC1	262	0	3.282	4.00	4	.8144	-.519	.150	-1.221	.300
TEC2	262	0	3.447	4.00	4	.7600	-.847	.150	-.588	.300
TEC3	262	0	3.523	4.00	4	.7814	-1.072	.150	-.269	.300
IND1	262	0	2.31	2.00	2	1.131	.618	.150	-.739	.300
IND2	262	0	1.763	1.00	1	1.0006	1.067	.150	-.103	.300
TTF3	262	0	3.794	4.00	4	.4053	-1.461	.150	.137	.300
TTF6	262	0	3.695	4.00	4	.4857	-1.150	.150	.035	.300
TTF7	262	0	3.740	4.00	4	.4392	-1.103	.150	-.789	.300
TTF8	262	0	3.756	4.00	4	.4305	-1.197	.150	-.571	.300
POU1	262	0	3.28	3.00	4	.756	-.521	.150	-1.079	.300
POU2	262	0	3.27	3.00	4	.741	-.473	.150	-1.050	.300
POU3	262	0	3.29	3.00	4	.712	-.496	.150	-.917	.300
UTI1	262	0	3.485	4.00	4	.6110	-.754	.150	-.404	.300
UTI2	262	0	3.756	4.00	4	.6076	-1.298	.150	2.697	.300
PEF2	262	0	2.763	3.00	3	.5718	.042	.150	-.377	.300
PEF3	262	0	2.710	3.00	3	.5535	-.001	.150	-.539	.300
PEF4	262	0	2.721	3.00	3	.5695	.072	.150	-.508	.300

** Note that the statistical mean less than 3 would be regarded as a "Low" score, whereas statistical mean greater than 3.1 would be regarded as a "High" score. Any statistical mean equal to 3 would have been regarded as a "medium" score. However, from this sample, no mean was medium.*

The following subsections give an account of the descriptive statistics of the variables and indicators.

4.6.3.1 Estimating Carbon Footprint

Section B of the questionnaire poses questions to measure the estimation of carbon footprint by individuals. The responses are represented by the descriptive statistics of item CFE2. Individuals agreed that estimation of carbon footprint would enable them to use less energy.

4.6.3.2 Offsetting Carbon Footprint

Offsetting of a carbon footprint is measured by items in Section B. Individuals agreed that tree planting and taking part in renewable energy projects would increase their awareness towards energy and resource conservation (CFO1 and CFO2). The respondents also agreed they would take part in renewable energy projects (CFO4), in order to offset their carbon footprint.

4.6.3.3 Mobile Technology

Most of the respondents agreed that the technology characteristics measured by network (TEC1 & TEC2) and user interface (TEC3) items would allow them to perform their carbon footprint tasks using a mobile phone. The median of three for TEC1 splits the perception of the respondents in half in terms of whether network coverage would affect the usage of the mobile phone to perform individual's carbon footprint tasks.

4.6.3.4 Individual characteristics

Most of the respondents disagree that they could use the mobile phone to estimate their carbon footprint if they could learn the process easily. This disagreement was expressed for item IND1. The highest education level of respondents was transformed to variable IND2 and used as an additional measurement of individual characteristics. This transformation was used as designed and presented in the research design chapter. Most respondents had IND2 with the least score (i.e. 1 = High School or less), as their highest educational level.

4.6.3.5 Task-technology fit

Most of the respondents agreed that they would use the mobile phone to perform their tasks if there was a fit between the mobile carbon footprint calculator and their carbon footprint tasks.

4.6.3.6 Precursors of utilization

The median of the items had a score of three whilst the mode was four. This shows that most of the respondents agreed that facilitating conditions, perceived usefulness and their attitude and beliefs would allow them to use mobile phones to perform their carbon footprint tasks. The standard deviations of items measuring the precursors of utilization were all approximately 0.7.

4.6.3.7 Utilization

Using the frequency of use items (*UTI1* and *UTI2*), the utilization variable can be further explored in terms of frequent and less frequent users. Based on the median of these two items, the researcher considered a median less than three to relate to a less frequent user and a median greater than three to describe a frequent user. Out of the 262 respondents, 231 were regarded as frequent users, whereas 31 users were regarded as less frequent users. This 88% majority, infrequent users, resulted in the utilization variable to have a “high” score. This data revealed that there were two individual groups based on utilization (perceived or actual utilization). These groups were further tested to determine how their utilization impacted performance on individual carbon footprint tasks.

4.6.3.8 Performance Impacts on individual carbon footprint tasks

The last section of the measurement instrument, Section G, collected responses to measure individual performance with regards to carbon footprint tasks. As designed, items with responses ranging from *Poor* to *Excellent* were transformed to numerical scores, from 1 to 5. All of the retained performance indicators (PEF2, 3, 4) had a performance score of 3. Overall, all statistical means for the performance sections were less than 3.1. This can be classified as a “low” performance score.

4.7 Normality Testing

Significance tests are conducted to rule out the possibility of data analysis results occurring as a result of random chance (Saunders et al., 2009). One of the assumptions of most data analysis methods is a normal distribution of data (Öztuna, Elhan & Tüccar, 2006). This assumption has given rise to a group of statistical tests known as non-parametric statistics, which do not require data to be normally distributed (Saunders et al., 2009). The other group of statistical tests which require data to be normally distributed among other assumptions is represented by parametric statistics (Saunders et al., 2009). This presents the need to determine the distribution of the data in order to inform the choice of data analysis methods.

The descriptive statistics presented earlier showed the skewness and kurtosis values for each observed measure. However, more analysis of the sets of variables measuring the latent variables is required.

Since each latent variable was measured by at least 2 observed variables, the mean of the observed variables was computed by considering the score for each observed measure and the number of items. SPSS was used for this transformation and the result was an aggregate variable for each group of observed variables. These aggregate variables are: IND (individual characteristics), TEC (technology characteristics), TAS (task characteristics), TTF (task technology fit), POU (precursors of utilization), UTI (utilization) and PERF (performance Impacts on individual carbon footprint tasks).

The following are the transformations which produced the aggregated variables:

COMPUTE **TAS**=*MEAN*(CFE2,CFO1,CFO2,CFO4).
COMPUTE **TEC**=*MEAN*(TEC1,TEC2,TEC3).
COMPUTE **IND**=*MEAN*(IND1,IND2).
COMPUTE **TTF**=*MEAN*(TTF3,TTF6,TTF7,TTF8).
COMPUTE **POU**=*MEAN*(POU1,POU2,POU3).
COMPUTE **UTI**=*MEAN*(UTI1,UTI2).
COMPUTE **PERF**=*MEAN*(TTF2,TTF3,TTF4).

The data distribution of these variables was assessed for normality. SPSS was used to determine the extent of skewness and kurtosis. Table 4.25 shows the skewness and kurtosis measures of distribution. A z-test was conducted to produce z-scores based on skewness and kurtosis.

Table 4.25 Statistics on Variable Distribution

		TAS	TEC	IND	TTF	POU	UTI	PERF
N	Valid	262	262	262	262	262	262	262
	Missing	0	0	0	0	0	0	0
Skewness		-1.259	-0.727	0.934	-1.224	-0.498	-1.654	-1.370
Std. Error of Skewness		0.150	0.150	0.150	0.150	0.150	0.150	0.150
Z-score of Skewness		-8.393	-4.847	6.227	-8.160	-3.320	-11.027	-9.133
Kurtosis		1.414	-0.459	-0.374	0.325	-0.762	2.095	0.859
Std. Error of Kurtosis		0.300	0.300	0.300	0.300	0.300	0.300	0.300
Z-score of Kurtosis		4.713	-1.530	-1.247	1.083	-2.540	6.983	2.863

For samples between 30 and 300, absolute values of z-scores above 3.29 represent non-normal distribution (Kim, 2013). The results presented above show that for the study's sample size (N=262), the z-score for skewness are all above 3.29. However, the absolute values of z-scores of kurtosis for variables TEC, IND, TTF, POU and PERF were below 3.29. To conclude the normality assessment for these variables, further tests are performed. For sample sizes less than 300, formal tests for normality such as the Kolmogorov-Smirnov (K-S) test and the Shapiro-Wilk test can be conducted (Kim, 2013). These formal normality tests were conducted and the results of the Kolmogorov-Smirnov test and the Shapiro-Wilk executed in SPSS are shown in the Table 4.26 below.

Table 4.26 Formal Tests of Normality

	Kolmogorov-Smirnov (Lilliefors Significance Correction)			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
TAS	.255	262	.000	.803	262	.000
TEC	.211	262	.000	.863	262	.000
IND	.266	262	.000	.830	262	.000
TTF	.301	262	.000	.746	262	.000
POU	.184	262	.000	.902	262	.000

UTI	.291	262	.000	.690	262	.000
PERF	.342	262	.000	.714	262	.000

The formal tests of normality presented (K-S and Shapiro-Wilk) compare the sample scores to a group of theoretical scores (with similar mean and standard deviation) that follow a normal distribution (Ghasemi & Zahediasl, 2012). This comparison is based on the null hypothesis that the distribution of the sample is not different from the normal distribution. The sample distribution is non-normal when the normality test is statistically significant (Ghasemi & Zahediasl, 2012). Using a significance level of 0.05, calculated significance values less than 0.05 results in the rejection of the null hypothesis and the conclusion that the sample is not normally distributed. Significance values greater than 0.05 results in the non-rejection of the null hypothesis and the acceptance that the sample is normally distributed.

Based on the K-S and Shapiro-Wilk tests, the significance (0.000) is less than 0.05 for all variables. This results in the null hypothesis that the sample distribution is normally distributed to be rejected. Therefore the sample distribution is non-normal.

For visual presentation, histograms were produced to show the sample distribution results. As expected of the non-continuous Likert item data, the skewness is visible. As an example, the histogram of the *TAS* variable, shown in Figure 4.8, displays a negatively skewed distribution. The other histograms, for the remaining aggregated variables, produced are shown in Appendix C.

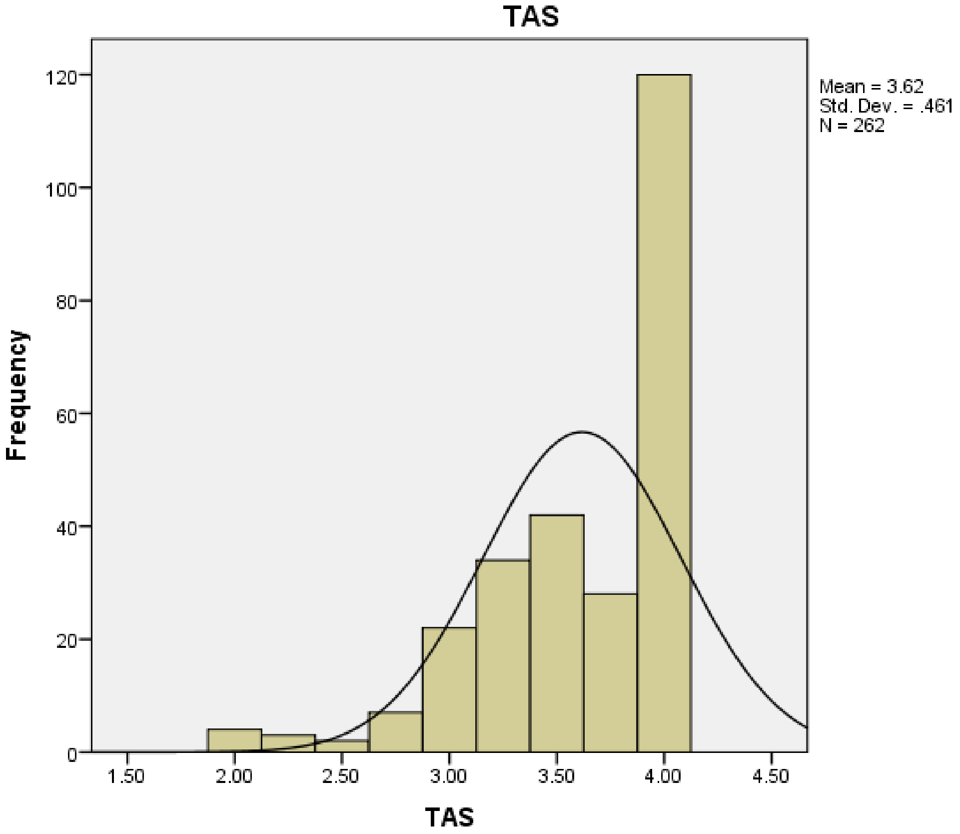

Figure 4.8 Histogram for Task variable

4.8 Correlation Analysis

The correlation coefficient, r, is the linear association between two ranked variables (Saunders et al., 2009). This bivariate correlation is represented by values between -1 and +1. Table 4.27 shows descriptions of the correlation coefficient values. As shown, correlation coefficient can be either weak or strong and either negative or positive.

Table 4.27 Correlation coefficient values (Saunders et al., 2009).

-1	-0.7	-0.3	0	0.3	0.7	1
Perfect negative	Strong negative	Weak negative	Perfect independence	Weak positive	Strong positive	Perfect positive

The strength of relationships between variables was tested using a non-parametric test since it was established that the variables followed a non-normal distribution. The correlation analysis was completed using Spearman's rank correlation coefficient and yielded the results shown in the following table. These results merely show the strength of relationships and not strength of cause-and-effect of relationships (Saunders et al., 2009).

Table 4.28 Correlation Analysis Results

Spearman's rho N=262		TAS	TEC	IND	TTF	POU	UTI	PERF
TAS	Correlation Coefficient	1						
	Sig. (2-tailed)	.						
TEC	Correlation Coefficient	0.009	1					
	Sig. (2-tailed)	0.89	.					
IND	Correlation Coefficient	0.038	0.078	1				
	Sig. (2-tailed)	0.536	0.206	.				
TTF	Correlation Coefficient	-0.056	0.101	.265**	1			
	Sig. (2-tailed)	0.37	0.102	0	.			
POU	Correlation Coefficient	-0.067	.186**	0.04	.291**	1		
	Sig. (2-tailed)	0.281	0.003	0.519	0	.		
UTI	Correlation Coefficient	0.103	0.011	0.066	-0.02	.162**	1	
	Sig. (2-tailed)	0.097	0.856	0.284	0.749	0.009	.	
PERF	Correlation Coefficient	0.005	0.087	.289**	.666**	.203**	0.054	1
	Sig. (2-tailed)	0.93	0.162	0	0	0.001	0.385	.

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

Most of the associations in the hypothesized research model showed significant positive relationships except for three associations which did not show a significant relationship. First, *task characteristics* did not show a significant relationship with *task technology fit* variable. Second, *technology characteristics* did not show a significant relationship with task *technology fit*. Third, *utilization* also showed no significant relationship with the *performance impacts on individual carbon footprint tasks*.

Individual characteristics showed a significant weak positive relationship with a coefficient of .265 on t*ask technology fit*. The association between t*ask technology fit* and the *precursors of utilization* was a significant weak positive association with a correlation of .291. There was a significant weak positive association between the *precursors of utilization* and *utilization*. This was represented by a correlation coefficient of .162. Lastly, there was a strong positive correlation of .666 between t*ask technology fit* and *performance impacts on individual carbon footprint tasks*.

The correlation analysis produced results which were not expected. In this case, associations not shown by the research model produced significant correlations. There was an unexpected significant weak positive correlation between *Individual characteristics* and *performance impacts on individual carbon footprint tasks*. In addition, *technology characteristics* were unexpectedly positively correlated to the *precursors of utilization* variable although the relationship was weak. Lastly, a significant weak positive relationship between the *precursors of utilization* and *performance impacts on individual carbon footprint tasks* was not hypothesized.

The results of the correlation analysis for the hypothesised relationships are summarised in Table 4.5.

Table 4.29 Summary on Statistical Significance of Correlations

Relationship	Correlation Coefficient	Strength	P-Value	Statistical significance
Tasks Characteristics on TTF	-0.056	N/A	0.370	Non-significant
Technology Characteristics on TTF	0.101	N/A	0.102	Non-significant
Individual Characteristics on TTF	$.265^{**}$	Weak	0.000	Significant
TTF on PERF	$.666^{**}$	Strong	0.000	Significant
TTF on Precursors of Utilization	$.291^{**}$	Weak	0.000	Significant
Precursors of Utilization on Utilization	$.162^{**}$	Weak	0.009	Significant
Utilization on PERF	0.054	N/A	0.385	Non-significant

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

The summary shows that three associations were non-significant as their p-values were greater than the significance level (0.01) while the other four relationships had p-values less than the significance level (0.01) and were thus regarded as significant. The relationships which are significant imply that the null hypothesis, which assumes variation of data are due to random variation/chance, can be rejected. However, to prove that one variable causes another the path coefficients were tested for statistical significance. The next sections evaluate the inner model and thereafter, hypotheses are tested.

4.9 Inner Model Fit

The fit of the outer model was examined through testing reliability and validity. In this section, the fit of the inner model is assessed. The inner model is comprised of variables which are connected to other variables by arrows (Garson, 2016). The strength of these interconnections is measured through the use of standardised regression coefficients. These are the loadings of the direct path which connect the variables.

There are a number of fit indices to assess the goodness of fit for a structural model (Hooper et al., 2008; Schermelleh-Engel et al., 2003). However, caution should be taken when relying on some of these probability values when the sample sizes are high (Bentler & Bonett, 1980; Schermelleh-Engel et al., 2003). Undesired results may be produced due to sample variation and this needs more interpretation. The chi-square test, χ^2, is one statistical test sensitive to sample size. Bentler and Bonett (1980) recommended an incremental fit index, Normed Fit Index (NFI), to evaluate models. Values for Normed Fit Index range between 0 and 1, with values closer to 1 indicating a better fit (Schermelleh-Engel et al., 2003). Although the NFI is affected by sample size, the present sample size (N=262), can be regarded to be of moderate size - neither small nor too high. The NFI for the inner model was calculated to be equal to 0.647. This fit index is argued to construe a moderate inner model fit.

4.10 Evaluation of Inner Model

The evaluation of an inner model should be preceded by an assessment of collinearity, particularly when formative measurement models are used to measure constructs (Hair et al., 2014). However, the measurement model is reflective, for the present study. Although multicollinearity is not an issue for reflective outer models (Garson, 2016), the passing of the discriminant validity assessment using the Fornell-Larcker criterion dismisses collinearity issues for reflective outer models (Hair et al., 2014). In hindsight, the collinearity statistics produced by SmartPLS all showed variance inflation factor (VIF) values less than the cutover values of 4 (Garson, 2016) or 5 (Hair et al., 2011). Hence, there was no evidence of multicollinearity.

Hair et al. (2014) suggests the criteria required to assess the hypothesized inner model's quality are the coefficient of determination (R^2), cross-validated redundancy (Q^2), path coefficients and the effect size (f^2).

4.10.1 Coefficient of determination (R^2)

The coefficient of determination, R^2, is a measure of variability in the dependent variable explained by the model through the independent variables (Hair et al., 2014). This entails that the endogenous variable shows the combined effect of the exogenous variables through the coefficient of determination. R^2 is one of the measures of fit for an inner model (Garson, 2016) as it is a measure of the model's predictive accuracy (Hair et al., 2014).

Figure 4.2 shows the inner model with the R^2 values of the endogenous variables, namely task technology fit, performance impacts on individual carbon footprint tasks, precursors of utilization and utilization.

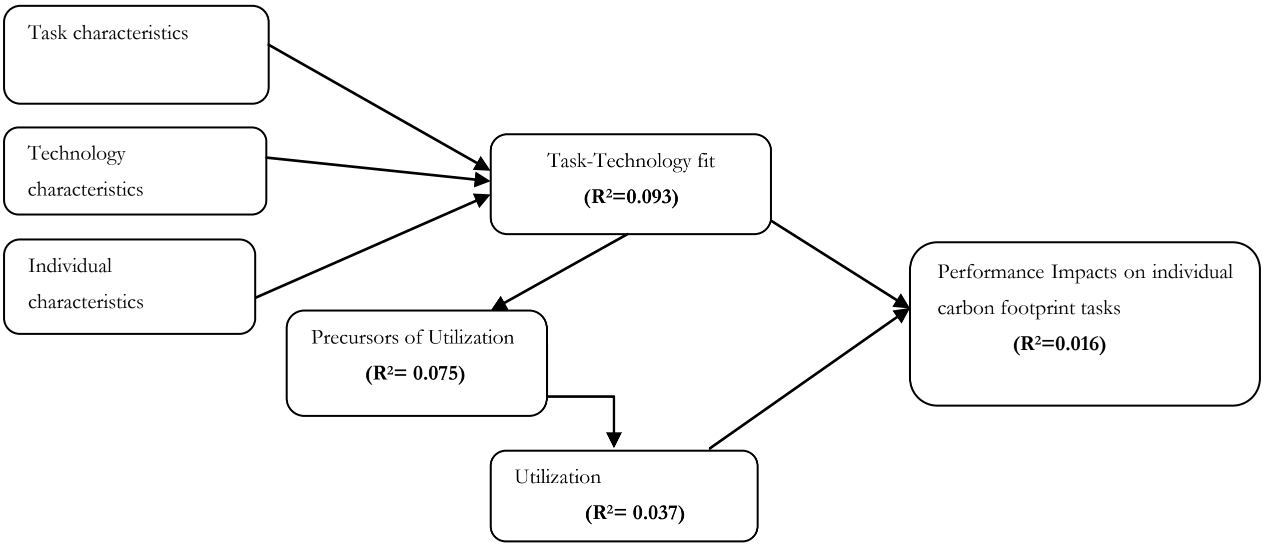

Figure 4.9 Evaluated Inner Model

For the endogenous variable task-technology fit, the R-square value is 0.093, meaning that about 9.3% of the variance in task-technology fit is explained by the inner model (i.e, mutually by task, technology and individual characteristics). The R^2 for the precursors of utilization is 0.075 i.e. 7.5% of the variance in the precursors of utilization is explained by the inner model. R-square value is 0.037 for utilization; that is 3.7% of the variance in the utilization variable is explained by the model. For the dependant variable, performance impacts on individual carbon footprint tasks, the R^2 is 0.016. This entails that 1.6% of the variance in the performance impacts on individual carbon footprint tasks variable is jointly explained by TTF and utilization variables.

Adjusted R^2 considers any bias introduced by adding predictors in a regression model (Hair et al., 2014). This can be calculated by the following formula:

Adjusted R square = $1 – \{ [(1 – R^2)*(n-1)]/[n-k-1] \}$ (Garson, 2016).

In the formula, R^2 is the R-square, n is the sample size and k is the number of exogenous variables used to predict a given endogenous variable (Garson, 2016). In essence, when selecting models based on predictive accuracy adjusted R^2 should be used rather R^2 (Hair et al., 2014). This is because adjusted R^2 is immune to changes in the number of constructs added to an inner model. Table 4.30 shows the adjusted R^2 for the inner model's endogenous variables.

Table 4.30 Inner model's adjusted R^2

	R Square Adjusted
Performance Impacts on individual carbon footprint tasks	0.009
Precursors of Utilization	0.072
Task Technology Fit	0.082
Utilization	0.033

Table 4.6 shows the statistical significance of the R^2. These are results of a bootstrapping procedure computed using a significance level (α) of 0.05 under a two-tailed test. The p-value for precursors of utilization (0.018) and task technology fit (0.000) are less than 0.05 (α). Therefore, the R squared values of 0.075 (precursors of utilization) and 0.093 (task technology fit) are statistically significant in inferring that the variance in the exogenous variables

(precursors of utilization and task technology fit) is explained by their independent variables as represented by the inner model. The R squared values for performance impacts on individual carbon footprint tasks and utilization are not significant as the statistical tests yielded p-values less that the significance levels.

Table 4.31 Statistical Significance of R^2

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (O/STDEV)**	**P Values**	**Significance**
Performance Impacts on individual carbon footprint tasks	0.016	0.032	0.017	0.970	0.332	Not Significant
Precursors of Utilization	0.075	0.082	0.032	2.363	0.018	Significant
Task Technology Fit	0.093	0.115	0.027	3.495	0.000	Significant
Utilization	0.037	0.045	0.026	1.429	0.153	Not Significant

The statistical significance of the adjusted R^2 values was also determined. Table 4.32 shows the results of the tests for significance. As with the R^2 values, precursors of utilization and task technology fit shows significant adjusted R^2 values while performance impacts on individual carbon footprint tasks and utilization values for adjusted R^2 are not significant.

Table 4.32 Statistical Significance of Adjusted R^2

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (O/STDEV)**	**P Values**	**Significance**
Performance Impacts on individual carbon footprint tasks	0.009	0.024	0.017	0.511	0.609	Not Significant
Precursors of Utilization	0.072	0.078	0.032	2.243	0.025	Significant
Task Technology Fit	0.082	0.105	0.027	3.062	0.002	Significant
Utilization	0.033	0.041	0.026	1.282	0.200	Not Significant

4.10.2 Q^2 Predictive Relevance

Q^2 is a measure of providing predictive relevance (Hair et al., 2014). In PLS, Stone-Gleisser's Q^2 is calculated through the use of a blindfolding technique which omits every *d*th data point and attempts to predict the omitted data (Chin, 1998). The value of this omission distance (d) should not be large (Chin, 1998). In practice, the number of observations (N) divided by d should not be an integer and values of d between 5 and 12 are feasible (Garson, 2016). A Q^2 value > 0 imply that the model is relevant in predicting the underlying endogenous variable (Chin, 1998; Garson, 2016). In this case, the endogenous variable is able to be predicted by the path's model (Hair et al., 2014). Q^2 values less than zero shows that the model lack relevance in predicting the endogenous variable.

Blindfolding was computed in SmartPLS using the default omission distance (d) of 7 as an appropriate setting since N/d (262/7=37.42) is not an integer. The redundancy based output as a result of running blindfolding in SmartPLS will be discussed. The Q^2 values are shown in Table 4.33.

Table 4.33 Construct Crossvalidated Redundancy Results

	SSO	SSE	Q^2 (=1-SSE/SSO)
Performance Impacts on individual carbon footprint tasks	786.000	781.124	0.006
Precursors of Utilization	786.000	751.200	0.044
Task Technology Fit	1,048.000	999.864	0.046
Utilization	524.000	513.826	0.019

In Table 4.33, SSE is the sum of squares of prediction error. This is calculated when the omitted data are predicted. SSO is the calculation of the sum of squares errors. All the endogenous variables have a Q^2 greater than 0. This means that all the endogenous variables can be predicted by the path's model. The variable with the smallest Q^2 value ($Q^2 = 0.006$) was *performance impacts on individual carbon footprint tasks*. *Task-technology fit* variable had the highest Q^2 value (of 0.046).

4.10.3 Path coefficients

Path coefficients are estimates which represent the hypothesized causal links between constructs of a path model (Hair et al., 2014). These estimates are produced by running the PLS model. The estimates range between -1 and +1, with values closer to -1 showing strong negative relationships while values close to +1 indicating stronger positive relationships (Hair et al., 2014). The path coefficients obtained should be tested for statistical significance using bootstrapping, followed by checking relevance of the significant relationships (Hair et al., 2014). The relevance can be determined by inspecting the sizes of the estimates in order to reveal which effect is small, medium or large.

Since PLS-SEM does not assume normal distribution of data, it applies a nonparametric technique to test the significance of PLS-SEM results such as path coefficients (Hair et al., 2011). In SmartPLS, bootstrapping is the nonparametric procedure which allows testing of the statistical significance of path coefficients amongst other PLS-SEM results (Garson, 2016; Ringle et al. 2015). The results of bootstrapping such as T-values and P-values can be used for hypothesis testing. Regarding p-values for path coefficients, paths which are nonsignificant or in the opposite hypothesised direction do not support the hypothesis while significant paths support a hypothesised causal relationship (Hair et al., 2011).

To test the significance of the paths for the hypothesised structural model, the PLS algorithm was run with bootstrapping. Table 4.34 shows the path coefficients, T statistics and P values for the path model. The values for **O** represent the path coefficient from the original sample i.e. without bootstrapping. The **M** values show the mean (of path coefficients) based on 5000 samples. The T statistics were computed using the sample mean and the standard deviations and will represent the T values.

Table 4.34 Path Coefficients and Statistical Significance

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (O/STDEV)**	**P Values**
Individual characteristics -> Task Technology Fit	0.273	0.272	0.044	6.177	0.000
Precursors of Utilization -> Utilization	0.193	0.200	0.067	2.860	0.004
Task Characteristics -> Task Technology Fit	-0.061	-0.072	0.082	0.742	0.458
Task Technology Fit -> Performance Impacts on individual carbon footprint tasks	0.127	0.134	0.064	1.977	0.048
Task Technology Fit -> Precursors of Utilization	0.274	0.281	0.057	4.808	0.000
Technology characteristics -> Task Technology Fit	0.083	0.101	0.087	0.949	0.343
Utilization -> Performance Impacts on individual carbon footprint tasks	0.004	0.009	0.097	0.041	0.967

4.10.4 Effect size (f^2)

Cohen's f^2 can be calculated to determine the effect size of a path model (Hair et al., 2014). The calculation of the effect size considers the difference in the coefficient of determination in the original model and when a specific construct in removed from the path model. Removal of exogenous variables will reduce the R^2 of endogenous variables and the magnitude of the reduction influences the size of the f^2 value (Hair et al., 2014). Table 4.35 shows the effect size for the inner model. Small effect sizes are 0.02, medium is 0.15 and 0.35 represents a large effect size (Cohen, 1988). In essence, a high effect size entails that the removed exogenous variable has a stronger effect in the explanation of an endogenous construct.

Table 4.35 Effect size

Exogenous/Independent variable	Endogenous variable	Effect size (f^2)	Effect interpretation
Individual characteristics	TTF	**0.080**	Small
Task characteristics	TTF	0.004	Not significant
Technology characteristics	TTF	0.007	Not significant
TTF	Performance Impacts on individual carbon footprint tasks	0.016	Not significant
TTF	Precursors of Utilization	**0.081**	Small
Precursors of Utilization	Utilization	**0.039**	Small
Utilization	Performance Impacts on individual carbon footprint tasks	0.000	Not significant

4.11 Hypothesis Testing

The PL-SEM results, namely path coefficients and R^2 were tested for their significance using bootstrapping analysis and these results are mapped in Figure 4.3 below.

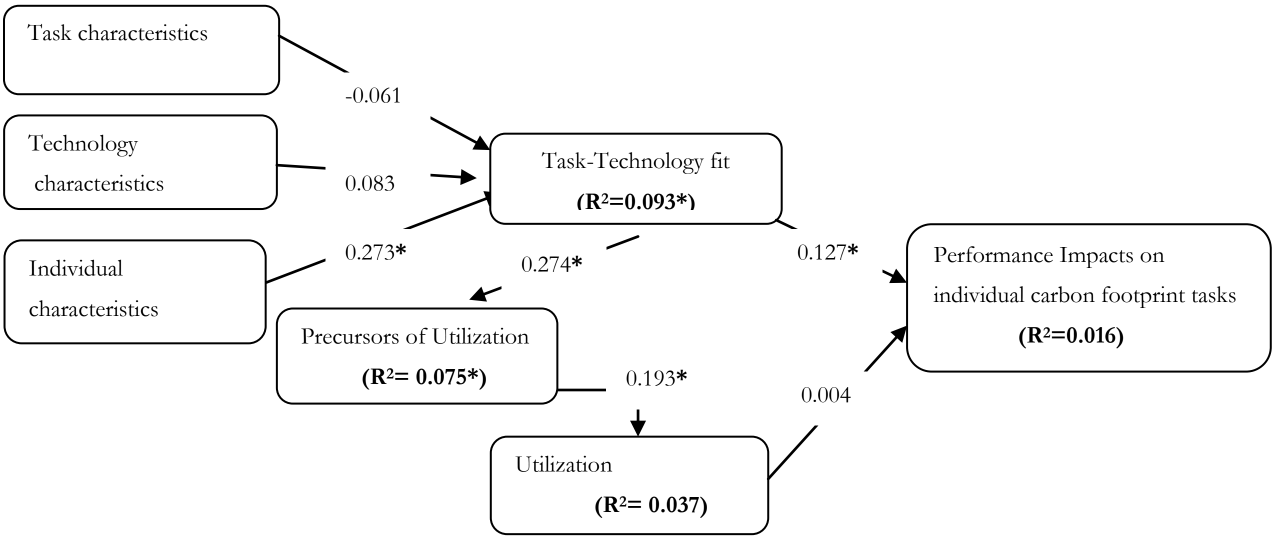

Figure 4.10 PLS-SEM Results of the Model Tested

* *This shows a PLS-SEM value (path coefficient or R^2) which is significant at the 0.05 significance level (based on a 2-tailed test).*

A probability value, p-value, can be used to make a decision on the null hypothesis (Wagner et al., 2012). The null hypothesis is rejected if the p-value is less than or equal to α, the level of significance (Gibbons & Chakraborti, 2011). Otherwise, if p-value > α, the null hypothesis is not rejected. In the present research, a significance level of 0.05 ($\alpha=0.05$) was used during the bootstrapping procedure and is thus selected as the threshold for assessing significance of path coefficients. This level of significance is compared to the p-values produced as a result of the PLS-SEM bootstrapping procedure.

Table 4.36 shows the results the statistical significance of hypothesized paths and interpretation of their significance.

Table 4.36 Statistical significance of hypothesised paths

Path	Path Coefficient	T Statistics	P Value	Significant
Individual characteristics -> Task Technology Fit	0.273	6.177	0.000	Yes
Precursors of Utilization -> Utilization	0.193	2.860	0.004	Yes
Task Characteristics -> Task Technology Fit	-0.061	0.742	0.458	No
Task Technology Fit -> Performance Impacts on individual carbon footprint tasks	0.127	1.977	0.048	Yes
Task Technology Fit -> Precursors of Utilization	0.274	4.808	0.000	Yes
Technology characteristics -> Task Technology Fit	0.083	0.949	0.343	No
Utilization -> Performance Impacts on individual carbon footprint tasks	0.004	0.041	0.967	No

Hypothesis 1a: Not Supported

$H_0$1a: Task characteristics will not influence task-technology fit

$H_1$1a: Task characteristics will positively influence task-technology fit

Table 4.37 Hypothesis 1a Summary

Hypothesis	Exogenous variable	Endogenous variable	P Value	Conclusion
H1a	Task characteristics	Task-technology fit	0.458	Do not reject null hypothesis ($H_0$1a)

The null hypothesis $H_0$1a was tested against the alternative hypothesis $H_1$1a using the results of a bootstrapping procedure of SmartPLS at a significance level of 0.05. The result of the two-tailed test was a p-value of 0.458. Since $p=0.458 > \alpha = 0.05$, the null hypothesis ($H_0$1a) is not rejected. Therefore, there is not statistically significant evidence to prove that task characteristics in carbon footprint will influence task-technology fit within a South African context. This implies that even if individuals in South Africa may find their tasks in estimating and offsetting carbon footprint to be appropriate, they however did not think that their tasks provided a fit for the mobile technology.

This result contradicts the studies of Goodhue and Thompson (1995) that purported that non-routine tasks have an influence on the task-technology fit of user tasks. This result might have been affected by the spread of respondent's perceptions of whether their current and perceived tasks would be sufficient to estimate and offset carbon footprint in South Africa.

Hypothesis 1b: Not Supported

$H_0$1b: Mobile technology characteristics will not influence task-technology fit

$H_1$1b: Mobile technology characteristics will positively influence task-technology fit

Table 4.38 Hypothesis 1b Summary

Hypothesis	Exogenous variable	Endogenous variable	P Value	Conclusion
H1b	Technology characteristics	Task-technology fit	0.343	Do not reject null hypothesis($H_0$1b)

The test of the null hypothesis $H_0$1b against the alternative hypothesis $H_1$1b was conducted following bootstrapping of 5000 samples with SmartPLS. The significance level used was 0.05 and the test was two-tailed. This produced a p-value of 0.343. Since $p=0.343 > \alpha=0.05$, the null hypothesis cannot be rejected. This entails that the survey data are not statistically significantly different from the null hypothesis. Therefore, there is not sufficient evidence to prove that mobile technology characteristics will positively influence task-technology fit in estimating and offsetting carbon footprint in South Africa. The implication from this is that even if individuals in South Africa rated the mobile technology as most likely to enable individuals to estimate and offset carbon footprint, their evaluations of the mobile technology was not sufficient to provide a fit for their carbon footprint tasks.

This result contradicts the findings of Goodhue and Thompson (1995) that found moderate support on the effect of technology characteristics on task-technology fit. This result might have been affected by other factors of task-technology fit which were rated differently on the technology characteristics. In light of this, Goodhue and Thompson (1995) admit that some technology characteristics may have less influence on the task-technology fit factors than others. This differing effect of the TTF factors may impact the association between technology characteristics and task-technology fit.

Hypothesis 1c: Supported

$H_0$1c: Individual characteristics will not influence task-technology fit

$H_1$1c: Individual characteristics will positively influence task-technology fit

Table 4.39 Hypothesis 1c Summary

Hypothesis	Exogenous variable	Endogenous variable	P Value	Conclusion
H1c	Individual characteristics	Task-technology fit	0.000	Reject null hypothesis ($H_0$1c)

Based on a two-tailed test at a significance level of 0.05, the bootstrapping of 5000 samples with SmartPLS produced a p-value of 0.000 for the test of the null hypothesis $H_0$1c. Since $p=0.000 < \alpha=0.05$, the null hypothesis is rejected in favour of the alternative hypothesis. This entails that the survey data are statistically significantly different from the null hypothesis. It may be concluded that the result of the test is statistically significant in inferring that individual characteristics will positively influence task-technology fit in estimating and offsetting carbon footprint in South Africa. Therefore, this entails that the more suitable the characteristics of the individuals, then the more they will be a fit for the mobile technology to estimate and offset carbon footprint tasks in South Africa.

This result was also supported by Lee et al. (2007) who found support for computer self-efficacy and education on influencing task-technology fit.

Hypothesis 1d: Supported

$H_0$1d: Task-technology fit will not influence performance impacts on individual carbon footprint tasks

$H_1$1d: Task- technology fit will positively influence performance impacts on individual carbon footprint tasks

Table 4.40 Hypothesis 1d Summary

Hypothesis	Mediating variable	Endogenous variable	P Value	Conclusion
H1d	Task-technology fit	Performance impacts on individual carbon footprint tasks	0.048	Reject null hypothesis ($H_0$1d)

A probability value of 0.048 was computed using the SmartPLS's bootstrapping procedure using a two-tailed test at a significance level, $\alpha=0.05$. This tested the null hypothesis $H_0$1d against the alternative hypothesis $H_1$1d. Since $p=0.048 < \alpha=0.05$, the null hypothesis is rejected in favour of the alternative hypothesis $H_1$1d. Hence the survey data are statistically significantly different from the null hypothesis. It may be concluded that there is sufficient evidence to support that task technology fit will positively influence performance impacts on individual carbon footprint tasks in South Africa. Hence this implies that the more the fit of the mobile technology for the carbon footprint tasks, then the more the individuals will achieve performance impacts on their carbon footprint tasks in South Africa.

This result is also supported by the findings of McGill and Klobas (2009) that found support for the relationship between task-technology fit and performance in learning.

Hypothesis 2a: Supported

$H_0$2a: Task-technology fit will not influence precursors of mobile technology utilization

$H_1$2a: Task-technology fit will positively influence precursors of mobile technology utilization

Table 4.41 Hypothesis 2a Summary

Hypothesis	Mediating variable	Endogenous variable	P Value	Conclusion
H2a	Task-technology fit	Precursors of utilization	0.000	Reject null hypothesis ($H_0$2a)

A two-tailed test at a significance level, $\alpha=0.05$, on the null hypothesis $H_0$2a against the alternative hypothesis $H_1$2a produced a p-value of 0.000. Since $p=0.000 < \alpha=0.05$, the null hypothesis is rejected in favour of the alternative hypothesis. Therefore, the survey data are statistically significantly different from the null hypothesis $H_0$2a and may be consistent with the alternative hypothesis $H_1$2a. This leads to the conclusion that task technology fit will positively influence precursors of mobile technology utilization in South Africa. Hence this implies that the more the fit of the mobile technology for the carbon footprint tasks, then the more the individuals will have positive attitudes and favourable conditions towards the mobile technology.

Staples and Seddon (2004) also found support for the positive association between task-technology fit and pre-cursors of utilization (expected consequences of use and affect toward use) when technology use was mandatory. In addition, there was also support for the positive association between task-technology fit and pre-cursors of utilization (expected consequences of use) for voluntary technology use (Staples & Seddon, 2004).

Hypothesis 2b: Supported

$H_0$2b: Precursors of mobile technology utilization will not influence utilization of mobile phones on carbon footprint tasks

$H_1$2b: Precursors of mobile technology utilization will positively influence utilization of mobile phones on carbon footprint tasks

Table 4.42 Hypothesis 2b Summary

Hypothesis	Mediating variable	Endogenous variable	P Value	Conclusion
H2b	Precursors of utilization	Utilization	0.004	Reject null hypothesis ($H_0$2b)

The test of significance for the null hypothesis $H_0$2b against the alternative hypothesis $H_1$2b using the bootstrapping of 5000 samples in SmartPLS produced a p-value of 0.004 based on a two-tailed test. Since $p=0.004 < \alpha=0.05$, the null hypothesis is rejected in favour of the alternative hypothesis. The survey data are statistically significantly different from the null hypothesis $H_0$2b and may be consistent with the alternative hypothesis that the precursors of mobile technology utilization will positively influence utilization of mobile phones on carbon footprint tasks. Therefore, the more the individual's attitudes and beliefs are positive towards use of mobile phones for carbon footprint tasks, then the more the mobile technology will be utilised to estimate and offset carbon footprint in South Africa.

When technology use is voluntary, there is a positive association between expected consequence of use and utilization (Staples & Seddon, 2004). These findings were consistent with the assumption made by Goodhue and Thompson (1995), which they suggested future researchers to test.

Hypothesis 2c: Not Supported

$H_0 2c$: Utilization of mobile technology will not influence performance impacts on individual carbon footprint tasks.

$H_1 2c$: Utilization of mobile technology will positively influence performance impacts on individual carbon footprint tasks.

Table 4.43 Hypothesis 2c Summary

Hypothesis	Mediating variable	Endogenous variable	P Value	Conclusion
H2c	Utilization	Performance impacts on individual carbon footprint tasks	0.967	Do not reject null hypothesis ($H_0 2c$)

As a result of running SmartPLS's bootstrapping procedure using a two-tailed test at a significance level, $\alpha=0.05$, the null hypothesis $H_0 2c$ was tested against the alternative hypothesis $H_1 2c$. This test produced a p-value of 0.967. Since $p=0.967 > \alpha=0.05$, the null hypothesis is not rejected. Hence the survey data are not statistically significantly different from the null hypothesis and may be consistent with it. Therefore, utilization of mobile technology will not influence performance impacts on individual carbon footprint tasks in South Africa. The implication for this is that even if individuals utilize mobile carbon footprint calculators, they may not attain greater performance in their overall estimation and offsetting of carbon footprint. This implication is further assessed in hypothesis 2d.

This result is contradictory to the findings of Goodhue and Thompson (1995) that purported the positive association between utilization and performance impacts when technology use is voluntary. However, Staples and Seddon (2004) did not find support for the association between utilization and performance impacts in neither mandatory nor voluntary use of technology.

Hypothesis 2d: Not Supported

$H_0$2d: Individuals with greater mobile phone utilization, in performing their carbon footprint tasks, will not achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization.

$H_1$2d: Individuals with greater mobile phone utilization, in performing their carbon footprint tasks, will achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization.

Two groups were extracted from the data, based on the utilization of mobile phones. A median of the utilization variables (UTI1 and UTI2) less than three was interpreted as low mobile phone utilization. This formed the first category in the utilization group. When the median was more than three, this was construed as showing high mobile phone utilization. This formed the second category of the utilization group. Based on these UTI1 and UTI2 observed variables, 31 respondents were identified as individuals having low mobile phone utilization while 231 were identified as individuals having high utilization. A performance score was computed as the median of the performance indicators (PEF2, PEF3 and PEF4) for each respondent. With this utilization group and the performance score, a Mann–Whitney U test was conducted to test the null hypothesis, $H_0$2d. Table 4.44 shows the results of the tests based on an *asymptotic only* exact test.

Table 4.44 Test Statistics for the utilization group variable

	Performance_score
Mann-Whitney U	3463.500
Wilcoxon W	3959.500
Z	-.306
Asymp. Sig. (2-tailed)	.760

The probability value resulting from this test is 0.760. This p-value is referred to when testing the null hypothesis ($H_0$2d).

Table 4.45 Hypothesis 2d Summary

Hypothesis	Independent variable	Dependant Variable	P Value	Conclusion
H2d	Utilization	Performance impacts on individual carbon footprint tasks	0.760	Do not reject null hypothesis (H_02d)

SPSS was used to run a two independent –samples non-parametric test using *Mann-Whitney U* as the test type. The result of the two-tailed test on "utilization_group" as the grouping variable and "performance_score" as the test variable was a p-value of 0.760. Since $p=0.760 > \alpha=0.05$, the null hypothesis is not rejected. This entails that the survey data are not statistically significantly different from the null hypothesis. Therefore, individuals with greater mobile phone utilization, in performing their carbon footprint tasks, will not achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization. The implication from this is that even if individuals in South Africa make use of mobile technology to estimate and offset carbon footprint, they however will not achieve the anticipated performance impacts on their carbon footprint tasks.

This contradicts the results of Goodhue and Thompson (1995) that purported that more technology utilization is associated with greater performance impact when use of a technology is voluntary.

Table 4.22 shows the summary of hypothesis testing.

Table 4.46 Summary of Hypothesis Testing

Hypothesis	**Description**	**Conclusion**
H1a	Task characteristics will positively influence task-technology fit	Not Supported
H1b	Mobile technology characteristics will positively influence task-technology fit	Not Supported
H1c	Individual characteristics will positively influence task-technology fit	Supported
H1d	Task technology fit will positively influence performance impacts on individual carbon footprint tasks.	Supported
H2a	Task technology fit will positively influence precursors of mobile technology utilization.	Supported
H2b	Precursors of mobile technology utilization will positively influence utilization of mobile phones on carbon footprint tasks	Supported
H2c	Utilization of mobile technology will positively influence performance impacts on individual carbon footprint tasks	Not Supported
H2d	Individuals with greater mobile phone utilization, in performing their carbon footprint tasks, will achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization	Not Supported

Chapter 5 : Discussion and Conclusion

The previous chapter showed the analysis of the collected data and presented the results. This current chapter is organised into 6 sections : Section 5.1 presents the discussion on the findings. Section 5.2 shows the refined model based on the supported hypotheses. Section 5.3 presents the conclusion of the thesis. Section 5.4 highlights the limitations of the study. Section 5.5 offers contributions of the research to both academia and practice. Section 5.6 suggests areas for future research.

5.1 Discussion

This study formulated eight hypotheses in order to answer the research questions presented in Chapter 1. The predicted constructs comprised of the fit of mobile technology for carrying out carbon footprint tasks (task-technology fit), precursors to mobile technology utilization (precursors of utilization), utilization of mobile carbon footprint calculators (utilization) and performance impacts on individual carbon footprint tasks. These constructs have been explained in Chapter 3. The next section focuses on discussing the results of the eight hypotheses in relation to the research questions.

How does fit of technology influence the performance impacts of mobile carbon footprint calculators for individuals?

This question is assessed through the discussion of the seven hypotheses namely H1a, b, c, d and H2a, b, c.

Task characteristics and Task-technology fit - Hypothesis H1a

Hypothesis H1a argued that task characteristics would positively influence task-technology fit. This hypothesis was not supported. The individual task characteristics in carbon estimates and offsets were not statistically significant in predicting task-technology fit. In addition, there was no statistically significant correlation between task characteristics and task-technology fit.

This result was not expected as this was contradictory to the study of Goodhue and Thompson (1995) that suggested that non-routine tasks would influence task-technology fit. Although the method (PLS-SEM) used to test this hypothesis can predict outcome based on small sample size, the variability of the respondent's perceptions on carbon footprint estimates and offsets could have benefited from a larger sample size than the size used in this study.

Mobile technology characteristics and Task-technology fit - Hypothesis H1b

The current study hypothesized that mobile technology characteristics would positively influence task-technology fit. The test for hypothesis H1b was not statistically significant; hence the hypothesis was not supported. Also, there was no statistically significant correlation between mobile technology characteristics and task-technology fit.

Goodhue and Thompson (1995) found moderate support for the link between technology characteristics and task-technology fit. However, they found that technology characteristics affect the factors of task-technology fit differently. In the present research, the measures of mobile technology were limited to network, user interface and technological advancements. The latter measure was dropped as it did not load at appropriate levels. This change in the measurement model could have affected the results of this hypothesized causal link.

Individual characteristics and Task-technology fit - Hypothesis H1c

The present research argued that individual characteristics would influence task-technology fit. A test of this hypothesized causal link supported hypothesis H1c. Therefore, individual characteristics influence task-technology fit for the use of mobile phones on carbon footprint tasks in South Africa. However, the relationship between individual characteristics and task-technology fit showed a weak positive correlation. Nonetheless, an increase in the individual characteristics favourable to technology adoption would result in an increase in task-technology fit.

Lee et al. (2007) also found that individual characteristics (computer self-efficacy and education) influence task-technology fit. With higher individual traits such as computer self-efficacy, there is more fit of the technology on the individual's tasks.

Worth noting is that the measures representative of the individual characteristics, namely computer self-efficacy and education, both were statistically significant in contributing towards the definition of the individual characteristics latent variable. Of the two measures, education had a slightly higher contribution than computer self-efficacy. Therefore, it may be argued that increasing the education measure will be associated with increasing the individual characteristics, resulting in increasing task-technology fit for mobile phone use in carbon footprint tasks.

Although the study collected biographic information such as age groups and employment status, these were only used for describing the respondents and were not used for further analysis. Since individual characteristics are a predictor for task-technology fit, future research might find it appropriate to determine the contribution of age and employment status on individual characteristics.

Task-technology fit and performance impacts on individual carbon footprint tasks - Hypothesis H1d

Hypothesis 1d examined whether task technology fit would positively influence performance impacts on individual carbon footprint tasks. The hypothesis testing for this causal link was statistically significant, thus finding support for hypothesis H1d. Therefore, task-technology fit positively influences the performance impacts on carbon footprint tasks in South Africa. In addition, there was a strong positive relationship between task-technology and performance impacts on individual carbon footprint tasks. McGill and Klobas (2009) also found a positive influence of task-technology fit on individual performance. The implication of this result is that individuals in South Africa will achieve greater performance in their carbon footprint tasks if the mobile technology provides a great fit for their carbon footprint tasks.

Task technology fit and precursors of mobile technology utilization - Hypothesis H2a

Hypothesis H2a argued that task-technology fit would positively influence precursors of mobile technology utilization.

The results of the correlation analysis show a positive correlation between task-technology fit (TTF) and the precursors of mobile technology utilization. This means that an increase in TTF would result in an increase in the precursors of mobile technology utilization. However, this relationship was found to be weak. Nonetheless, testing significance of this association resulted in the causal link being statistically significant, meaning that TTF influences the precursors of mobile technology utilization. This statistically significant causal link resulted in the hypothesis to be supported.

Staples and Seddon (2004) also found support for the positive influence of task-technology fit on pre-cursors of utilization when technology use was mandatory or voluntary.

The highest statistically significant contributors to the definition of the precursors of utilization were found in perceived usefulness, consequence of use and voluntariness measures. From these, perceived usefulness was the strongest, followed by consequence of use and then voluntariness. Measures in social norms and technological support had the last contribution to the definition of the precursors of utilization latent variable.

Therefore, the perceived usefulness of the mobile phones in performing carbon footprint tasks had the most significance. As social norms were the least contributor, individuals would find the mobile phones fit for their carbon footprint tasks if the technology was relevant regardless of what their peers thought.

Precursors of mobile technology utilization and utilization - Hypothesis H2b

The current research hypothesized that precursors of mobile technology utilization would positively influence utilization of mobile phones on carbon footprint tasks.

To begin with, there was a positive association between the precursors of utilization and utilization. This entails that an increase in the precursors of utilization results in an increase in the utilization of mobile phones on carbon footprint tasks. The hypothesis testing for this hypothesized path proved to be statistically significant, thus finding support for the hypothesis (H2b). Therefore, precursors of utilization influence utilization of mobile phones for carbon footprint tasks in South Africa. Testing this hypothesis fulfilled the recommendation for future studies suggested by Goodhue and Thompson (1995). Staples and Seddon (2004) also tested this link and found that expected consequence of use positively influences utilization, when technology use was voluntary.

Individual's current technology utilization and perceived future utilization measures for the utilization variable contributed significantly to the latent variable's definition. However, perceived future utilization contributed the most. Therefore, the influence of precursors of utilization on utilization of mobile technology can be argued to be impacted more by perceived future utilization than by current technology utilization.

Utilization and Performance impacts on individual carbon footprint tasks - Hypothesis H2c

The present research examined whether utilization of mobile technology would positively influence performance impacts on individual carbon footprint tasks.

Hypothesis H2c was not supported. In addition, correlation analysis showed that the proposed relationship between utilization and performance impact on individual carbon footprint tasks had no statistical significance. Although this result is contradictory to the findings of Goodhue and Thompson (1995) that found support for the influence of utilization on performance impacts when technology use is voluntary, Staples and Seddon (2004) did not find support for this association in neither mandatory nor voluntary use of technology.

The lack of support for this hypothesized causal link could be explained by the minute predictive relevance displayed by the predicted latent variable, i.e. performance impacts on individual carbon footprint tasks. None of the measures of performance impacts on individual carbon footprint tasks were statistically significant in contributing towards the definition of the latent variable albeit the factor loadings were all significant. Therefore, mobile technology utilization does not influence performance impacts on individual carbon footprint tasks in South Africa.

What is the relationship between performance impacts on individual carbon footprint tasks and use of mobile phones amongst individuals in South Africa?

This question on the frequency of use in relation to performance is assessed through discussing the results of hypothesis H2d.

Frequency of use and Performance impacts on individual carbon footprint tasks - Hypothesis H2d

The final hypothesis of the research concerned the impact of frequency of use in two groups of individuals. It was hypothesized that individuals with greater mobile phone utilization, in performing their carbon footprint tasks, would achieve greater performance impacts on individual carbon footprint tasks than individuals with lesser mobile phone utilization.

Based on the non-parametric test conducted on the two individual groups identified within the survey data, the association between frequency of use and performance proved to be not statistically significant. Therefore, the hypothesis was not supported. This result differs from the studies of Goodhue and Thompson (1995) that found an increase in individual performance when technology usage increased, especially under voluntary settings.

Discussion of Unexpected Results

The correlation analysis between constructs also produced results which were not expected. In this case, associations not shown by the research model emerged.

There was an unexpected positive correlation between individual characteristics and performance impacts on individual carbon footprint tasks. In addition, technology characteristics were unexpectedly positively correlated to the precursors of utilization variable. There was also a positive association between the precursors of utilization and performance impacts on individual carbon footprint tasks. However, the statistical significance of these associations was not determined. Therefore, it is not known whether individual characteristics influence performance impacts on individual carbon footprint tasks. Also unknown is whether technology characteristics influence the precursors of mobile technology utilization. It has also not been determined whether precursors of utilization influence performance impacts on individual carbon footprint tasks. These results might require further investigations.

5.2 Refined Model

Figure 2.7 presented the research model which outlined seven factors that were modelled to explain whether the fit of mobile technology influenced the performance impacts of mobile carbon footprint calculators for individuals in South Africa. These factors are:

1. Task characteristics
2. Technology characteristics
3. Individual characteristics
4. Task-Technology fit
5. Precursors of Utilization
6. Utilization
7. Performance Impacts on individual carbon footprint tasks

These factors resulted in the proposal of eight hypotheses that were tested after reliability and validity of the hypothesized model was evaluated. As a result of the hypothesis testing, four hypotheses were supported. Figure 4.4 shows the paths for causal relationships that the research found support for.

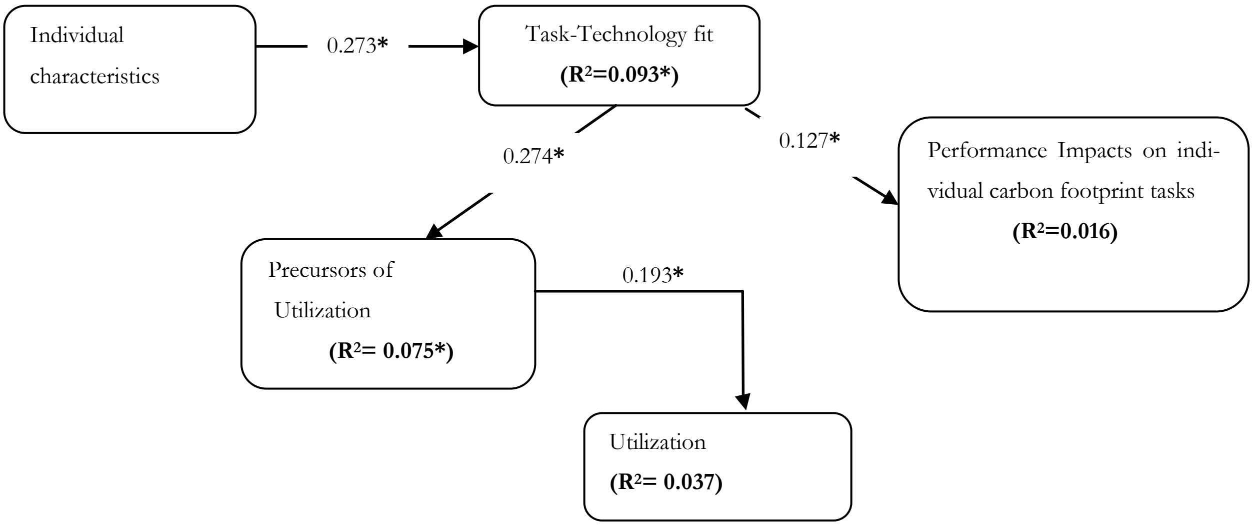

Figure 4.11 Refined Model

**. The asterisk (*) shows a PLS-SEM value (path coefficient or R*^{2}*) which is significant at the 0.05 significance level (based on a 2-tailed test).*

5.3 Conclusion

The aim of this research was to investigate the impact of mobile technology in the estimation and offsetting of carbon footprint for individuals in South Africa. In particular, the researcher studied: (1) how the fit of mobile technology influenced the performance impacts of mobile carbon footprint calculators for individuals; and (2) whether individuals who used mobile phones more frequently would achieve greater performance impacts on individual carbon footprint tasks than individuals who used mobile phones less frequently. To address this, a research model was adapted from the vast number of existing theories in information systems. The constructs used in the research model were: task characteristics, technology characteristics, individual characteristics, task-technology fit, precursors of utilization, utilization and performance impacts on individual carbon footprint tasks.

By following a rigorous scientific method, the design of the research was conducted to ensure reproducibility and validity. To start with, the measures for the aforementioned constructs were selected from prior research to ensure validity. New measures were subjected to further reviews from field experts. A questionnaire with closed-ended items was distributed through a survey in the city centre of Cape Town. The survey participants were selected randomly and valid responses represented 262 individuals that were in possession of mobile phones and utilized electricity for lighting. Cleansed data were submitted to exploratory and confirmatory factor analysis to determine and confirm the number of factors explaining the measurement items. Following the determination of factors, the measurement model of the research was submitted to PLS-SEM to examine the reliability and validity of the constructs. A bootstrapping procedure was run to determine the statistical significance of the paths in the hypothesized model.

The results showed that performance impacts on individual carbon footprint tasks could be predicted by the research model. However, only 1.6% of the variance in the performance impacts on individual carbon footprint tasks was explained by task-technology fit. This result evidently shows that the research model had a weak predictive strength in explaining the performance impacts on individual carbon footprint tasks. The non-significant hypothesized association between utilization and performance impacts on individual carbon footprint tasks diluted the predictive strength of the model. Therefore, the South African respondents in the survey possessed beliefs and behaviour that influenced the utilization of mobile carbon footprint calculators and this may require further research. However, fit of mobile technology for carbon footprint tasks influenced the performance impacts on individual carbon footprint tasks.

The main contribution of this research is theory testing and prediction. The technology-to-performance chain model was tested within a context that prior studies had not investigated, i.e. the context of carbon footprint and mobile technology in a developing nation. Some causal links which were purported by prior studies, but had limited investigations were tested and support for the links was found. Within the context of carbon footprint and mobile technology there was support for the causal link between task-technology fit and precursors of utilization. These findings can inform a mobile application technical developer in considering mobile application features which favour the usage and success of the users in estimating and offsetting carbon footprint in South Africa as well as other areas of mobile services.

This study provided new evidence for the resilience of the technology-to-performance chain model within a carbon footprint and mobile technology context. It identified a refined model, which explains the fit of technology that influences the performance impacts of mobile carbon footprint calculators for individuals. The finding that individuals who use mobile carbon footprint calculators do not achieve greater performance impacts on their carbon footprint tasks than individuals who do not was not expected. This is contradictory to the expectations of field practitioners such as conservationists who campaign that individuals need to be aware of their carbon footprint in order to reduce it. The implication of this to field practitioners is formulation of alternative strategies such as towards energy efficiency rather than relying on lifestyle changes for individuals.

5.4 Limitations

There is no research without limitations (Simon & Goes, 2013). Every study has issues that are out of the control of the researcher and this research is no exception. This study is limited in the following areas:

Sample size. The researcher considered a number of inputs to determine the study's sample size. These inputs included the number of individuals living in an urban area in South Africa with mobile phones and electricity for lighting. In addition, a margin of error, confidence level and the response rate was factored and resulted in an estimated sample size of 271 participants. Based on the data analysis approach, PLS-SEM, which has minimal demands on the sample size (Chin, 1998) and that the estimated sample size was at least ten times the largest number of causal paths directed at a latent variable (Barclay, Higgins & Thompson, 1995), the researcher asserted that the sample size was adequate. Unfortunately, the cleansed responses yielded a lower sample of 262 than was anticipated. This limited the research from carrying out certain group comparisons as some categories within the data groups had too few cases.

It can also be argued that the proportion of students (28%) could have affected the results and affect the extent to which the results can be generalized. Since students operate on a more stringent budget than the working members of the population, their use of mobile technology is likely to be reduced if the budget allocated to them is lower. Therefore, a larger sample size is essential and this can also increase generalizability of the findings.

Cross sectional time horizon. The adopted performance-to-chain model also posits that user feedback impacts task-technology fit and utilization. However, the research model developed disregarded the need for user feedback and rather justified the suitability of a cross sectional study. The selection of a cross sectional study, therefore, suited the research model. As a consequence, this timeframe entails that the research cannot determine whether the changes in individual's attitudes and behaviour based on their usage of the mobile technology affects future usage and the fit of the technology. The impact of usage on user beliefs which in turn affect future usage and fit cannot be ascertained in a cross sectional study. This is better captured with a longitudinal time frame.

Reverse coding. Negatively worded questionnaire items ensure that the responded pays attention during the completion of the survey. The validity of the survey instrument was established through the adoption of validated instrument items from prior studies. In addition, expert reviews of the measures were conducted for the entire questionnaire. Nevertheless, none of the adopted instrument items were reversely coded. Should negatively worded items be considered for future research, Roszkowski and Soven (2010) recommends against the use of numerous reversely coded items amid positively worded items in a questionnaire.

Moderating effects. Comparisons of causal paths between the participating groups such as males versus females were conducted. It was found that in some cases there were differences between participant groups. However, the research did not assess the moderating effects of demographic factors (such as gender and age) on the fit of mobile technology. Therefore, additional research may investigate the moderating effects of these factors on the fit of mobile technology on carbon footprint tasks as well utilization of technology.

5.5 Contributions

The findings of this research can be summarized in terms of their contribution to theory and practice. These contributions are reviewed in sub-sections that follow.

5.5.1 Contributions to Theory

In order to advance the current understanding of estimating and offsetting carbon footprint using carbon calculators, the researcher adopted an existing model to explain a mobile approach to this phenomenon. The technology-to-performance chain (TPC) model was the adopted model to determine the fit of mobile carbon footprint calculators and also predict the performance impacts of using mobile technologies on individual carbon footprint tasks. The TPC model consists of factors of the theory of task-technology fit (TTF) and factors on users' attitude and behaviour that influence utilization (Goodhue & Thompson, 1995). The TPC model's outcome variable, i.e. performance impacts, was contextualized to performance impacts on individual carbon footprint tasks.

This study contributes to theory in that it fulfils the need for further research proposed by Goodhue and Thompson (1995) to test the influence of TTF on the precursors of utilization. The findings revealed that task-technology fit positively influences the precursors of utilization of mobile carbon footprint calculators. Another theoretical contribution is the testing of the technology-to-performance chain model within a newer and different context relative to prior studies. This study reveals the possibility of predicting performance impacts within the context of carbon footprint and mobile technology in a developing country. The factors evaluated for TTF were: authorization, systems reliability, relationship with users and ease of use. As for the precursors of utilization, this construct was reflected through measures of voluntariness, perceived usefulness and consequences of use. The findings of this study showed a predictive power of 1.6% in the prediction of the performance impacts on individual carbon footprint tasks based on task-technology fit. The evaluation of the study's model has advanced theory as follows:

- Individual characteristics were found to be a significant predictor of the fit of mobile technology for carbon footprint tasks. This result entails that increasing individual traits such as education increases the fit of technology for individual tasks in a developing nation such as South Africa.

- Task-technology fit influences performance impacts on individual carbon footprint tasks, although the predictive power was reviewed as low.
- Task-technology fit impacts on the precursors of utilization. This reinforces that fit of technology affects the beliefs of individuals in the technology.
- The precursors of utilization influence on utilization. This finding emphasizes that positive beliefs in technology lead to greater technology utilization.

5.5.2 Contributions to Practice

The theoretical contribution offered in the previous section provides a pertinent background to the implication to practitioners. The practitioners implicated by these findings are the conservation organizations and mobile technology developers.

The direct effect of task-technology fit on performance impacts on individual carbon footprint tasks shows that an individual has to get value (e.g. satisfaction, effectiveness, efficiency, e.t.c.) from using the mobile carbon calculators in completing carbon footprint tasks. By implication, some carbon footprint tasks (such as estimating and offsetting carbon) can be offered using mobile technology based services. Due to the importance of individual characteristics in explaining task-technology fit, the researcher proposes that the carbon footprint campaigns target individuals to educate them on their impact on the environment and the availability of tools which can assist them to save energy and reduce climate change attributed to human behaviour.

Through education and the use of energy efficient technology sufficient levels of computer self-efficacy in individuals may be reached and result in individual's attaining a greater fit for related technology such as carbon calculators. Decision makers in conservation or non-governmental organizations can formulate alternative strategies towards the reduction of carbon footprint by individuals given that the research has revealed that utilization of mobile carbon footprint calculators does not result in performance impacts in individual carbon footprint tasks.

In hindsight, mobile application developers are encouraged to design carbon calculators which offer ease of use and system reliability so as to retain the usage of these tools in individuals who see their usefulness.

5.6 Future Research

Through presentation of the limitations of this research, some ideas about the direction which can be adopted by future research emerged. In addition to resolving these limitations, future studies can also consider some of the following ideas:

1. Use a longitudinal time horizon. As this study delimited user feedback as out of scope, the use of a cross-sectional study was appropriate. Future research should consider user feedback in order to determine its effect on utilization and performance impacts on carbon footprint tasks.
2. Engage moderating effects. Moderator variables affect the direction or strength of a hypothesized relationship (Fairchild & MacKinnon, 2009). The following moderation effects are suggested:
    a. Moderating effects of gender. Individual characteristics were found to positively influence task-technology fit. In addition, this causal link was found to be statistically significantly different between the gender groups. These findings require further investigation. In particular, it is suggested that further research pursue whether gender has a moderating effect on the association between individual characteristics and task-technology fit.
    b. Moderating effects of age. The precursors of utilization positively influence the utilization of mobile technology. Additionally, the influence of the precursors of utilization on utilization was different between the younger age group (18-25) and the older age group (36-45). Therefore, future studies should investigate whether age moderates the relationship between the precursors of utilization on utilization.
    c. Moderating effects of occupation. Task-technology fit positively influences precursors of utilization. During the assessment of the difference between

occupational groups, the findings revealed a statistically significant difference between the employed and unemployed groups for this relationship. Therefore, it would be interesting if future research could reveal whether an individual's occupation status has a moderating effect on the relationship between task-technology fit and precursors of utilization.

3. Influence of individual characteristics. Individual characteristics positively influenced task-technology fit (TTF) whereas task and technology characteristics did not influence TTF. There was also an unexpected significant positive correlation between individual characteristics and performance impacts on individual carbon footprint tasks. This finding requires further investigation.

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Appendices

APPENDIX A: COVER LETTER

Department of Information Systems
Faculty of Commerce
University of Cape Town
Private Bag Rondebosch 7701
Phone: +27 (0)21 650 4375

27/10/2015
Dear Participant:

My name is Martin Munetsi and I am studying towards a master's degree at the University of Cape Town. For my dissertation, I am conducting research on whether the use of mobile phones results in improved individual performance on carrying out carbon footprint tasks. Because you own a mobile phone and use electricity for lighting, you are invited to participate in this research survey.

To participate in this research, you are kindly requested to complete the attached questionnaire. The questionnaire is focused on carbon footprint tasks, mobile characteristics, individual perceptions, fit of technology on carbon footprint tasks, utilization and perceived performance on the carbon footprint tasks. The aim of collecting this data are to determine whether the relationships of these factors affect individual performance of carbon footprint tasks.

Your participation in this research is voluntary. You can choose to withdraw from the research at any time. You will not be requested to supply any identifiable information, ensuring anonymity of your responses.

Yours sincerely,

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Martin Munetsi	Michael Kyobe
(Student)	(Supervisor)
mntmar031@myuct.ac.za	michael.kyobe@uct.ac.za

APPENDIX B: QUESTIONNAIRE

Introduction

The aim of this research is to investigate whether mobile carbon footprint calculators[1] (MCFCs) are fit for carbon footprint tasks and whether their use affects individual performance on carbon footprint tasks. The researcher would like to determine whether characteristics of individuals, mobile phones and carbon footprint related tasks are fit for MCFCs. The study also needs to determine whether utilization and fit of such calculators affects individual performance on carbon footprint tasks.

Section A: Biographical Information

This section deals with the personal information about the respondent.

Gender:

Male		Female	

Age group:

Under 18		18-25		26-35		36-45		46+	

Highest Education level: (Mark the highest education level reached)

High School or less		Grade 12		Tertiary		University Degree		Post Graduate Degree	

Employment Status: (Mark all that apply)

Student		Employed		Unemployed		Retired	

Do you have a mobile phone?

Yes		No	

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[1] Mobile carbon footprint calculator (MCFC) is any application or service that runs on a mobile phone and is used to estimate or monitor carbon footprint[2].

[2] Carbon footprint refers to the total amount of greenhouse gas[3] emissions caused by human activities either directly or indirectly.

[3] Greenhouse gas is the collective term referring to any of carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, sulphur hexafluoride or perfluorocarbons.

Section B: Carbon footprint tasks

This section enquires about tasks related to monitoring transport or energy usage and activities in order to reduce carbon emission.

Carbon estimate:

	The ratings are: Never=1, Rarely=2, About half the time/ Sometimes=3, Frequently=4, Always=5 Put an X on the appropriate answer	1	2	3	4	5
CFE1	I monitor my energy usage or transport costs?					

	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5 Put an X on the appropriate answer	1	2	3	4	5
CFE2	Estimating my average energy consumption daily or monthly increases my awareness towards using less energy					

Carbon offset:

	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5 Put an X on the appropriate answer	1	2	3	4	5
CFO1	Tree planting increases my awareness towards resource conservation.					
CFO2	Taking part in renewable energy activities (such as solar and wind energy) increases my awareness towards energy conservation.					

	The ratings are: Not at all=1, Slightly=2, Moderately=3, Very=4, Extremely=5. Put an X on the appropriate answer	1	2	3	4	5
CFO3	I am likely to contribute towards tree planting activities in the near future					
CFO4	I am likely to contribute towards renewable energy activities (such as in generation of solar and wind energy) in the near future					

Section C: Mobile phone and individual traits

The questions in this section provide overview of the traits of mobile phones and the respondent.

	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5 Put an X on the appropriate answer	1	2	3	4	5
TEC1	I would use the mobile phone to perform my carbon footprint tasks if the network coverage is sufficient.					
TEC2	I would use the mobile phone to perform my carbon footprint tasks if the phone is always responsive with little or no network downtime.					
TEC3	I would use the mobile phone to perform my carbon footprint tasks if the user interface is simple to use.					
IND1	I would use the mobile phone to monitor carbon footprint if l could learn the process easily.					
TEC4	I would use the mobile phone to monitor carbon footprint if the device keeps update with technology advancements.					

Section D: Task-technology fit

These questions rate the fit of mobile phones for carbon footprint tasks.

	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5 Put an X on the appropriate answer. The mobile carbon footprint calculator would be fit for my carbon footprint tasks if:	1	2	3	4	5
TTF1	the information provided is accurate					
TTF2	the meaning of data are easy to find out					
TTF3	I have access to data to allow me to achieve my tasks					
TTF4	I get the information I need on time					
TTF5	using the mobile system is compatible with all aspects of my tasks.					
TTF6	the calculator is not subject to unexpected errors					
TTF7	user technical support is available when I need it.					
TTF8	the calculator is easy to use.					

Section E: Precursors of Utilization

The questions in this section are related to the conditions leading to use of the mobile carbon footprint calculator.

	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4, Strongly agree=5 Put an X on the appropriate answer	1	2	3	4	5
POU1	The mobile carbon footprint calculator would enable me to accomplish my tasks more quickly.					
POU2	I would find the mobile carbon footprint calculator useful for my tasks.					
POU3	I am not forced to use the mobile carbon footprint calculator.					
POU4	People close to me would think it is important to monitor my carbon footprint using this mobile carbon footprint calculator.					
POU5	I would use the mobile carbon footprint calculator if there is sufficient support from service providers.					

Section F: Utilization

The questions in this section give an overview of the perceived utilization of the mobile carbon footprint calculator.

	The ratings are: Never=1, Rarely=2, About half the time/ Sometimes=3, Frequently=4, Always=5 Put an X on the appropriate answer	1	2	3	4	5
UTI1	I use a carbon footprint calculator to calculate energy usage or transport costs					
UTI2	I would use the carbon footprint calculator to calculate energy usage or transport costs in the future					

Section G: Individual performance

These questions assess individual performance on carbon footprint tasks.

	Put an X on the appropriate answer	Poor	Fair	Good	Very Good	Excellent
PEF1	How do you rate your performance on monitoring transport and energy usage?					

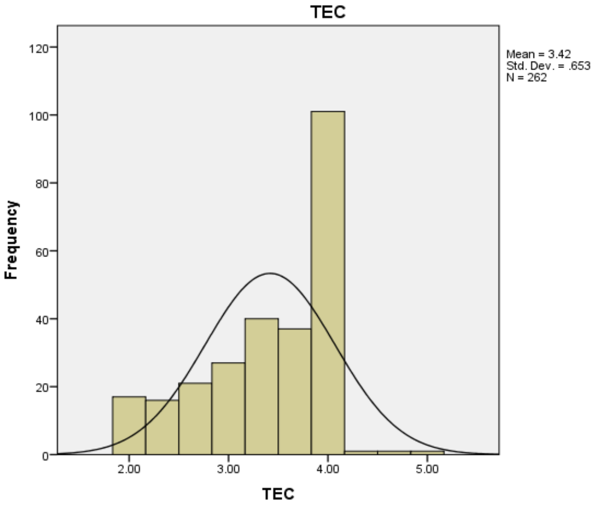
	The ratings are: Strongly disagree=1, Disagree=2, Neither agree nor disagree=3, Agree=4,	1	2	3	4	5

	Strongly agree=5 Put an X on the appropriate answer					
PEF2	I would monitor my energy usage effectively if I used a mobile carbon footprint calculator					
PEF3	I would monitor my transport usage effectively if I used a mobile carbon footprint calculator					

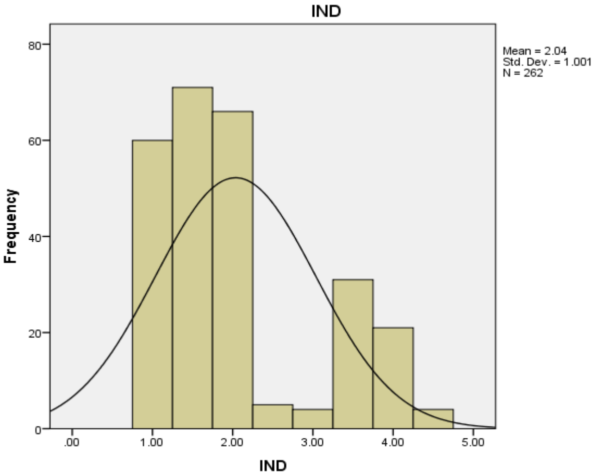
	Put an X on the appropriate answer	Poor	Fair	Good	Very Good	Excellent
PEF4	How would you rate the mobile carbon footprint calculator in carrying out your carbon footprint tasks?					

APPENDIX C: NORMALITY HISTOGRAMS

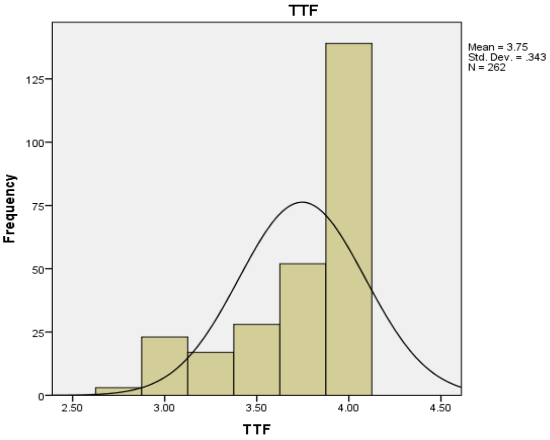
Technology characteristics



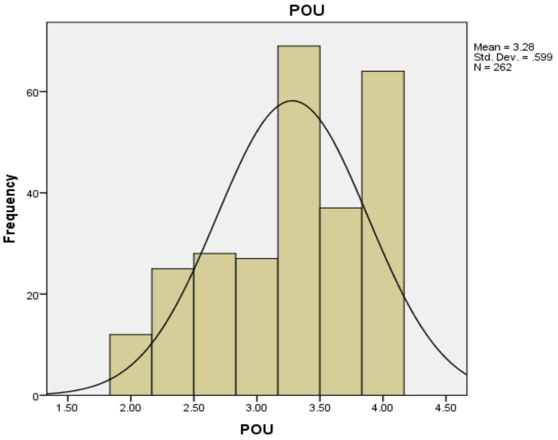
Individual characteristics



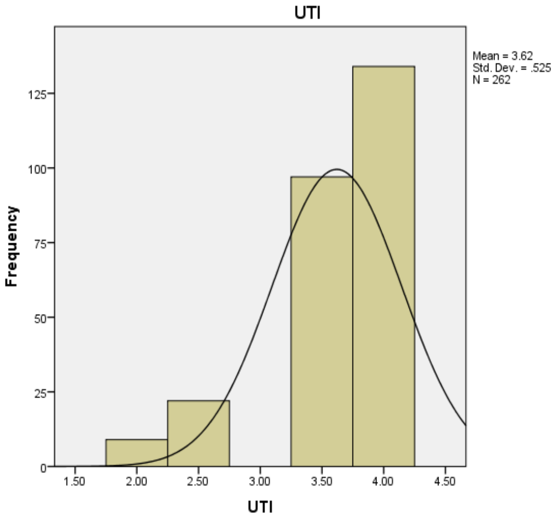
Task technology fit



Precursors of utilization



Utilization



Performance impacts on carbon footprint tasks