Using survey data to estimate the prevalence of diabetes in South Africa - from risk factor analysis to action

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Abstract

South Africa is a developing country which has in the last decades experienced a sharp rise in the number of diagnosed diabetes cases. Significant uncertainty exists about the true prevalence of diabetes in South Africa, since many of those suffering from diabetes remain undiagnosed.

The large financial burden imposed by diabetes on the public health sector places significant pressure on its ability to effectively deliver quality healthcare to all who rely on it. The Indian Diabetes Risk Score (IDRS) was developed as a low-cost screening tool to assess the potential undiagnosed case prevalence of type 2 diabetes using analysis of risk factors and their association to diabetes.

The South African General Household Survey (SAGHS) (StatsSA, 2021a) is used to analyse the risk factors of diabetes on a population through a generalised linear regression model. A synthetic IDRS was calculated from the available population trends and an illustrative prediction of the diabetes prevalence rate was performed using this score.

The IDRS could be modified and used in South Africa to model undiagnosed cases of diabetes. Furthermore, the IDRS would allow for government screening to be targeted, thereby allowing for the potential healthcare cost savings.

Keywords: Diabetes, South Africa, National Survey, IDRS, Prevalence, risk factors

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List of Acronyms

EC - Eastern Cape

FS - Free State

GLM - generalised linear model

GP - Gauteng

HDL - high-density lipoproteins

IDF – International Diabetes Federation

IDRS - Indian Diabetes Risk Score

KZN - KwaZulu-Natal

LP - Limpopo

MP - Mpumalanga

NC - Northern Cape

NCD – Non-communicable disease

NW - North West

SADHS – South African Demographic Health Survey

SAGHS - South African General Household Survey

TG - triglycerides

UK – United Kingdom

USA – United States of America

WC - Western Cape

WHO – World Health Organization

Section 1. Introduction

In 2019, seventy-one per cent of deaths worldwide were attributed to noncommunicable diseases (NCDs) (Ramesh and Kosalram, 2023). The disease burden brought on by NCDs has seen an increase over the last four decades (WHO, 2016). Significant global effort (in terms of funding, research, clinical intervention, and population education) is underway to combat the burden and costs associated with NCDs. Diabetes is one such NCD, which has seen a rise in prevalence rates globally (WHO, 2016). Historically thought to be confined to the developed world, new diabetes research indicates that lower-income populations may be suffering even higher diabetes disease burdens (WHO, 2016). Figure 1 shows how the estimated diabetes prevalence rates in higher-income populations have been overtaken by the prevalence in lower-income populations and that the gap is widening (WHO, 2016).

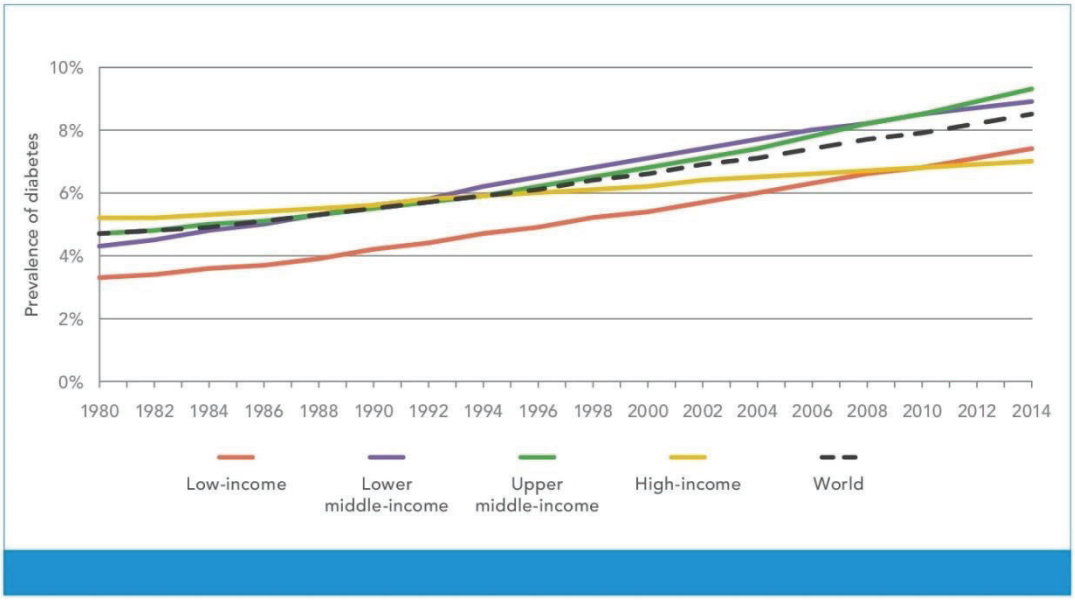


Figure 1: Trends in prevalence of diabetes, 1980-2014, by country income group

Source: WHO (2016)

South Africa is a developing country which has in the last decades experienced a sharp rise in the number of diagnosed diabetes cases (IDF, 2023). For the period 2016 to 2020, roughly 800,000 new diabetes diagnoses were reported in South Africa by the International Diabetes Federation (IDF) (IDF, 2021). The South African population (diagnosed or estimated to be) living with some form of diabetes has increased from around 7 per cent in 2016 (IDF, 2021) to around 11.3 per cent by 2021 (IDF, 2023).

However, this figure likely underestimates the true prevalence of diabetes in South Africa, since a significant proportion of the population suffering from diabetes remain

undiagnosed (Health E-News, 2016). Estimates from 2021 report roughly 1.9 million undiagnosed diabetes individuals in South Africa (Health E-News, 2016).

The rising prevalence of diabetes is resulting in a strain on public healthcare resources. Erzse *et al.* (2019) have reported that in 2018 the total cost to the South African Government for diagnosed and undiagnosed diabetes mellitus was R2.7 billion and R21.8 billion respectively, which, at the time, represented approximately 12 per cent of the total healthcare budget. With the increasing prevalence of diabetes, the inflation-adjusted cost is expected to rise, in real terms, by more than 60 per cent by 2030 (Erzse *et al.*, 2019).

The large financial burden imposed by diabetes on the public health sector places significant pressure on its ability to effectively deliver quality healthcare to all who rely on it. This highlights the importance of reducing the incidence of diabetes and effectively and efficiently managing the condition for those who have diabetes.

Based on their systematic review, Li *et al.* (2010) recommend that the prevention of diabetes should be prioritised, as this is the most cost-effective measure (found across multiple countries) to reduce the overall cost associated with diabetes. Targeted screening of people aged 45 to 54 and education around changes in lifestyle are found to be highly effective in reducing the prevalence of diabetes (Li *et al.*, 2010).

The South African Government has enacted a few pieces of legislation since 1999 which aim to reduce the prevalence of diabetes in the country. Some of these include the National School Nutrition Programme (DBE, 2009), introduced in 2009, the Sodium Reduction Regulations which was introduced in 2013 (South Africa, 2013) and the Health Promotion Levy (or the "sugar tax" as it is more commonly known) (South Africa, 2017), which was introduced in 2018 (Ndinda and Hongoro, 2017).

Whilst these measures have been implemented, it remains difficult to measure their effectiveness at reducing diabetes incidence and prevalence in the South African population through its behavioural and associated lifestyle changes. Rising numbers of diabetes deaths (Clarke, 2019) in recent years indicate that these measures may, in part or on the whole, be ineffective by themselves in achieving the government's national strategic health vision.

When considering the undiagnosed cases of diabetes, the South African Demographic Health Survey (SADHS) reported that of those who had never been diagnosed with diabetes mellitus, 10 per cent of women and 6 per cent of men had blood sugar levels indicating that they had diabetes (DHS, 2016). Furthermore, of that same population, 67 per cent of both men and women had blood sugar levels that indicated that they were pre-diabetic (DHS, 2016). The missing information around undiagnosed diabetes cases make it difficult to measure the

effectiveness of interventions as well as targeting where to allocate limited resources to have the highest impact.

This research project aims to estimate the prevalence of diabetes in South Africa to assist in data-driven policy design and implementation to maximise the benefit of interventions to the public healthcare sector in terms of cost saving and quality of healthcare delivery.

A study by Schmittdiel *et al.* (2018) provides more insight into modelling diabetes in a country. This retrospective study suggested that using a linear regression model on the American Community Survey Five-year Summary File for 2006 to 2010 (US Census Bureau, 2010) in the United States of America (USA) could reasonably predict the trends in diabetes incidence and prevalence in a population (Schmittdiel *et al.*, 2018). This research project aims to build on this research paper to model diabetes in South Africa using the South African General Household Survey (SAGHS) in order to gain a better understanding of which segments of the population may be most at risk of being diagnosed with diabetes and may have significant numbers of undiagnosed individuals living with diabetes. It aims to provide a statistical framework within which diabetes and its associated risks can be evaluated and targeted for intervention.

Furthermore, the Indian Diabetes Risk Score (IDRS) was developed as a screening tool to assess the potential undiagnosed case prevalence of type 2 diabetes (Dudeja *et al.*, 2017). The IDRS has been developed using an analysis of risk factors and their association to diabetes and could provide a low-cost tool to identify individuals who are at a high risk of contracting diabetes in South Africa (Dudeja *et al.*, 2017).

Section 2.1 gives an overview of NCDs around the world and, specifically, their prevalence in South Africa. Section 2.2 focuses specifically on diabetes, the various types of diabetes, their complications and the treatment options for diabetes. Section 2.3 outlines the risk factors for diabetes, which helps to inform the initial choice of variables for the analysis of diabetes in South Africa. Section 2.4 considers diabetes mellitus in South Africa as well as the aetiology and the impact of diabetes on individuals and households in South Africa. This section concludes by looking at the cost of diabetes to the South African healthcare system. Section 2.5 introduces diabetes risk score models in use, with a particular emphasis on the IDRS. Section 3.1 provides a backdrop for the generalised linear regression model, the synthetic IDRS model and their respective aims. Section 3.2 outlines the datasets used for the aforementioned models and Section 3.3 highlights the limitations of the data and chosen models. Section 3.4 outlines the methodology followed in the construction of the GLM (generalised linear model) and the model validation performed on this model of self-reported

cases of diabetes in South Africa. Section 3.5 describes the IDRS simulation model used to identify individuals at risk of potential undiagnosed diabetes, its assumptions, the calibration of risk scores and the model validation performed. In Section 4 the results of the data analysis and modelling are presented together with key findings. Section 4.1 outlines the results of the GLM exercise and discusses the key findings of this model. In Section 4.2, the simulated IDRS results and their trends over time are presented. Section 5 presents a discussion of the results compared to the findings from the literature and Section 6 provides a summary and concludes the research project, highlighting opportunities for further research and policy implications.

Section 2. Literature Review

2.1 Background

2.1.1 Non-communicable diseases - the global picture

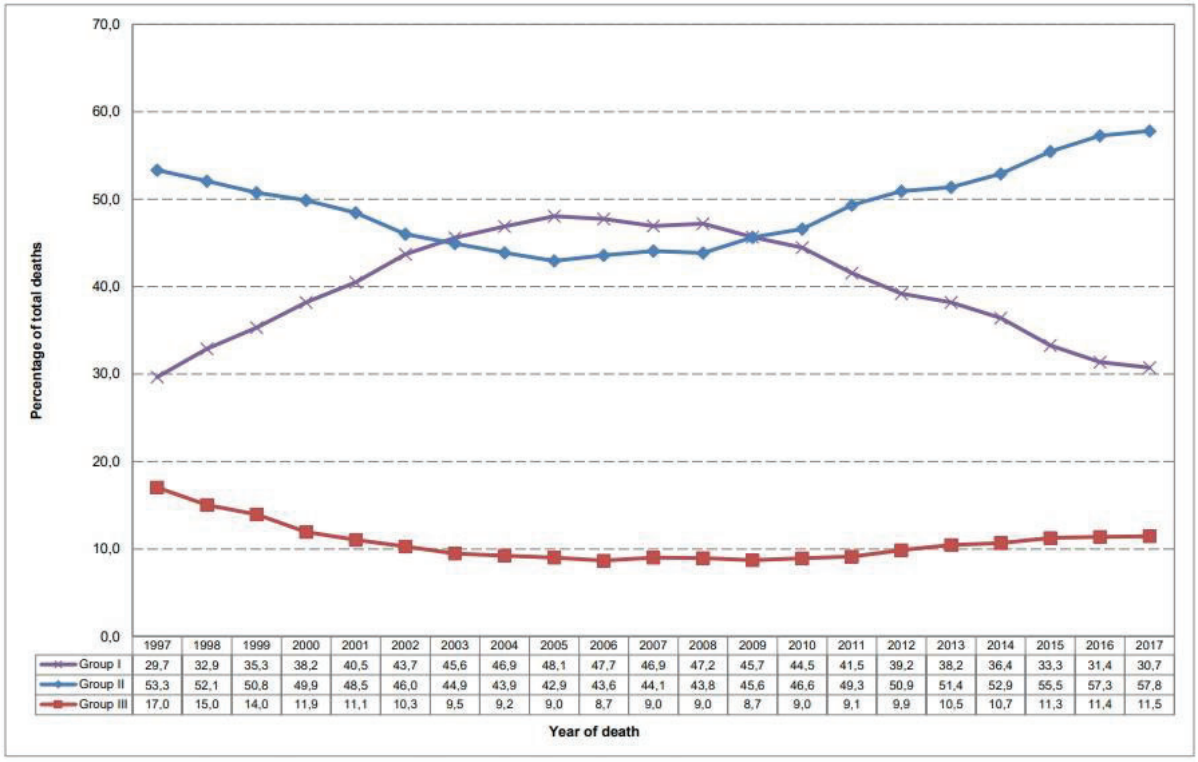
Non-communicable diseases (NCDs) result in the death of 41 million people each year, representing approximately 71 per cent of the world's annual deaths (WHO, 2023). The World Health Organization (WHO) reported that fifteen million people died prematurely from an NCD. The classification of a premature death is a death between the ages of 30 and 69 (WHO, 2023). NCDs are grouped into four main types of diseases, namely cardiovascular diseases, chronic respiratory diseases, cancers and diabetes. These account for roughly 80 per cent of all premature deaths (WHO, 2023).

These current statistical trends, with no additional intervention, indicate a continued rise in NCDs over the coming decades. The global proportion of deaths due to NCDs is expected to rise to 75 per cent (Y. Wang and J. Wang, 2020). A WHO (2011)-recommended strategy for NCD intervention is one which spans multiple different sectors of a country (also called a "multi-sectoral approach"). This strategy aims to tackle the prevention, diagnosis and management of NCDs in order to reduce the prevalence and mortality associated with NCDs in a country (Juma *et al.,* 2016). According to Juma *et al.* (2016), a multi-sectoral approach is described as key in achieving the health goals of a country by addressing sectors that are outside the traditional health sector to take action in achieving the government's healthcare policies (Juma *et al.*, 2016). Some examples of these other sectors include agriculture, education, and transportation (Juma *et al.*, 2016). One of the main benefits of this healthcare approach is the ability to impact the social behaviour of individuals in a country through empowering them with choice (Juma *et al.*, 2016).

Of the premature deaths reported by WHO in 2023 (WHO, 2023), 86 per cent occur in the low- and middle-income countries. This aligns with the trend shown in Figure 1 with low- and middle-income countries experiencing much higher NCD prevalence than the high-income countries. Therefore, low- to middle-income countries are challenged to consider strategies such as the multisectoral approach to intervene against the rising tide of NCDs (Pulvemacher, 2017).

2.1.2 Prevalence of NCDs in South Africa

In recent decades South Africa has experienced a significant rise in the prevalence of non-communicable diseases (StatsSA, 2023a). In 2020, Statistics South Africa (StatsSA) released a 2017 historical analysis of deaths in South Africa and their various causes (StatsSA, 2020a:32). Figure 2 shows that since 2008, there has been a consistent increase in the proportion of deaths due to NCDs, despite the deaths from NCDs falling below communicable diseases from 2002 until 2008, due to the rise of HIV/AIDS in South Africa.



	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Group I	29,7	32,9	35,3	38,2	40,5	43,7	45,6	46,9	48,1	47,7	46,9	47,2	45,7	44,5	41,5	39,2	38,2	36,4	33,3	31,4	30,7
Group II	53,3	52,1	50,8	49,9	48,5	46,0	44,9	43,9	42,9	43,6	44,1	43,8	45,6	46,6	49,3	50,9	51,4	52,9	55,5	57,3	57,8
Group III	17,0	15,0	14,0	11,9	11,1	10,3	9,5	9,2	9,0	8,7	9,0	9,0	8,7	9,0	9,1	9,9	10,5	10,7	11,3	11,4	11,5

* (1) Data for 1997–2016 have been updated with late registrations / delayed death notification forms processed in 2018/2019.
(2) Redistributed ill-defined diseases R00-R99 proportionately to causes in Group I and Group II.

Figure 2: Percentage of deaths due to communicable diseases (Group I), non-communicable diseases (Group II) and injuries (Group III) by year of death, 1997 to 2017

Source: StatsSA, 2020a:32

In 2016, South Africa pledged to reduce its premature mortality rate due to NCDs by a third before 2030 under the United Nations Sustainable Development Goal target 3.4 (Bennett *et al.*, 2018). For South Africa's female population, Bennett *et al.* (2018) estimate that it will take between 2036 and 2040 for the country to achieve this target, and later than 2050 to achieve this target for its male population.

In understanding how NCDs are currently addressed in South Africa's regulations, there have been a number of significant drivers identified to increase the risk of a person contracting

an NCD. The risk factors of an NCD include modifiable risk factors such as tobacco use, harmful use of alcohol, physical inactivity and unhealthy diet as well as metabolic factors (Global 2015 Risk Factors Collaborators, 2016). These metabolic factors include raised blood pressure, being overweight or obese, hyperglycaemia and hyperlipidaemia (Global 2015 Risk Factors Collaborators, 2016). Ndinda and Hongoro (2017) reported that there were twenty-one government Acts, amendments and regulations from 1989 to 2015 that targeted the NCD risk factors prevalent in South Africa.

Of these twenty-one Acts, five policies were put in place which target unhealthy diets, in an attempt to try and reduce obesity rates in South Africa during the period of 2009 to 2015 (Ndinda and Hongoro, 2017). These policies include the National School Nutrition Programme (DBE, 2009) to target school meals given to public school students and the Sodium Reduction Regulations (South Africa, 2013) which set about setting maximum sodium limits on processed meat and other food products (Ndinda and Hongoro, 2017). These policies were aimed at reducing the consumption of sugar, high carbohydrates and salt (Ndinda and Hongoro, 2017). Other parts of the 21 health Acts focused on reducing the tobacco consumption in South Africa (Ndinda and Hongoro, 2017). Amongst other health impacts, tobacco consumption has been linked to 65 per cent of cardiovascular deaths from diabetes mellitus (Suarez and Barrett-Connor, 1984). The reduction in South African smoking rates has been observed over the period of this regulatory implementation; however, further monitoring of smoking rates and associated risk factors is required before a judgement of success or failure of these regulations can be drawn (Reddy *et al.*, 2015).

Ronquest-Ross *et al.* (2015) report that despite the Sodium Reduction Regulations, the diet of South Africans has still leaned towards sugar-sweetened beverages and processed food. In 2015 there had been a 68 per cent rise in sugary drink consumption, resulting in the average South African consuming 93 litres of soft drink every year (IOL, 2015). This is contrary to the expected improvements in the South African population's diet (Ronquest-Ross *et al.*, 2015). Diet plays a large role in the increasing obesity rates experienced in South Africa, which in turn, is one of the key risk factors for diabetes mellitus (OECD, 2019a). According to a survey about the eating habits of South Africans, it was found that whilst 82 per cent of respondents believe that it is easier to access healthier foods, only 52 per cent think that these healthier alternatives are affordable (FoodStuff South Africa, 2020).

Recommendations are made to improve the education around eating healthily, as it is believed that this is an area of opportunity in the government's current efforts to fight NCDs, according to Pretorius (2013). Education appears to play a key role in creating awareness of

the importance of healthy eating. There is a large distrust of online sources, with 62 per cent of respondents indicating that they acquire their nutritional information from friends and family (Pretorius, 2013).

In South Africa, Lambert and Kolbe-Alexander (2013) reported that roughly 40 per cent of deaths are attributable to just four chronic conditions, namely cardiovascular disease, diabetes, chronic lung disease and certain cancers. Diabetes, specifically, made up 20 per cent of NCD deaths in South Africa in 2015 (WHO, 2018a), causing diabetes mellitus to be the second-highest cause of natural deaths behind tuberculosis in 2017 (StatsSA, 2020a:36). Additionally, for the female population, it was the leading cause of natural deaths (StatsSA, 2020a:36).

Efforts to quantify the number of people living with diabetes are predominately performed using the South African Demographic Health Survey of 2016 (Walker *et al.*, 2023). Dawson *et al.* (2022) estimated a prevalence of 14.6 per cent of South Africans who are diabetic. Furthermore, Walker *et al.* (2023) reported that 70 per cent of the non-diabetic South African population is pre-diabetic.

2.2 Diabetes

Diabetes is characterised by the phenomenon of high levels of blood glucose (or blood sugar) in the body (American Diabetes Association Professional Practice Committee, 2022). Also known as diabetes mellitus, there are four main types of diabetes, namely type 1 diabetes, type 2 diabetes, diabetes due to other causes and gestational diabetes mellitus (American Diabetes Association Professional Practice Committee, 2022).

2.2.1 Type 1 diabetes

Type 1 diabetes or insulin-dependent diabetes is a chronic condition where the person's pancreas cannot produce enough insulin to regulate the blood sugar level of the body (American Diabetes Association Professional Practice Committee, 2022). This is usually due to the immune system of the body destroying specific cells in the pancreas (β-cells) which impairs the operation of the pancreas's production of insulin (American Diabetes Association Professional Practice Committee, 2022).

Type 1 diabetes has been linked to having a genetic predisposition (Hober and Sauter, 2010). This genetic predisposition is said to be influenced by environmental factors which influence the presence of certain "high risk" genes. Enteroviruses, which negatively impact the

β-cell production in the pancreas through either sustained or repeated infections, are also said to influence this genetic predisposition (Hober and Sauter, 2010).

Enteroviruses (EVs) are a group of small ribonucleic acid (RNA) viruses which have been causally linked to several medical conditions including neurological diseases (Pons-Salort *et al.*, 2015). Multiple strains of the well-known EVs have been theorised to influence the susceptibility of a person to develop type 1 diabetes (Yeung *et al.*, 2011). A good example of this is the coxsackievirus B-4 which has been shown to have a positive association with the development of diabetes (Yeung *et al.*, 2011). The phenomenon was first noticed by researchers when, during EV epidemics, there was a rise in the number of cases of type 1 diabetes (Yeung *et al.*, 2011). In more recent studies, Yeung *et al.* (2011) suggest that the relationship may be causal as opposed to merely correlated.

The main theory to explain this causation effect is that the EVs can cause many persistent or successive infections (Hober and Sauter, 2010). These EV infections potentially lead to disruption of the β-cells' natural regulatory process and invoke an antiviral antibody response that promotes the destruction of these same pancreatic cells (Kim *et al.*, 2016). Through the destruction of these pancreatic cells (β-cells), this limits the overall insulin production capacity in the body and, eventually, the development of type 1 diabetes (Hober and Sauter, 2010).

2.2.2 Type 2 diabetes

Type 2 diabetes is characterised by either the pancreas slowing the production of insulin over time or the body becoming more resistant to insulin, which leads to blood glucose levels which are above what is considered normal (American Diabetes Association Professional Practice Committee, 2022). As in the case of type 1 diabetes, this higher-than-normal blood sugar level can, over time, cause major damage to various body organs (heart, eyes, kidneys, and so on). The key distinguishing factor between type 1 and type 2 diabetes is that type 2 diabetes occurs as a result of specific cells in the pancreas which are responsible for the secretion of insulin, specifically the β-cells, being lost over time (Riddle *et al.*, 2018). This loss of β-cells is often combined with a degree of insulin resistance in the patient's body (Riddle *et al.*, 2018). In contrast, type 1 involves the destruction of these pancreatic cells (Riddle *et al.*, 2018). Type 2 diabetes is most commonly found in adults, and has become more prevalent, globally, over the last 30 years (WHO, 2018b).

2.2.3 Other specific types of diabetes

Outside of type 1 and type 2 diabetes, there are other specific categories of diabetes all relating to different methods of impacting the glucose levels in the body. The first of these other types involves diabetes diseases which impact what is called the exocrine pancreas (Kerner and Brückel, 2014). The exocrine pancreas is the function of the pancreas to release important digestive enzymes during the digestion of a person's food (Pancreas Center, 2024). According to Kerner and Brückel (2014), these diseases of the exocrine pancreas include cystic fibrosis-related diabetes, which is a specific complication of cystic fibrosis where the thick mucus which characterises the disease causes damage to the pancreas and impairs its function to produce insulin (Cystic Fibrosis Foundation, 2024). According to Kerner and Brückel (2014), this is known as hemochromatosis, which is a genetic disorder characterised by absorption of abnormally high levels of iron from the digestive system. This results in damage being caused to, amongst other organs, but in the case of diabetes, the pancreas (Raju and Venkataramappa, 2018). A final example of these diseases is pancreatitis (Diabetes.co.uk, 2023a), which is defined as a disease where the pancreas becomes inflamed. This can lead to the development of diabetes due to the impact this inflammation has on the production of insulin (Diabetes.co.uk, 2023a).

Kerner and Brückel (2014) continue listing other types of diabetes by categorising them as endocrinopathies or diseases that impact the pancreatic release of hormones into the body (of which insulin is one). One of these diseases that can lead to the development of diabetes is Cushing syndrome, which is defined as a disorder where the body has too much of a hormone called cortisol, which, amongst other functions, helps with the regulation of the blood sugar levels (Kerner and Brückel, 2014). Another endocrinopathic disease is acromegaly, which is an imbalance of a growth hormone (Kerner and Brückel, 2014). In this case, the high amounts of this growth hormone cause the individual to develop an insulin resistance (Kerner and Brückel, 2014).

A further category of other types of diabetes that Kerner and Brückel (2014) describes is the induced forms of diabetes. These forms of diabetes are where external substances lead to the development of diabetes (Kerner and Brückel, 2014). This mainly includes the drug-induced diabetes, namely the excessive use of glucocorticoids and neuroleptics (Kerner and Brückel, 2014). Glucocorticoids are drugs used to reduce inflammation of other autoimmune disorders (as well as promote consistent glucose levels in the blood) (Bauerle and Harris, 2016). Neuroleptics, also known as antipsychotics, are used to treat mental problems such as schizophrenia (Lean and Pajonk, 2003).

There is also a category of diabetes specific to the female population. This type of classified diabetes is gestational diabetes, which occurs during pregnancy (Kerner and Brückel, 2014). Gestational diabetes mellitus (GDM) should only be diagnosed in the second or third trimester of pregnancy and only if the patient did not have overt diabetes prior to their pregnancy (Riddle *et al.*, 2018).

The final category of two potential developing types of diabetes mentioned by Kerner and Brückel (2014) are genetic defects that can impact the insulin regulation and resistance of the body, as well as viral infections that may impact the β-cells in the body in various ways (Filippi and von Herrath, 2008). These genetic defects are specific to influencing the β-cell function and defects of the insulin effectiveness, amongst many other genetic disorders (Kerner and Brückel, 2014).

All these categories of diabetes will often lead to similar symptoms and result in a variety of different complications. These complications can be split between macrovascular and microvascular complications.

2.2.4 Macrovascular complications

Macrovascular diseases are diseases which impact the large blood vessels in the body such as, in the case of diabetes, the arteries (specifically the coronary arteries, which are found within the heart), as well as the arteries that run blood to all the different organs of the body, which are otherwise known as peripheral arteries, as defined by Zimmerman (2016). They arise from plaque made up of mainly fat, cholesterol and calcium (otherwise also known as atherosclerotic plaque) (NIH, 2022) slowly building up in the various arteries that supply blood to the main organs of the body (Zimmerman, 2016).

When it comes to macrovascular diabetes-related diseases of the coronary arteries (also known as cardiovascular disease or CVD), this can present with obvious signs of blocked arterial pathways such as stable or unstable chest pain, heart attacks, or an abnormal rhythm of a person's heartbeat (Zimmerman, 2016). However, according to Zimmerman (2016), the patient may present with no clear set of symptoms for CVD, which can make diagnosis difficult.

2.2.5 Microvascular complications

Whilst macrovascular diseases are impacted by the larger atherosclerotic plaque, the microvascular complications arise from distinct effects on the smallest blood vessels (also called microvessels) in the process of circulating blood (Orasanu and Plutzky, 2009). These

microvessels are made up of the arterioles, capillaries, and venules, and they play an important role in the delivery of nutrients to the rest of the body as well as the regulation of a person's blood pressure (Orasanu and Plutzky, 2009).

Microvascular complications involve the slow damage of these small blood vessels in various parts of the body through the thickening of what is known as the capillary basement membrane (Orasanu and Plutzky, 2009). According to Pozzi *et al.* (2017), the capillary basement membrane is essentially a thin layer of molecules and minerals that act as barriers to offer protection from harmful cells. This thickening leads to these microvessels becoming weaker which, amongst other things, slows the flow of blood in the body, which is otherwise known as diabetic microangiopathy (Orasanu and Plutzky, 2009). Microangiopathy often leads to many of the symptoms of microvascular diabetic complications (Orasanu and Plutzky, 2009). With the slowed flow of blood, there is a lack of oxygen in the various bodily tissues (also known as tissue hypoxia) (Orasanu and Plutzky, 2009). Another occurrence is that there is a slower rate of healing for cuts (Orasanu and Plutzky, 2009). The slowed blood flow also leads to problems of high blood pressure, also known as hypertension (Orasanu and Plutzky, 2009).

There are many organs that rely on the microvessels to circulate blood, but some organs experience complications more commonly than others (Orasanu and Plutzky, 2009). These organs are namely the retina (a small component of the eye, responsible for converting light into brain signals) (Healthline, 2018), kidneys, and peripheral nervous system (a system of nerves that exist outside the spinal cord and brain (Queensland Brain Institute, 2024)) (Orasanu and Plutzky, 2009). The impairment of those organs by the slowed flow of blood as a result of diabetes has been observed to result in three main conditions, which are called retinopathy, nephropathy, and neuropathy (Zimmerman, 2016).

Retinopathy is a disease that occurs when the retina of the eye is damaged, causing partial or complete loss of sight (Harvard Health Publishing, 2023a). Retinopathy for diabetic patients takes years to occur from the transition from nonproliferative, where there is a deterioration where the blood vessels in the eyes become blocked or deformed (Boyd, 2023). This can lead to the vessel leaking fluid into the retina, potentially causing a deterioration of the person's ability to see (Boyd, 2023). The later form is proliferative, which is when there are structurally unstable blood vessels that grow to the surface of the retina, which can bleed, leading to scarring and irritation in the eye (Boyd, 2023). In more serious cases, there has been complication of the retina being lifted off the back of the eye (Boyd, 2023).

A second microvascular cluster in the body that has been observed to experience complications due to diabetes, is located in the smallest blood vessels of the kidney (Harvard Health Publishing, 2023b). This complication is called nephropathy and results in the kidneys slowly beginning to lose their ability to clean the blood of any waste materials (Harvard Health Publishing, 2023b).

Other microvascular complications that can arise are found in the nerve centres around all the parts of the body excluding the head and spinal cord (also known as neuropathy - Harvard Health Publishing, 2023b). A few of the nerve centres impacted include the linking nerves between the brain and the spinal cord (also known as peripheral neuropathy), the nerves that are responsible for unconscious bodily functions (also known as autonomic neuropathy) or other nerves that control some sort of muscle function (also known as localised nerve failures – Harvard Health Publishing, 2023b).

These microvascular complications have been shown to be influenced by the blood-glucose level (UKPDS Group, 1998). The UKPDS (UK Prospective Diabetes Study) Group (1998) managed to show that there was a substantial decrease in the risk of microvascular complications if either sulphonylureas, a drug used to improve the production of insulin in the pancreas (Diabetes.co.uk, 2023b) or insulin was used to control the blood-glucose level in type 2 diabetes patients.

2.2.6 Diabetes testing

For a diagnosis of diabetes to be determined, there are different tests that doctors will use to make such a judgement. The first is a haemoglobin A1c (HbA1c) test, which measures the quantity of glucose-infused haemoglobin in the oxygenated red blood cells (Diabetes.co.uk, 2023c). This final product of the joining of the haemoglobin glucose in the blood is called glycated haemoglobin (Diabetes.co.uk, 2023c). Haemoglobin is a protein responsible for oxygen transportation found in the red blood cells (Diabetes.co.uk, 2023c). Therefore, glycated haemoglobin is a good indicator for a monthly average blood sugar level (Diabetes.co.uk, 2023c). For diagnosis of diabetes to be confirmed, the traditional HbA1c test must read a glycated haemoglobin level of greater than or equal to 6.5 per cent (Kerner and Brückel, 2014). In other words, the two-to-three-month average blood glucose level is above 6.5.

According to Kerner and Brückel (2014), the HbA1c test first became the recommended diagnosis test for the German Diabetes Association in 2010, which was made possible through international efforts to standardise the approach for the diagnosis of diabetes. The test is, however, not accurate (NIDDK, 2022) for people with anaemia or other blood conditions.

Further research across a number of different studies, suggests that the test is inaccurate in correctly diagnosing patients of African, Mediterranean, or Southeast Asian descent.

The HbA1c is also sensitive to a person's age, which is why it is recommended only to be administered on adult populations (Cowie *et al.*, 2010). Despite this sensitivity, additional caveats have been added to the pathology of care, as Arslanian *et al.* (2018) showed that the HbA1c test as well as the fasting plasma glucose (FPG), or two-hour glucose, in venous plasma were still appropriate for use in diagnosis of type 2 diabetic children and adolescents. This is subject to the child or adolescent being overweight and having one or more additional risk factors (Riddle *et al.*, 2018).

A test that could be used instead of the HbA1c test is the FPG, which tests the blood sugar levels of a person who has been fasting from all food and drink except water for eight hours before the test (ADA, 2024). A blood sugar level of greater than or equal to 126 milligrams per decilitre (mg/dl) leads to a diagnosis of diabetes (Kerner and Brückel, 2014).

Another test used was the random plasma glucose, which tests the same thing as the FPG test, but can be performed on the patient at any time, regardless of whether they have fasted or not. If at any time, the blood sugar levels exceed 200 mg/dl, then a diagnosis of diabetes is suggested (Kerner and Brückel, 2014).

Finally, the oral glucose tolerance test (OGTT) monitors a patient's blood sugar levels before and after the consumption of a high glucose beverage (ADA, 2024). If, after two hours of the consumption of the beverage, the patient's blood sugar levels are greater than or equal to 200 mg/dl, then a diagnosis of diabetes is suggested (Kerner and Brückel, 2014).

2.2.7 Diabetes treatment

With the complexities of diagnosis in mind, treatment for diabetes can be different depending on the source of healthcare that the patient has decided to seek. It also involves addressing the different risk factors and symptoms present in a particular patient. With a number of different methods of treatment, it is important to understand what these methods are and the availability of these different treatments.

Upon an initial diagnosis requiring glucose-lowering therapy, a drug called *Metformin* is often recommended to be prescribed to the patient and will be continued with until it is no longer effective (ElSayed *et al.*, 2023). Insulin can be added later to the *Metformin* in order to counteract the progressive loss of insulin production from the β-cells in the pancreas (ElSayed *et al.*, 2023). Insulin can be prescribed earlier in the process if the patient is experiencing any weight loss, symptoms of hyperglycaemia, or they are experiencing extremely high blood sugar

levels in their HbA1c test (ElSayed *et al.*, 2023). Intensive *Metformin* therapy has been recommended ahead of insulin prescriptions, since studies have shown that this therapy can be significantly effective in reducing the risk of diabetes-related deaths and medical procedures (UKPDS Group, 1998).

Regardless of the medication, the patients should have their prescriptions reviewed very regularly and adjusted to include any other factors that may be influencing the patient's condition (ElSayed *et al.*, 2023). Since the human body is such a complex, interconnected matrix of cells, the treatment recommended is usually not restricted to just medication and can include both mental care and lifestyle adjustments (ElSayed *et al.*, 2023).

The emotional well-being of patients who have been diagnosed with diabetes has been shown to lead to the development of psychological problems which have been observed to impact the patient's social life and well-being (Kalra *et al.*, 2018). There is also strong evidence that the mental stress that a person can experience due to relevant social factors (also known as psychosocial factors) can impact the self-care behaviours and other psychosocial variables (such as depression) which are strong known indicators for medical outcomes such as hospitalisation and mortality (Rubin and Peyrot, 1999).

Delahanty *et al.* (2007) reported that in past studies, the method of treatment for many primary care patients of diabetes can have a significant impact on the emotional state of a patient. Delahanty *et al.* (2007) further reported that the levels of emotional distress were highest amongst patients with insulin-treated symptoms rather than oral-treated or diet-treated patients.

Therefore, the perception of control over the disease plays a significant factor in the ability for a patient to both continue regularly taking the prescribed medication as well as the regulation of their blood sugar levels, specifically amongst adults (Gonzalez *et al.*, 2015). Other significant factors that have been observed to exhibit higher emotional distress due to a diagnosis of diabetes include an association with younger-age females (Rubin and Peyrot, 1999), higher HbA1c (Polonsky *et al.*, 1995) and more frequent blood glucose testing (Delahanty *et al.*, 2007).

These findings have resulted in a few proven treatments for combatting emotional distress for diabetic patients (Rubin and Peyrot, 1999). Two such treatments involve the education of patients around the managing of their diabetes and providing appropriate counselling for their mental health needs (Rubin and Peyrot, 1999). It is further recommended by the ADA (the American Diabetes Association) (2019) that the timing of these counselling and education treatments should focus mainly upon diagnosis. These mental health impacts

should be evaluated as a need (rather than as an add-on to care) and progress of the patient, and should be annually reviewed for complications (ADA, 2019).

Further developments of this care have been made in recent years, with a virtual clinic called the Onduo Virtual Diabetes Clinic being studied regarding the ability to provide access to these treatments (Polonsky *et al.*, 2020). One early study investigating the emotional benefits of the Onduo Virtual Diabetes Clinic reported early promising results from an introductory study (Polonsky *et al.*, 2020). If the promising results continue, this could play a key role in providing emotional and educational support to members of the community who find it difficult to access professional counselling services, often due to the cost, geographic distance or absence of medical professionals in their area (Polonsky *et al.*, 2020).

The mind is connected to all the other parts of the body and hence why mental care often goes hand-in-hand with a patient's lifestyle (ElSayed *et al.*, 2023). Type 2 diabetes, specifically, is a disease where the lifestyle factors have been observed to play an important role in the recovery of a patient and this care often involves a change to the patient's lifestyle, often to prevent or combat obesity (ADA, 2019). These changes to a patient's lifestyle usually involve a change in the patient's diet and exercise routine, promoting a more streamlined diet and more frequent and regular physical activity (ADA, 2019). Whilst there is general acceptance that the regulation of a patient's energy and nutritional intake plays a significant role in reducing the risk of further complications from type 2 diabetes (Mann *et al.*, 2004), adherence to specific lifestyle changes remains a significant problem for this type of treatment (Ary *et al.*, 1986). This adherence is usually related to either social pressures to break away from the prescribed diet or experiencing undesirable physical reactions from their physical activity (Ary *et al.*, 1986).

When looking specifically at a change in a patient's diet, the recommended approach to treating type 2 diabetes is to encourage weight loss through both eating plenty of nutrients and by cutting down on the consumption of certain foods (Mann *et al.*, 2004). The exact nutritional breakdown of which nutrients to consume more or less of is a controversial topic, with many different views and results from various studies (ADA, 2019). Overall, the current recommendation for nutrition is to prescribe the patient with a healthy and attainable diet which is rich in nutrients and comes in appropriate portion sizes (ADA, 2019). This is balanced with a little pleasure eating to allow for the patient to enjoy the diet (as well as remove some of the emotional distress caused by the treatment prescription), which promotes sustainability of the diet (ADA, 2019).

Further lifestyle changes are often recommended, such as reducing or eliminating alcohol consumption as well as smoking, whether it be e-cigarettes or traditional tobacco (ADA, 2019). Counselling for quitting both behaviours is often required and should be included in the care of a type 2 diabetic patient (ADA, 2019).

2.3 Risk factors for diabetes

Various studies into the risk factors for type 2 diabetes have shown a difficulty in the ability to clearly identify such factors on account of their interrelated nature (Fletcher *et al.*, 2002). The risk factors have generally been grouped into genetic, lifestyle and insulin resistance factors (Fletcher *et al.*, 2002). The genetic risk factors include levels of family history of diabetes, age and demographic group (Fletcher *et al.*, 2002). The lifestyle risk factors include levels of physical activity, obesity, diet, blood pressure and smoking (Akhuemonkhan and Lazo, 2017). Studies segment by sex when analysing the risk factors (Dawson *et al*., 2022).

Under the genetic risk factors group, family history is a well-established risk factor for type 2 diabetes (Akhuemonkhan and Lazo, 2017). Studies across the world report a significant association between family history and diabetes (Akhuemonkhan and Lazo, 2017; Chaudhuri *et al.*, 2021; Samocha-Bonet *et al.*, 2010). The common trend is that the more direct family members who have diabetes, the higher the chance of development of diabetes in the individual (Akhuemonkhan and Lazo, 2017). Family history appears to have influences that are both genetic, as described by Meigs *et al.* (2000) and Warram *et al.* (1990) as well as modifiable lifestyle factors, as described by Akhuemonkhan and Lazo (2017). Local studies from South Africa show a similar association between family history and diabetes (Peer *et al.*, 2012).

A further identified genetic risk factor is the age of the individual (Fletcher *et al.*, 2002). Type 2 diabetes is often induced later in life, with the risk of diabetes increasing the older someone is (Sifunda *et al.*, 2023). However, in countries such as the UK (United Kingdom), there is a trend of type 2 diabetes becoming more prominent amongst the younger generation (Wilmot *et al.*, 2010).

Demographic groups are the final genetic risk factor identified by Fletcher *et al.* (2002). Wilmot *et al.* (2010) report that the less affluent socio-economic groups, (who are likely obese and have a sedentary lifestyle) are most likely to develop type 2 diabetes. In South Africa, Sifunda *et al.* (2023) report the highest prevalence of type 2 diabetes in the Indian and white population with 32 per cent and 16 per cent respectively. However, Dawson *et al.* (2022) includes the black and other populations in South Africa as having increased odds of diabetes in comparison to the white population.

Of the lifestyle risk factors, Sifunda *et al.* (2023) reported that obesity was the risk factor most correlated to a case of diabetes in South Africa. Of the populations classified as overweight and obese, between 10 and 14 per cent and 23 and 24 per cent respectively have an HbA1c level which is greater than 6.5 per cent (DHS, 2016). This is twice to four times greater than within the populations classified as underweight and normal (DHS, 2016).

The insulin resistance grouping includes several different risk factors. Hyperinsulinemia, which according to Thomas *et al.* (2019), occurs when there is a higher than usual level of insulin in the blood, is one such risk factor for diabetes (Fletcher *et al.*, 2002). Another insulin regulation deficiency risk factor for diabetes, according to Fletcher *et al.* (2002), is impaired glucose tolerance (also known as impaired fasting glucose), which is a condition where the patient experiences higher than normal levels of blood sugar levels, but those levels are not high enough to be diagnosed as diabetic (Diabetes.co.uk, 2023d).

Fletcher *et al.* (2002) have also reported that deficiencies in the fat cells (also known as lipoproteins) found in the blood to be a major risk factor for type 2 diabetes. This phenomenon is called atherogenic dyslipidaemia and is characterised by a disorder within the fat cells of the plasma in the blood (Adiels *et al.*, 2008). This disorder occurs when there is an overproduction of certain fatty cells, that is, very low-density lipoprotein (Adiels *et al.*, 2008). These low-density lipoproteins lead to, amongst other things, an imbalance of higher amounts of low-density lipoprotein and lower amounts of high-density lipoprotein (Adiels *et al.*, 2008). This may result in type 2 diabetes after several years, if left untreated (Adiels *et al.*, 2008).

The next three insulin resistance risk factors outlined by Fletcher *et al.* (2002), are related to blood and its flow through the body. The first of these involves the medical condition where the pressure in the blood vessels is too high, putting too much strain on the heart, also known as hypertension (WHO, 2024).

The second risk factor is if the patient is in a position where their blood abnormally coagulates, also known as clotting (BMJ Best Practice, 2023; Fletcher *et al.* 2002). A person who is at higher risk than normal of these blood clots is said to be in a hypercoagulable state (BMJ Best Practice, 2023). Fletcher *et al.* (2002) lists a final blood-related risk factor, which is called hyperuricemia, which is when there are elevated levels of a waste product called uric acid in the blood (ChemoCare, 2024). Adiels *et al.* (2008) comment that changes in these high levels of uric acid have revealed to be more useful risk factors in determining the risk of diabetes than simply a single static measurement. It follows that better monitoring of a patient's uric acid levels will better inform medical professionals in their diagnosis of diabetes, resulting

in those with access to tests such as these potentially benefiting from an earlier diagnosis of diabetes.

A final risk factor which Fletcher *et al.* (2002) list is specific to the female population and is called polycystic ovary syndrome. It occurs when the usual ovulation process does not take place because the eggs are not released from their egg sacks (NHS, 2022).

Women in the South African population are reported to have a higher prevalence of diabetes than men, with self-reported prevalence of five per cent and four per cent respectively (DHS, 2016). After testing, DHS (2016) reported that 10 per cent of women who had never been diagnosed with diabetes were diabetic, compared to 6 per cent of men. After further analysis, Dawson *et al.* (2022) estimated that females have a higher risk of diabetes compared with their male counterparts.

On the whole, there is an interplay between all three of these broad categories of risk factors (Fletcher *et al.*, 2002). In general, the more risk factors that an individual has, the more likely they are to develop type 2 diabetes (Fletcher *et al.*, 2002). However, according to Abbasi *et al.* (2002), when trying to predict type 2 diabetes in a population, both obesity and the broad category of insulin resistance were found to be particularly powerful.

An analysis of obesity in the South African population has revealed clear trends emerging over the past 20 years. Reddy *et al.* (2012) reported that the rate of obesity in the South African population had almost doubled in male adolescents, increasing from 6.3 per cent in 2002 to 11.0 per cent in 2008; and in female adolescents, increasing from 24.3 per cent in 2002 to 29.0 per cent in 2008. Reddy *et al.* (2012) concluded that in 2011 South Africa was amidst a transition into a major risk of chronic disease. Studies such as Puoane *et al.* (2002) suggest that one part of the explanation for this rapid increase in obesity in South Africa could be due to poor diet (and in particular amongst black people living within an urban environment). In South Africa, higher obesity rates are found in the female population when compared to their male counterparts (DHS, 2016). Statistics published in 2016 reported that 68 per cent of women and 31 per cent of men were overweight or obese (that is, an individual having a body mass index (BMI) of greater than 25kg/m^2) (DHS, 2016).

Case and Menendez (2009) made two observations in their analysis of a small population of women in Khayelitsha, Cape Town, South Africa. From this small population subset, Case and Menendez (2009) saw that women who were nutritionally deprived in their youth experienced a higher probability of becoming obese as adults, whilst men did not experience the same risk. Another observation from Case and Menendez (2009) was that women of higher adult socio-economic status have a higher risk of becoming obese, which is not true for men.

The reasons for these observed differences are not known, but there is a clear higher risk of obesity for the females (Statista, 2024a). Without an appropriate strategy from the South African health system, the obesity rates, and eventual diabetes rates, could continue to grow into the future (Statista, 2024a).

A study by Cois and Day (2015) warns of this future through the use of the growing rate of BMI, a common measure for diagnosing obesity in South Africa. This trend of BMI is likely going to continue (Cois and Day, 2015). The most at-risk population groups identified were female individuals with a high socio-economic status (Cois and Day, 2015). This study also found that individuals living in rural areas were identified as a high-risk group, something not yet identified in many of the previous studies (Cois and Day, 2015). This increasing average BMI rates in rural areas is believed to be driven by the higher consumption of processed food in conjunction with lower physical activity (Cois and Day, 2015).

This BMI trend is not a simple one to curb for the South African Government. South Africa also faces issues like limited resources and inadequate healthcare infrastructure (Udjo and Lalthapersad-Pillay, 2014) and the ageing population (StatsSA, 2020b), who are likely to lead to South Africa experiencing higher mortality rates in the future (Udjo and Lalthapersad-Pillay, 2014). Another contribution to the obesity rate is that many South Africans report to not exercise. Kapwata and Manda (2018) conducted a survey and reported that between 72 per cent and 80 per cent of respondents said that they never exercise.

With the high rate of obesity in South Africa and the potential risk of this rate increasing in the near future, the clear link between obesity and insulin resistance leads to a reality which may see the diabetes rate continue to increase. Kahn and Flier (2000) highlight the known association that has been observed between obesity and its impact on reducing insulin resistance within the body.

Furthermore, upon investigation into the population differences, insulin resistance in South Africa has seen mixed results from studies investigating the changes over the years in South Africa. Davids *et al.* (2020) had inconclusive findings on the results of a longitudinal study from 2008 until 2016. However, there seemed to be significant differences between different demographic groups, specifically women (Davids *et al.*, 2020). Whilst no clear conclusion could be drawn, Kalk and Joffe (2008) found a demographic breakdown that black men and women, when compared with their white counterparts, exhibited lower insulin resistance amongst diabetic patients, contributing to a lower risk of coronary heart disease. This was consistent across both male and female black people, and the study showed a significantly lower prevalence of hypertriglyceridemia (a state where the body experiences a prolonged

higher than normal level of energy stored in the blood as a specific form of fat also known as triglycerides (MedScape, 2021)) (Kalk and Joffe, 2008).

When predicting insulin resistance in a population, noting these potential differences between different demographic groups of black, white, Indian and other, a common measurement that is used in many first-world countries and applied to overweight women is the triglycerides (TG) to high-density lipoproteins (HDL)-cholesterol (TG/HDL-C) ratio (Knight *et al.*, 2021). The success rate of this ratio in predicting disease in different demographic groups in South Africa was tested on overweight black women from South Africa (Knight *et al.*, 2021). As the success rate was below threshold for this demographic group, the TG/HDL-C ratio was shown to be ineffective amongst women of African descent (Knight *et al.*, 2021).

It is not just the insulin resistance and obesity rate trends that are prevalent within South Africa, it is also the ageing population that is cause for concern with the risk of diabetes faced by this developing country. The phenomenon of the ageing population has been observed across the whole continent of Africa (Nabalamba and Chikoto, 2011). South Africa is no exception to this phenomenon, as it has been experiencing an increasingly ageing population (StatsSA, 2020b). The proportion of the South African population that was elderly in the period from 2002/2003 to 2019/2020 has grown from one per cent to three per cent respectively. From 2009 to 2019, there was a 14 per cent increase in the proportion of South Africans aged sixty-five and above (Statista, 2024b). The total South African population aged sixty-five and above was 5.42 per cent in 2019 (Statista, 2024b).

2.4 Type 2 diabetes in South Africa

2.4.1 Current prevalence of diabetes in South Africa

The International Diabetes Foundation (IDF) reported that in 2022, South Africa had roughly 4,2 million cases of diabetes, which is roughly 11.3 per cent of the adult population (IDF, 2023) (these 4.2 million cases include an estimated 1.9 million undiagnosed cases). Furthermore, in December 2021, South Africa was ranked the forty-eighth country in the world for the overall prevalence of diabetes amongst individuals aged 18 to 79 (IndexMundi, 2021). The number of cases has more than doubled since 2011, where South Africa experienced just under 1.9 million cases (including undiagnosed cases) (IDF, 2021). With roughly 800,000 new diabetes diagnoses in South Africa being reported for the period 2016 to 2020 by the International Diabetes Federation (IDF), cases of diabetes have become more prevalent in recent years (IDF,

2023). The average healthcare expenditure per person per year from 2011 to 2021 increased from approximately R18,000 to approximately R26,000 using a current day exchange rate and adjusting for inflation (IDF, 2021). With the rising case numbers of diabetes as well as the rising expenditure on these patients, South Africa faces another issue, which is the low rate of diagnosis, as roughly 45 per cent of the 4.2 million diabetes cases are undiagnosed (IDF, 2021).

2.4.2 Inequality of diabetes prevention and treatment amongst South Africa's population segments

Ataguba *et al.* (2011) studied the trends in diagnosis and treatment for diabetes from the South African General Household Survey (SAGHS) for the years 2002, 2004, 2006 and 2008. Ataguba *et al.* (2011) found that the reported cases of diabetes amongst the higher socioeconomic classes, which traditionally had experienced the highest diabetes prevalence rates, are rising at a slower rate than amongst the lower socioeconomic classes. This result is an international trend of reported diabetes cases and not simply restricted to the South African population (Ataguba *et al.*, 2011).

Stokes *et al.* (2017) reported that the diabetes prevalence rates were higher amongst the non-white populations in South Africa. Further disparity was seen when the study revealed that more than 50 per cent of the black population were not screened for diabetes, compared to only 8 per cent of the white population not being screened (Stokes *et al.*, 2017). Harris *et al.* (2011) identified that the black population faces the largest barriers regarding affordability, acceptability and availability in attaining proper diabetes diagnosis and treatment. Regarding the availability barrier, Stokes *et al.* (2017) reported that the screening rates are lower in rural areas, compared with urban areas (roughly 68 per cent to roughly 40 per cent respectively). This contrasts the finding by Stokes *et al.* (2017) that diabetes is more prevalent in urban areas compared to rural areas. This could be due to the lower screening and diagnosis rates in rural areas (Stokes *et al.*, 2017). The ability to understand the current access to care challenges faced by the different population groups in South Africa is key to be able to identify the groups in society most at risk to diabetes in society and providing care to those groups.

2.4.3 History of healthcare in South Africa

From 1948 to 1994 South Africa was governed by the "apartheid" regime of racial segregation (Susser and Cherry, 1982). This segregation extended to the healthcare system, which was designed and resourced to the benefit of the minority white population (Susser and Cherry, 1982). Access to healthcare and employment for non-white citizens was severely restricted

(Kon and Lackan, 2008). The lasting impact of apartheid on the healthcare system is still evident to this day (Kon and Lackan, 2008). Susser and Cherry (1982) reported that the effects of this segregation can most clearly be seen in the contrast of sicknesses such as malnutrition and childhood infections. In 1970, mortality rates for black and coloured populations were higher across all ages than for the white populations (Susser and Cherry, 1982).

Specifically regarding diabetes, Susser and Cherry (1982) reported that the age-adjusted rate of death from diabetes in 1970 was higher for the white population than the black and coloured population respectively (5, 2 and 2 per 1,000 deaths respectively). This may, however, be inaccurate for black populations, as the data on them only came from selected magisterial districts (Susser and Cherry, 1982). This was due to the data collection at the time being restricted to the more economically developed areas (Susser and Cherry, 1982). At the time, the black population living in urban areas had a higher proportion of diagnosed cases of diabetes than their rural counterparts (Susser and Cherry, 1982). Susser and Cherry (1982) suggested that may be due to a combination of economic and dietary changes.

In 1994, the first democratically elected government came into power in South Africa, abolishing the previous political structures of segregation, including those structures in healthcare (Lalloo *et al.*, 2004). There was a perception at that time that there would be better access to healthcare (Lalloo *et al.*, 2004). Despite these perceptions, Lalloo *et al.* (2004) later found that the actual access to healthcare was still dependent on socio-economic status. A further study by Harris *et al.* (2011) was performed to assess the best indicators for access to healthcare. Harris *et al.* (2011) attempted to determine the effectiveness of the regulatory measures put in place by the South African Government to reshape the healthcare system. The aim of these regulatory measures was to ensure access to healthcare was equal across all demographic groups (Harris *et al.*, 2011). Harris *et al.* (2011) reported that socio-economic status was still significant (specifically, the higher your socio-economic status was, the better access to healthcare was generally available to you). Additional risk groups identified as significant variables affecting access to healthcare include race, insurance status and urban-rural location (Harris *et al.*, 2011). Harris *et al.* (2011) reported that black people, poor, uninsured and rural respondents experienced the greatest barriers to the access of healthcare.

Coming from the physically segregated society of the apartheid era, the legacy of having the main healthcare centres near predominantly white areas is still present (Kapwata and Manda, 2018). Figure 3 shows that just under twenty years after the first democratically elected government came into power, there still is a large concentration of healthcare facilities in the historically white areas (Kapwata and Manda, 2018). This introduces barriers such as transport

costs as well as the time it takes to seek care (Burger and Christian, 2020). Kapwata and Manda (2018) found that some patients travelled over thirty-nine kilometres to the nearest medical facility.

The concentration of healthcare facilities is in the areas with high economic activity, which Kapwata and Manda (2018) argue leads to a severe disadvantage to the poor population in South Africa. This is similar to the conclusions of Harris *et al.* (2011). The quality of healthcare received is not necessarily informed by the concentration of healthcare facilities in the area. There could be many hospitals in an area, but, as a systematic review by Halm *et al.* (2002) concluded that the variances in outcome can be due to the volume and number of physicians present in a hospital, the hospital's case mix as well as the types of treatments performed.

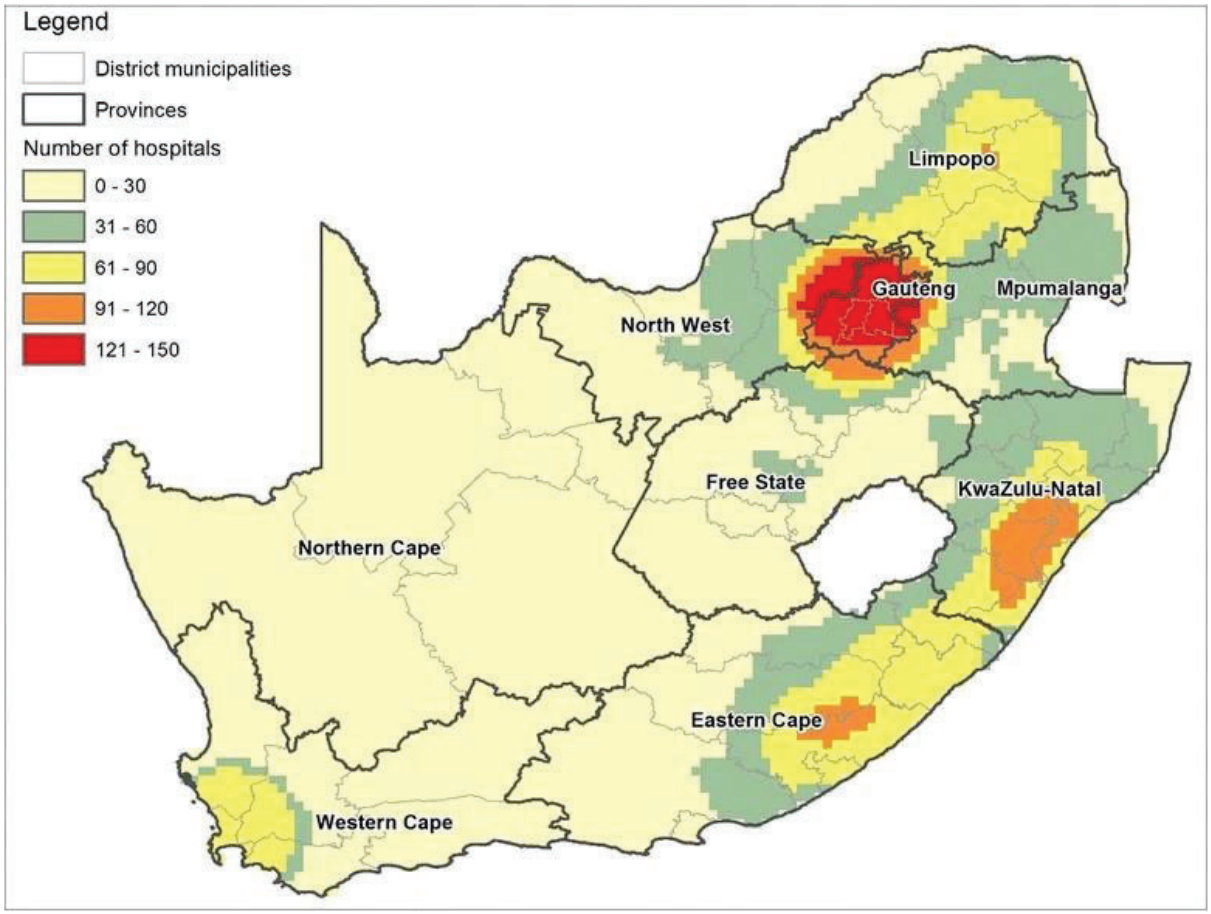


Figure 3: Density of health facilities in municipal districts of South Africa

Source: Kapwata and Manda (2018)

Despite the high concentration of hospitals in those higher economic areas, there are still far fewer healthcare facilities per person within those higher economic areas, as seen in Figure 4 (Kapwata and Manda, 2018).

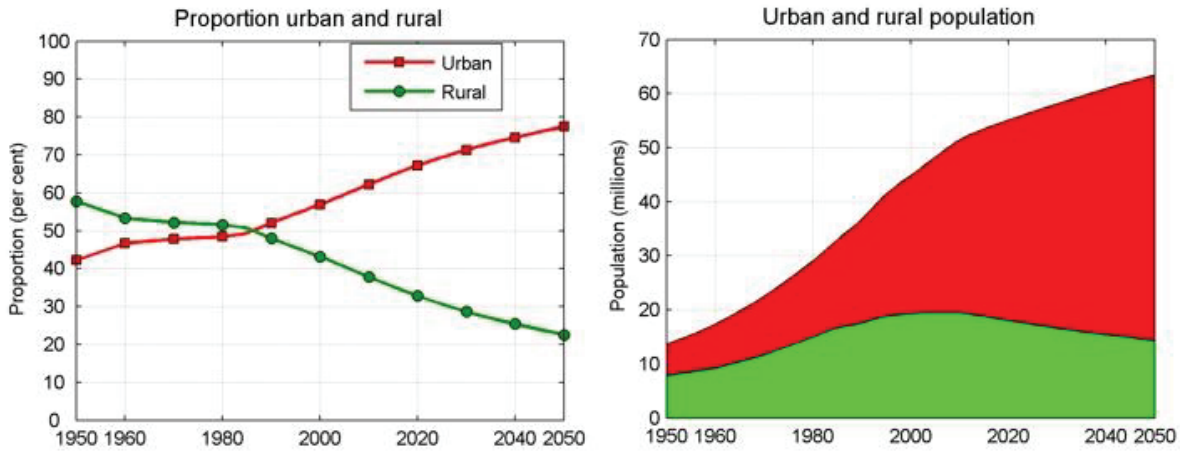


Figure 4: Proportion of population living in urban and rural areas

Source: Kapwata and Manda (2018)

Kapwata and Manda (2018) report that this is due to the prioritisation of the government to provide healthcare to the rural areas over the urban areas. However, this could be as a result of the growing numbers of people living within these higher economic areas (Kapwata and Manda, 2018).

Halm *et al.* (2002) report that the relationship between the number of people who are cared for in a hospital is not a simple association to better healthcare outcomes. Improving healthcare outcomes does not simply depend on building more hospitals but on other factors specific to each hospital, including, but not limited to, the number of physicians, the number of patients the hospital can treat, and the specific procedures and conditions which are performed (Halm *et al.*, 2002).

A study by Bakker *et al.* (2016) shows that there has been a large "migration shock" to the more densely populated areas in South Africa since 1994. Bakker *et al.* (2016) report that the more densely populated urban areas have seen a higher relative population increase than the less densely populated rural areas but the utility of those living in the rural areas versus those who move to the urban areas remains the same. The added possible income earned from migrating to urban areas is offset by the higher relative cost of living (Bakker *et al.*, 2016). Figure 5 shows that the increase in the absolute population living in the urban areas in South

Africa and the decrease in the rural area population which is expected to continue in the future (BusinessTech, 2014).

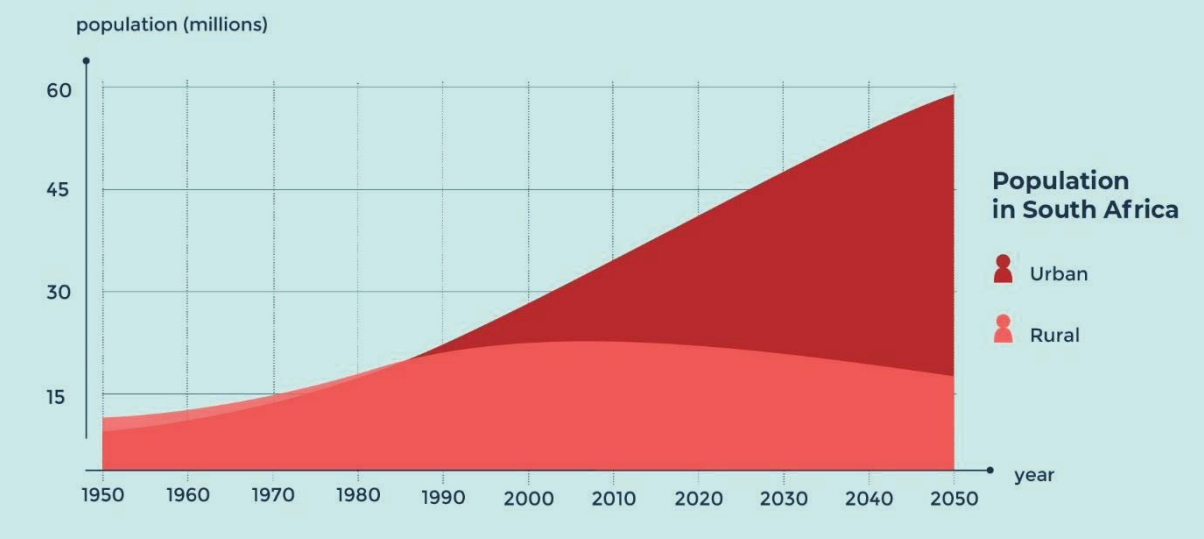


Figure 5: Urban and rural population

Source: Kapwata and Manda (2018)

Moving from a rural area to an urban area, whilst reducing the barrier of travel time to a hospital, does not necessarily reduce the barrier of cost of attaining care. The barrier of cost remains where other vulnerable subgroups are less likely to have access to healthcare that is effective (Burger and Christian, 2020). Besides living in a rural area, these vulnerable subgroups include black people, the less educated, the unemployed and the poor (Burger and Christian, 2020).

2.4.4 Potential for improvements in access to healthcare in South Africa

For many South Africans, unemployment is a significant barrier to improving their socio-economic status, and in so doing, obtaining better access to healthcare. According to Statistics South Africa, as at the fourth quarter of 2021, South Africa's unemployment rate was approximately 35.3 per cent (StatsSA, 2021b). This unemployment percentage is derived from a survey undertaken by Statistics South Africa (2021) and only includes the economically active individuals who have not worked for more than seven days before the survey was conducted, who had a desire to work and had taken active steps in the previous four weeks to find employment (StatsSA, 2021b). As of 1 June 2022, South Africa was ranked as having the

highest unemployment rate in the world, followed by Namibia with 33.4 per cent, and Nigeria with 33.3 per cent (Trading Economics, 2024).

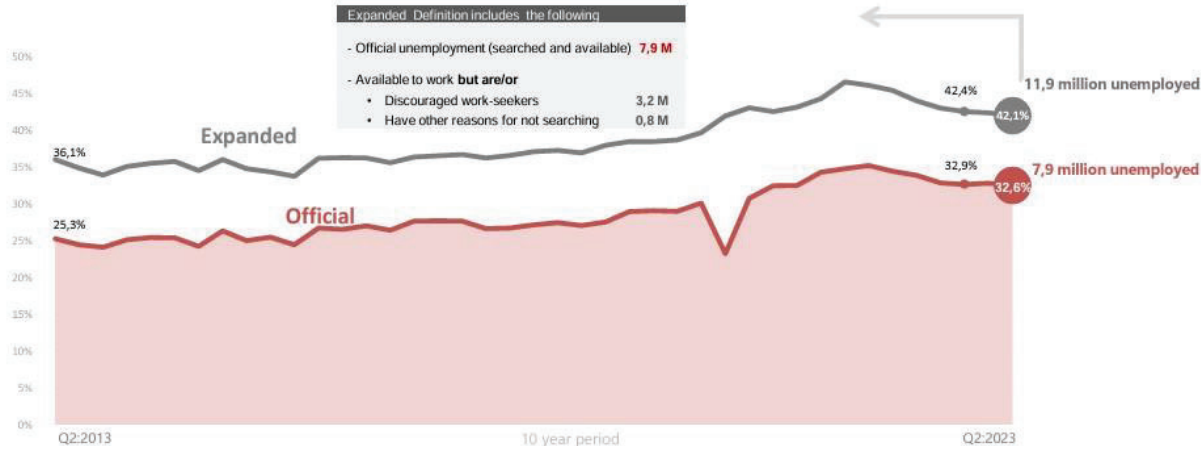


Figure 6: Official and expanded South African unemployment rates from 2013 until 2023

Source: StatsSA (2023b)

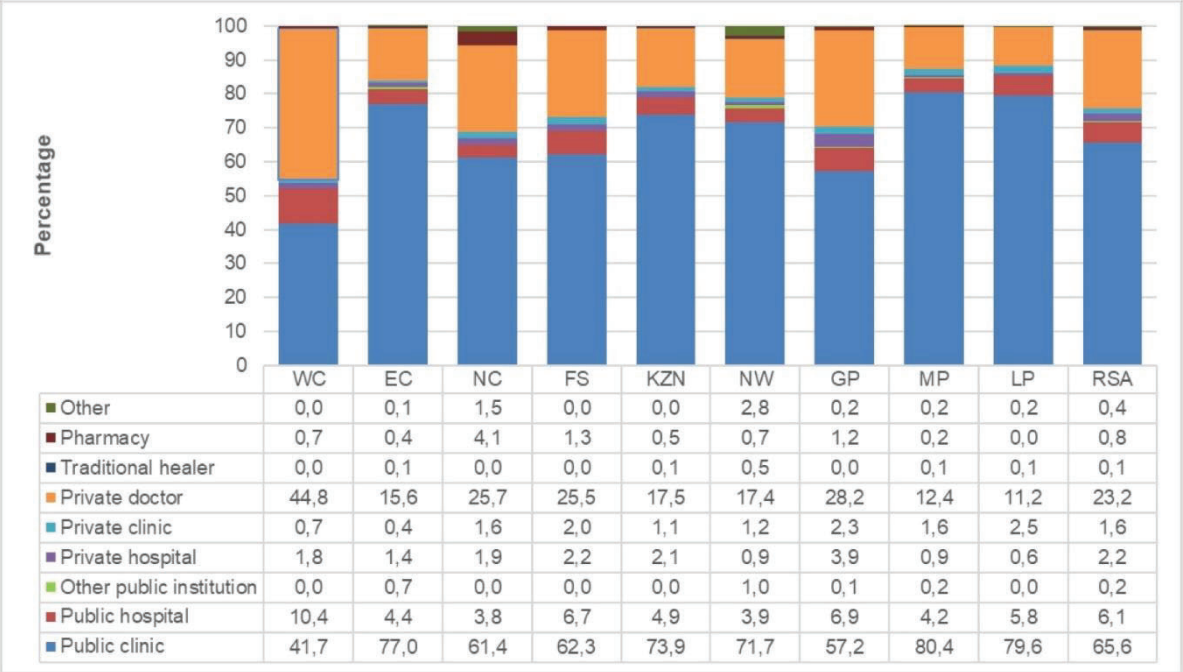
As seen in Figure 6, there has been a steady climb in unemployment, with a large discrepancy in the second quarter of 2020 due to the influences of the Coronavirus disease 2019 (COVID-19) pandemic impacting South Africa and the government calling a national "lockdown" on 26 March 2020 (SAnews.gov.za, 2020). This change saw 2.2 million more unemployed persons.

Over and above unemployment in South Africa, the tertiary education levels of its population are one of the lowest in the world (OECD, 2019b). Only 6 per cent of adults aged 25 to 34 complete tertiary education (International Standard Classification of Education levels 5-8 (OECD, 2019b). There has been an improvement in attaining secondary education, with 27 per cent of 25 to 34-year-olds not attaining upper secondary education 9 (International Standard Classification of Education levels 3-4) in 2008, compared to only 18 per cent in 2018.

However, more than half of those South Africans who attained upper secondary education were neither employed nor in education or training (OECD, 2019b). Areas with low education levels and high unemployment have been linked to a higher risk of type 2 diabetes (Müller *et al.*, 2015).

2.4.5 The current structure of healthcare in South Africa

The South African health system consists of both a private and a public sector. As per Figure 7, over 70 per cent of households will use public healthcare facilities as their first point of access to healthcare, with 27 per cent choosing to consult a private facility (StatsSA, 2021a).



	WC	EC	NC	FS	KZN	NW	GP	MP	LP	RSA
Other	0,0	0,1	1,5	0,0	0,0	2,8	0,2	0,2	0,2	0,4
Pharmacy	0,7	0,4	4,1	1,3	0,5	0,7	1,2	0,2	0,0	0,8
Traditional healer	0,0	0,1	0,0	0,0	0,1	0,5	0,0	0,1	0,1	0,1
Private doctor	44,8	15,6	25,7	25,5	17,5	17,4	28,2	12,4	11,2	23,2
Private clinic	0,7	0,4	1,6	2,0	1,1	1,2	2,3	1,6	2,5	1,6
Private hospital	1,8	1,4	1,9	2,2	2,1	0,9	3,9	0,9	0,6	2,2
Other public institution	0,0	0,7	0,0	0,0	0,0	1,0	0,1	0,2	0,0	0,2
Public hospital	10,4	4,4	3,8	6,7	4,9	3,9	6,9	4,2	5,8	6,1
Public clinic	41,7	77,0	61,4	62,3	73,9	71,7	57,2	80,4	79,6	65,6

Figure 7: South Africa's distribution of the first consultation of a healthcare facility

Source: StatsSA (2021a)

The public healthcare sector is funded largely from public sources, which includes taxation, and payments from private individuals (Ataguba and McIntyre, 2012). The South African Government provides funding for roughly 40 per cent of the total cost of public healthcare and charges patients based on their income and number of children (Expatica, 2024). Primary care is provided free of charge to South African citizens, as well as minimal charges for inpatient care in public hospitals (Govender *et al.*, 2013). However, concerns have been raised around the quality of care provided in those hospitals (McIntyre *et al.*, 2009). More specifically, concerns regarding the public hospitals, from the competence of staff working in public hospitals, poor doctor-patient interactions, the facilities not being properly cleaned, to waiting times to be treated and availability of the drugs (McIntyre *et al.*, 2009).

The private healthcare sector is largely funded through private sources such as private insurance and out-of-pocket payments for procedures not covered by insurance (Ataguba and McIntyre, 2012). If the patient does not possess medical aid, which was estimated in 2017 to

be 82 per cent of the population, they need to self-fund their own healthcare costs. (Ataguba and McIntyre, 2012). With private healthcare and hospitals, many individuals will take out medical insurance to cover the sizeable costs of treatment (Ataguba and McIntyre, 2012). These schemes are voluntary; however some employers do require their staff to have some form of medical cover (Ataguba and McIntyre, 2012). These medical schemes are non-profit entities and must cover all prescribed minimum benefits (PMBs), as outlined in the legislation of South Africa (Ataguba and McIntyre, 2012). The schemes typically reimburse providers on a fee-for-service basis. Subject to the rules of the scheme, limits, exclusions, and so on. members can often incur large co-payments for specific procedures (Ataguba and McIntyre, 2012).

Private healthcare costs are significantly higher than the costs of public healthcare (Goudge *et al.*, 2009). This cost of private care is often far higher than many South Africans can afford (Goudge *et al.*, 2009). That, coupled with concerns over the quality of care provided in public facilities (McIntyre *et al.*, 2009) and the costs of seeking care (transport costs, loss of income, and so on) (Goudge *et al.*, 2009), lead to a large number of patients choosing not to seek care for their ailments. Goudge *et al.* (2009) reported that around 38 per cent of participants who reported being sick chose not to seek help. Furthermore, the lower the socio-economic class the participant was in, the higher proportion of these cases of not seeking care were as a result of some barrier to access healthcare (Goudge *et al.*, 2009).

2.4.6 Other sources of healthcare in South Africa

Whilst there exists public and private healthcare, many South Africans will seek help from traditional healers, despite the costs of such treatment being comparable to the cost of seeking private healthcare (Goudge *et al.*, 2009). Goudge *et al.* (2009) found that roughly 7 per cent of participants in their Mpumalanga study chose to seek health advice from a traditional healer first, and then consult the public health system. The choice of using traditional sources of care is most commonly seen amongst the black population, with an estimated 72 per cent seeking care from African traditional medicine at an average rate of about five times a year (Mothibe and Sibanda, 2019).

A further problem experienced by the South African healthcare system is that whilst the public healthcare system is more affordable than the private healthcare system for most people, the public healthcare system's quality of care is perceived to not be up to the standard expected by the South African population (McIntyre *et al.*, 2009). The main concerns of this care are around the engagement that patients have with providers when seeking care as well as the availability of medication (McIntyre *et al.*, 2009). So, even when there are affordable

healthcare facilities available within a specific area, the quality of care provided to those people can vary greatly. This can have both a social impact of sowing seeds of distrust in the health system, which can lead persons to not seek help for their medical conditions as well as forcing people to travel further for the quality of care they expect.

It can be seen that clear lines are drawn between socioeconomic classes in considering access to quality care. Those who can afford a medical aid or medical insurance will have access to the care provided by private healthcare providers. In 2016, it was estimated that 16 per cent of the South African population are members of a medical scheme (StatsSA, 2021a). From Figures 8 and 9, it can be seen that there is a clear difference in the socio-economic distribution of this financial tool of medical schemes. Medical schemes are utilised by 77 per cent of white people: 24 per cent and 23,7 per cent residing in Gauteng and the Western Cape respectively (StatsSA, 2021a).

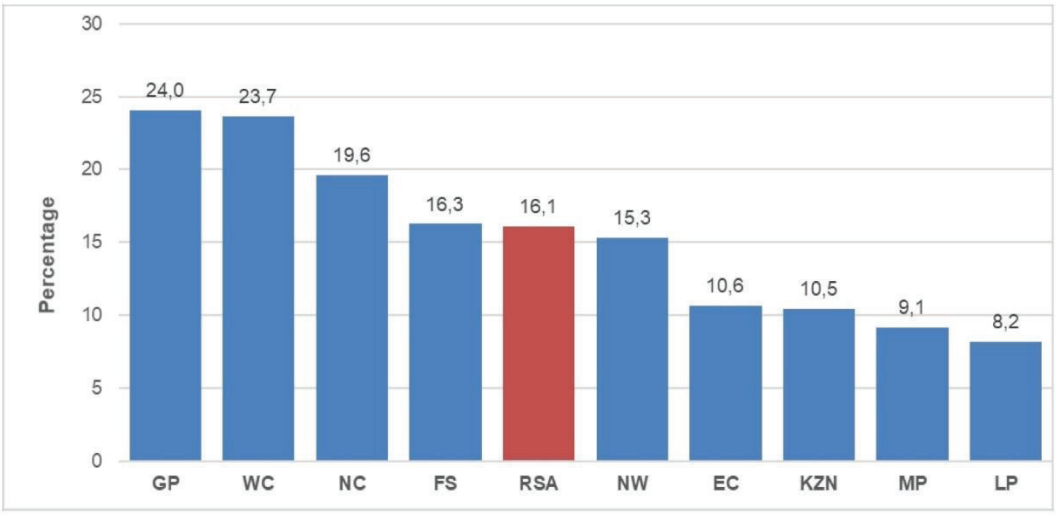


Figure 8: South Africa's proportion of the population who are members of a medical scheme in 2021 by province

Source: StatsSA (2021a)

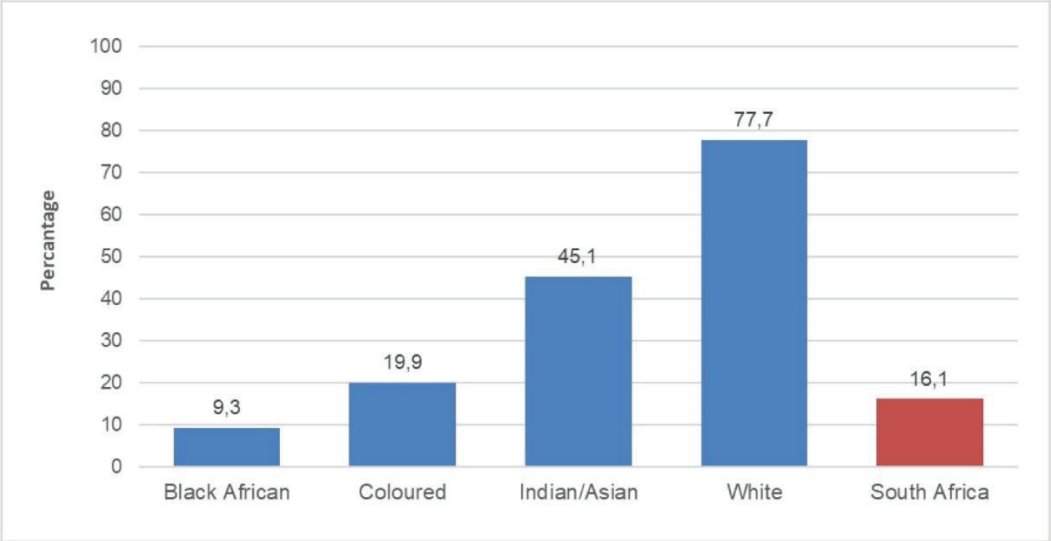


Figure 9: South Africa's proportion of the population who are members of a medical scheme in 2021 by population group

Source: StatsSA (2021b)

Those who cannot afford a medical aid or medical insurance often face difficult decisions around who to seek care from (faith healer or an indigenous healer, public or private healthcare providers), potentially over-paying for care by seeking more care from more than one provider and incurring high outpatient costs and travel expenses to find the care they need, all whilst those who do manage to seek care, often will not receive the same quality of care as those who go to private healthcare providers do.

2.4.7 The insurance industry in South Africa

This inequality of access to healthcare in South Africa has been an issue for many years and the government has tried a number of reforms in an attempt to bridge the socio-economic gap in access to quality healthcare. In 2005 the Government Employee Medical Scheme (GEMS) was introduced which provided medical scheme cover to a large number of government employees (Govender *et al.*, 2013). GEMS is currently the second largest medical aid insurer, with approximately 1.9 million beneficiaries, with Discovery Health being the largest medical aid scheme with roughly 2.8 million beneficiaries as at the end of 2020 (CMS, 2021).

An important principle used in medical schemes in South Africa is the principle of social solidarity. This principle requires all medical schemes to charge the same contribution to every member of the scheme, regardless of their rating factors such as age (Kirch, 2008). This is a key difference to private medical insurance that will charge a premium based on the individual's risk profile rather than just their income (also known as the principle of

equivalence) (Kirch, 2008). This introduces a barrier to entry in the private medical insurance market as the rating-factor-based premium may be higher than the potential member income can afford.

Furthermore, some medical schemes are restricted by the members who can join (for example GEMS is a restricted scheme only available to government employees) (FedHealth, 2020). Therefore, unless the potential member works for a particular employer or in a particular occupation or occupations, they will not have access to those medical insurance schemes. These factors play into the slow increase and subsequent stagnation of the number of beneficiaries who are members of medical schemes in South Africa (StatsSA, 2021a).

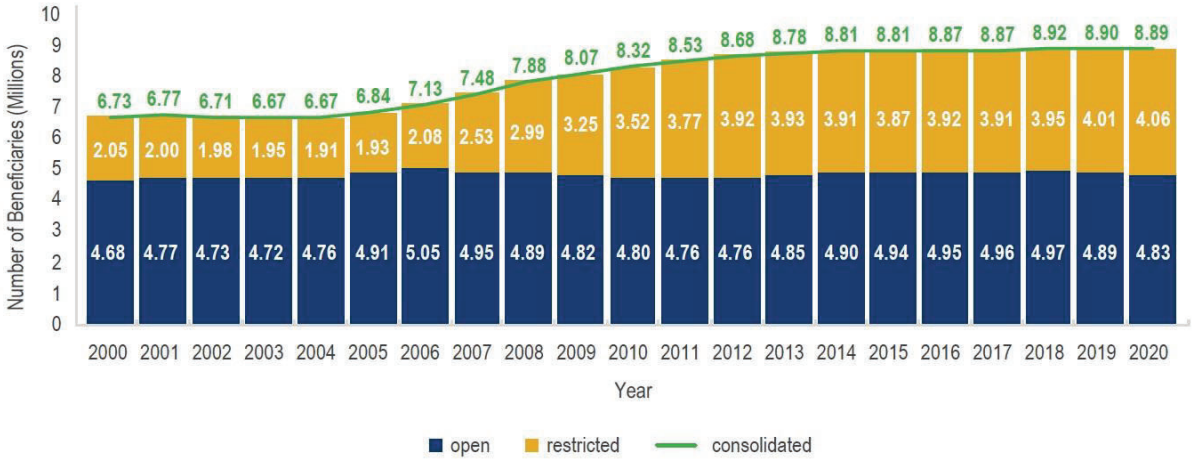


Figure 10: The number of "principal members" and dependents in South African medical schemes

Source: Kirch (2008)

In an effort to provide equal health insurance cover to all, in 1994 the African National Congress (ANC) government launched an investigation into a form of national health insurance (NHI), and in 2011 announced a 14-year plan to implement the NHI (Govender *et al.*, 2013). The NHI is intended as a nation-wide pool of funding, primarily funded by tax, which is used to provide universal access to healthcare for all South Africans, irrespective of their socio-economic status and state of wealth (South Africa, 2024). The NHI will attempt to provide quality healthcare as close to members' homes as possible, thereby reducing the transport and time costs that act as barriers for many citizens seeking healthcare (South Africa, 2024).

The government has implemented various regulations within the insurance industry to protect the interests of the members of medical schemes. One such way the government achieves this is through regulating the coverage that medical insurance contracts provide to

their members. This coverage included in medical aid schemes regarding diabetes-related costs sees the PMBs covered across all medical schemes. These PMBs are mandated under the Medical Schemes Act 131 of 1998 (South Africa, 1998) and includes diabetes as one of 25 chronic conditions for which specific minimum treatments and medications must be covered in full (CMS, 2024). The main aim of enacting this legislation was to avoid the old and sick being denied cover and care for specific ailments (CMS, 2024).

Medical schemes will aim to find ways to provide cost-effective access to the various ailments that their beneficiaries may currently, or in the future, suffer from. With diabetes specifically, there is the use of prescribed lists of medications for diabetes, also called formularies, and provider networks where medical schemes prescribe the health facilities that a patient may use without any excess payments and co-payments on non-prescribed medication (Perumal-Pillay and Suleman, 2020). Medical schemes typically cover for regular screening to identify at-risk individuals and ensure treatment commences sooner rather than later (Perumal-Pillay and Suleman, 2020).

Large schemes, such as Discovery, with their Vitality rewards programme (Discovery, 2024) or Momentum with their Multiply rewards programme (Momentum, 2024), also try to manage their risk by incentivising beneficiaries to lead healthier lifestyles through wellness programmes. These medical schemes will indirectly attempt to reduce the risk of obesity (and by extension, diabetes) by offering discounts and other rewards for the member providing evidence of sustained exercise in the form of cardiovascular ('cardio') exercise and gymnasium ('gym') sessions. These are usually measured by the effort an individual puts into the session (measured by heart rate) as well as the duration of such an exercise. They include regular annual testing, which helps to identify any potentially at-risk individuals and provide advice and care sooner than might otherwise be possible. The rewards systems are geared to improve the health of their members by offering discounts to healthy food options, memberships to gyms with exercise equipment, amongst other things.

2.4.8 Problems facing the statistics of the prevalence of type 2 diabetes in South Africa

A study conducted by Mutyambizi *et al.* (2019), took data from 2012, which estimated that 38 per cent of the people with diabetes go undiagnosed. Manne-Goehler *et al.* (2016) reported that the older and more educated the individual was, the lower the proportion of diabetes cases went undiagnosed.

These results seem to indicate that even though there is an increase in the number of cases of diabetes, the actual number of people with diabetes is unknown and could be growing at a

faster or slower rate than is being reported. The low diagnosis rates for diabetes in South Africa has been criticised by Mutyambizi *et al.* (2019) for not being recognised sooner as a problem. Mutyambizi *et al.* (2019) reason that because of the method in which studies would only analyse the self-reported cases, this led to a number of undiagnosed cases being ignored, thereby underestimating the diabetes rates in South Africa. Mutyambizi *et al.* (2019) further reported that there was an inequality in diagnosis rates, which favours the rich. This favouritism becomes more apparent once clinical data are included in a study (Mutyambizi *et al.*, 2019). This "rich bias" relates to the proportion of people with undiagnosed diabetes is lower amongst wealthier individuals when compared with less wealthy individuals (Mutyambizi *et al.*, 2019). This becomes easier to see once clinical rates are included in a particular study. Manne-Goehler *et al.* (2016) argue that one of the reasons for so many undiagnosed people in South Africa is access to healthcare. More specifically, insufficient access to the relevant tests and other medical facilities as well as the poor medical infrastructure existing in South Africa (Manne-Goehler *et al.* (2016).

Another possible reason could be the low screening rates within South Africa, as a study by Stokes *et al.* (2017) found that in 2012 around 45 per cent of diabetes cases were unscreened. A person is unscreened if they had had no prior diagnosis of diabetes and had never been for a blood glucose level test before (Stokes *et al.*, 2017). Stokes *et al.* (2017) reported that 15 per cent of respondents were screened but were undiagnosed. Furthermore, with almost half the cases of diabetes being unscreened, better and more targeted screening programmes could be used to reduce the rates of undiagnosed diabetes (Stokes *et al.*, 2017).

Analysing the reported cases of diabetes, it exposed yet another challenge facing the South African healthcare system: poor access to effective treatment for diabetes. Mutyambizi *et al.* (2019) reported that 61 per cent of the reported people with diabetes claimed to be on treatment for their diabetes, of which only 31 per cent of those people undergoing treatment experienced their conditions to be under control. Overall, estimates from Stokes *et al.* (2017) estimate that around 80 per cent of the diabetic population in South Africa have their treatment needs unmet, classified as no screening, screened but not diagnosed, or screened or diagnosed with ineffective treatment. This treatment is deemed to be ineffective, because it leaves the disease uncontrolled either through no treatment being offered or ineffective treatment being prescribed (Stokes *et al.*, 2017). The low diagnosis rates, coupled with the rate of ineffective treatment rates may contribute to the increase of death rates due to diabetes in South Africa in recent years, despite the regulations that have been passed and implemented (Stokes *et al.*, 2017).

2.4.9 Healthcare costs of providing care for diabetes in South Africa

To look deeper into the financial burden that diabetes has on the healthcare system, it is important to consider costs as either direct or indirect costs of providing care. The direct costs of treating type 2 diabetes in South Africa are broken down into treatment, management and any complications that could occur. Erzse *et al.* (2019) reported that for the 240,000 type 2 diabetes-diagnosed patients, the direct costs for the public healthcare sector came to R2.7 billion. The study further estimates that the cost of treating all the undiagnosed cases in the public health sector would increase the direct cost to R19.1 billion (Erzse *et al.*, 2019).

The highest contribution to these direct costs is the complications in health attributable to diabetes (Erzse *et al.*, 2019). These complications make up approximately 49 per cent of the total R2.7 billion (Erzse *et al.*, 2019). This is closely followed by 33 per cent of the costs pertaining to providing medication and 12 per cent for investigations and other diabetes-related tests, usually relating to diagnosis of diabetes (Erzse *et al.*, 2019). When breaking down the cost of complications, Erzse *et al.* (2019) found that the most expensive complications were retinopathy and renal disease (also known as end-stage renal disease or kidney failure) (American Kidney Fund, 2022). These procedures can cost the public healthcare system approximately R500,000 for a single patient to attend two haemodialysis sessions per week for a year (Erzse *et al.*, 2019). Haemodialysis is a procedure which involves siphoning blood out of the body into a machine, where it is filtered and returned back to the body (NHS, 2021).

This excludes all the indirect costs of diabetes which include, but are not limited to, the burden on alternative care providers such as family members caring for the diabetes patients and the days of work missed, potential for reduced productivity and other work-related burdens such as premature mortality (ADA, 2018). The value of these costs on the South African economy is not currently known, but a study by ADA (2018) estimated that the USA's indirect cost of diabetes exceeded R1.2 trillion in 2017. With the scale of costs involved for diabetes, preventative measures are critical to being able to reduce this expenditure.

2.4.10 Effects of prevention strategies on healthcare costs

The early control of the diabetes risk factors has been shown to have an impact on healthcare costs. The initial proven method of reducing the risk of type 2 diabetes in a population is preventative care. In the USA, simulations were performed in 1998 which showed that whilst the incremental costs of screening were fairly high, they were well exceeded by the postponement of complications later in life (CDC Diabetes Cost-Effectiveness Study Group,

1998). The study concluded by suggesting that early prevention and treatment, especially amongst the younger and African American demographic groups, was a key cost savings mechanism on the healthcare system as well as contributing significantly to the quality-adjusted life-year (QALY) of the population (CDC Diabetes Cost-Effectiveness Study Group, 1998).

Icks *et al.* (2005) reviewed the available literature and concluded that there simply was not enough data to make a certain conclusion around whether or not early screening for diabetes was cost-effective as a form of government spending. However, whilst the HbA1c and oral glucose tolerance tests (OGTT) were more expensive than a single test of OGTT or fasting glucose testing, these tests did show to be cost-effective because of having a better success rate of identifying diabetes cases (Icks *et al.*, 2005). These early screening campaigns require a non-inconsequential investment from the government, but the cost is recovered within a few years through the reduction in public healthcare costs (Sortsø *et al.*, 2018).

A systematic literature review was conducted by Li *et al.* (2010) on a number of different interventions for achieving type 2 diabetes goals within the USA. Li *et al.* (2010) further reviewed the advice given by the American Diabetes Association (ADA) on preventing and treating diabetes. Amongst other findings, there was a considerable cost savings (specifically $6,900 per QALY) for annual screening for type 2 diabetic retinopathy (Li *et al.*, 2010). Targeted screening for undiagnosed type 2 diabetes was also found to be significantly cost-effective for a country to implement with a range of $46,800 per QALY to $70,500 per QALY depending on the age of the patient (Li *et al.*, 2010).

Whilst targeted screening proved cost-effective, universal screening was shown to be another cost-ineffective method of reducing the impact of diabetes, especially when considering the USA population over the age of 45 years of age (Li *et al.*, 2010). This suggests that the better a country can identify where to provide screening for type 2 diabetes (as well as other diabetic conditions), the more cost-effective that screening can be. This can enable the government to discern more easily what the most efficient allocation of healthcare system resources is in order to reduce the overall cost of diabetes in the country.

Other highly cost-effective measures identified were: statin therapy; the identification and assistance for patients to stop smoking; and offering assistance to change the lifestyle of a patient with diabetes in a manner that reduces the risk of developing complications for diabetes. (Li *et al.*, 2010). This intensive change to a patient's lifestyle has been more recently shown in South Africa and is a principle central to large South African insurers' offerings for their rewards programme (Lambert *et al.*, 2009). According to Lambert *et al.* (2009), a case study

looking into Discovery Health's rewards programme, showed that incentivising policyholders to exercise more and eat healthier saw the average claims between the different levels of engagement differ by R 5,025.

Li *et al.* (2010) concluded that the ability to target a pre-specified risky sub-group of the population for screening purposes is more cost-effective than universal screening. Therefore, if the South African Government could leverage existing information to better inform the identification of these risky sub-groups, this could result in further savings in cost of screening. A study by Schmittdiel *et al.* (2018) has taken one of the first steps along this line of thought. With a study into retrospectively analysing past prediabetes cases and linking them to a national survey in the USA, Schmittdiel *et al.* (2018) were able to conclude that it is possible to predict the development of diabetes using a national survey.

2.5 Diabetes risk score models

There are many different risk score models that can be used to identify individuals who are most at risk of having type 2 diabetes (Noble *et al.*, 2011). Some risk scores, such as one proposed by Lindström and Tuomilehto (2003), are more questionnaire-focused. Specifically, Lindström and Tuomilehto (2003) use risk factors such as age, body mass index (BMI), waist circumference, consumption of fruit, history of high blood pressure, doing more than four hours of exercise a week and history of using blood pressure medication to calculate the risk score. Other risk score models, such as the Framington Risk Score, focus on other risk factors of total cholesterol, high density lipoprotein cholesterol, systolic blood pressure which require more physical tests (Jahangiry *et al*., 2017).

The Indian Diabetes Risk Score was developed as a screening tool to assess the potential undiagnosed case prevalence of type 2 diabetes (Dudeja *et al.*, 2017). This score uses known risk factors to establish a score between 0 and 100 (Dudeja *et al.*, 2017). These risk factors are age, waist circumference, family history and exercise frequency per week, as outlined in Table 1 (Dudeja *et al.*, 2017).

Table 1: IDRS components

Indian Diabetes Risk Score Components	Criteria	Risk Score
Age Band (years)	*<35*	0
	35-49	20
	>49	30
Waist Circumference (cm)		
Females	*<80*	0
	80-89	10
	>89	20
Males	*<90*	0
	90-99	10
	>99	20
Exercise Frequency	*Exercise regularly during the week and strenuous physical work*	0
	Exercise regularly during the week or strenuous physical work	20
	Little to no exercise during the week and sedentary work	30
Family History	*Neither parent has diabetes*	0
	One parent has diabetes	10
	Both parents have diabetes	20
Maximum Score		**100**

The Indian Diabetes Risk Score (IDRS) has been developed based on an analysis of risk factors and their association to diabetes (Dudeja *et al*., 2017). A score of 60 or above has been tested and shown to be effective at predicting the risk of type 2 Diabetes with 95 per cent previously undiagnosed cases of diabetes being identified (Dudeja *et al.*, 2017). Similar results were found when assessing women in India using fasting blood glucose levels to test for diabetes (Bala *et al.*, 2019).

The major advantage of using the IDRS over other risk scores and universal testing techniques is its low cost and simplicity of application (Joshi, 2005). Often, in third world countries such as India, a large proportion of the population is undiagnosed and universal screening or other risks scores such as the Framington Risk Score require a large investment of time and money to perform (Joshi, 2005). The IDRS uses two modifiable and two non-modifiable risk factors to measure its score, allowing for the tracking of an element of a population's lifestyle adjustments (Joshi, 2005).

The IDRS is considered to be an effective tool at a community level (especially amongst urban populations) with a powerful low-cost ability to identify high-risk individuals, and therefore areas, of type 2 diabetes (Joshi, 2005). This allows for a targeted screening intervention of early diagnosis and treatment (thereby, in many cases, avoiding large diabetes complications) (Joshi, 2005).

Section 3. Data and Methodology

3.1 Model background

Two models have been created to model the undiagnosed cases of diabetes in South Africa. The first is a generalised linear model (GLM). Its purpose is to investigate the relationship of various diabetes risk factors and the self-reported cases of diabetes and to develop a predictive model of self-reported cases from the GHS data. The main risk factors (as identified in Section 2.3) that are available in the GHS questionnaire are analysed for their predictive power in modelling these self-reported cases of diabetes. The GLM is then constructed and used to predict these self-reported cases based on the methodology of Schmittdiel *et al.* (2018) as outlined in Section 2.4.10. The model results are used to infer the relationships between each of the chosen explanatory variables and a diagnosed case of diabetes. An example of such a relationship is the correlation between being diagnosed with diabetes and increasing age. The key question of this model is: which of the variables contained in the GHS are most useful in predicting a self-reported case of diabetes? This assessment consisted of comparing the findings from the GLM to those reported by Dudeja *et al.* (2017) as outlined in Section 2.5.

The second model simulates the IDRS of each respondent of the GHS. The purpose of this model is to make an initial estimate of the undiagnosed cases of diabetes across South Africa. Due to the required information not being available in the GHS data, the model relies on modelled assumptions for: *waist circumference*, *family history of diabetes* and *exercise frequency*. The key use of this model is to simulate the IDRS and calibrate it to the South African population to calculate the estimated number of undiagnosed cases of diabetes. The calibration was conducted by calculating a risk score threshold which represents the 2016 South African Demographic Health Survey (SADHS) undiagnosed cases of diabetes. The IDRS used to determine a case of diabetes is also calibrated to the South African population using the available population testing information presented in the SADHS of 2016 (DHS, 2016). Finally, accuracy of the model is assessed based on how well it identified the reported cases of diabetes in the 2021 GHS dataset.

3.2 Data background

Both these models rely on the annual survey responses from surveys conducted between 2008 until 2021. The General Household Survey (GHS) is performed by StatsSA in an attempt to track the progress of development in South Africa (StatsSA, 2021a). The aim is to collect, on a per household level, information on the individuals within the households' living conditions

in order to estimate the living conditions of the broader South African population (StatsSA, 2021a). The survey's target population are the private households and residents in workers' hostels across each of South Africa's nine provinces (StatsSA, 2021a). The survey does not include student accommodation, hospitals, old-age homes, hospitals, prisons or military barracks (StatsSA, 2021a). The survey has been conducted annually since 2002, and actively measures the effectiveness of the various government programmes embarked on within South Africa. As a secondary advantage, the GHS can be used to track changes in the day-to-day lifestyle of citizens (StatsSA, 2021a). The survey's questions aim to investigate the country's overall health and social development, the living conditions and the level of education in South Africa, and the development of agriculture, amongst other things (StatsSA, 2021a).

The IDRS simulation model relies on the results of the SADHS to calibrate the risk score to the demographics of the South African population. The 2016 SADHS is a survey undertaken between June and November 2016, and is administered by Stats SA and the South African Medical Research Council (SAMRC) at the request of the National Department of Health (NDoH) (DHS, 2016). The 2016 SADHS aimed to update the basic demographic and health metrics of South Africa from the previous survey in 1998. A key difference from the GHS performed in 2016 is that it included additional questions as well as performed biometric testing for various biomarkers of the respondent. This testing included blood pressure measurement and HbA1c testing. This testing is useful as it allows for better measurement of undiagnosed cases of diabetes at a South African population level. This identification allows for the calibration of the IDRS to the South African population. The remainder of the biomarkers, such as waist circumference, can be used to inform the assumptions underlying the IDRS simulations.

3.3 Limitations of the data

The response variable in the GLM is the number of self-reported cases of diabetes. It excludes all undiagnosed cases of diabetes. As seen in Section 2.4.2, this may be a large proportion of the cases of diabetes in South Africa. There is also no clinical check to verify the validity of the respondent's declaration that they are pre-diabetic or diabetic. This introduces the potential for errors to be included, as people may falsely report that they have or have not been diagnosed with diabetes.

The results of the 2016 SADHS include HbA1c testing, but do not conclude whether the respondent has diabetes or not. As discussed in Section 2.2.6, the HbA1c test in isolation is

only an indication of potential diabetes. A true diagnosis of diabetes can only be provided by a medical practitioner.

3.4 Modelling self-reported cases of diabetes - GLM approach

3.4.1 GLM Data definition

The data from the General Household Survey of 2018 are used to calibrate the initial GLM. The 2019 GHS dataset is used to test the accuracy of the calibration. The model is calibrated and tested to before the onset of the COVID-19 pandemic to ensure that the impact of the pandemic is not present in the model calibration or analysis. The 2018 GHS calibration dataset consists of 185 variables with 71,137 entries of individual responses to the various questions contained in the survey. Each response is pre-coded as a binary variable of either a one representing "yes" or a two representing a "no" response to the question of whether they have been diagnosed with diabetes or not. The data are filtered for the variables that are most applicable for the study, based on which variables would best identify the respondent (for example, metropolitan code, sex, age). Other variables of the questionnaire are removed as there is currently no scientific correlation between these variables and diabetes found in the literature. The final variables chosen for the study are displayed in Table 2.

Table 2: Filtered GHS 2018 variables most applicable for the GLM

Variable	Options	Coded as
Reported case of diabetes	Yes, no or unspecified	1-3
Province of the household	Western Cape Eastern Cape Northern Cape Free State KwaZulu-Natal North West Gauteng Mpumalanga Limpopo	1-9
Primary sampling unit (PSU) number	Unique area number defined by StatsSA (2021a)	Numeric
Metro code of where the household resides	WC – Non-metro WC – City of Cape Town	1-17

	EC – Non-metro EC – Buffalo City EC – Nelson Mandela Bay NC – Non-metro FS – Non-metro FS – Mangaung KZN – Non-metro KZN – eThekwini NW – Non-metro GP – Non-metro GP – Ekurhuleni GP – City of Johannesburg GP - City of Tshwane MP – Non-metro LP – Non-metro	
Sex of the occupant	male or female	1 or 2
Age of occupant	Age between 0 and 108 with age less than 1 is mapped to 0	Numeric
Population group	Black, coloured, Indian / Asian or white	1-5
Marital status	Legally married Living together like husband and wife/partners Divorced Separated, but still legally married Widowed Single, but have lived together with someone as husband/wife before Single and have never been married/never lived together as husband/wife before Unspecified	1-8
Education level	Differing levels of education	0 to 31
Medical aid status	Yes No Do not know Unspecified	1-4
Individual's annual salary	Valid range R10-R999,999 with "Do not know" and "Unspecified" = R0	Numeric

Whether the individual is on a social grant or not	Yes or No	1 or 2
Whether the individual has been diagnosed with depression	Yes, no or unspecified	1-3
Whether the individual has been diagnosed with HIV/AIDS	Yes, no or unspecified	1-3
Whether the individual has been diagnosed with hypertension or high blood pressure	Yes, no or unspecified	1-3
Whether the individual has been diagnosed with any mental health problems	Yes, no or unspecified	1-3
Whether the individual is pregnant or not	Yes No Do not know Not applicable Unspecified	1-5

The response variable chosen is the self-reported diagnosis of diabetes, with all the other variables listed above are used as explanatory variables. The purpose of this variable is to see how well the explanatory variables are able to predict self-reported cases of diabetes.

The response variable is recorded as one of three response options that the respondent can select. As per Table 2, these are yes, no or unspecified. All entries that were unspecified entries (145 in total) were removed to exclude some erroneous entries. The self-reported diabetes variable includes both type 1 and type 2 diabetes as well as any other kinds of diabetes. The survey data do not allow for a more granular split between types of diabetes.

The location-based variables such as province, PSU number and metro code are categorical variables (that is, a limited set of options). These are used to glean insights as to where high-risk areas for diabetes are, as well as to provide a proxy for the lifestyle factors identified by Akhuemonkhan and Lazo (2017), for example, smoking, obesity and low physical activity. The “Province” variable captured all nine provinces of South Africa. The “Metro code” variable captured seventeen options which are displayed in Table 2. Not all provinces

have areas that meet the criteria for being considered a metro. The PSU number is a unique number given to a particular region where the household is situated. It represents area codes defined by StatsSA (2021a) in order to more accurately identify the location of each household. This was treated as a categorical variable with 3,242 unique response options.

Other identifying characteristics of particular respondents are included in the form of categorical variables, namely sex, age, population group, marital status and education level. Sex, age and population group are chosen to be consistent with known risk factors for diabetes (Dawson *et al.*, 2022; Fletcher *et al.*, 2002). Education level is used as a proxy for lifestyle risk factors such as diet and blood pressure (Akhuemonkhan and Lazo, 2017). This is consistent with an approach by Hill-Briggs *et al*. (2020), who used education level as a proxy for health literacy. These are all categorical variables with the following number of response options: two for sex, four for population group, eight for marital status and 32 for education status. Age is considered as a categorical variable with values ranging between 0 and 108 (with age 0 referring to anyone aged less than one year old).

Indicators of the respondent's financial position are represented by categorical variables, namely: "medical aid status" and "recipient of social grant(s)", and a continuous variable: "salary". Medical aid status has four response options and whether the respondent is on a social grant at the time of answering or not has two response options. The financial position of the individual is used as a proxy for the lifestyle factors identified by Akhuemonkhan and Lazo (2017) to be associated with diabetes risk. The salary variable in the survey included entries of 888,888,888 for "Do not know" and 999,999,999 for "Unspecified", which are changed to 0 so as not to skew the results of the regression analyses. This resulted in 50,950 responses being changed to 0 (or 72% of the responses).

Answers relating to the respondent's current health is also included in the analyses to explore the links between mental health and pregnancy with diabetes as was found to exist by Lean and Pajonk (2003) and Kerner and Brückel (2014), respectively. Other comorbidities are also included, for example, hypertension given their reported links to diabetes (Orasanu and Plutzky, 2009). HIV/AIDS is included for exploratory purposes due to potential links which are reported by Kubjane (2023). Indicators of the respondent's health and other co-morbidities are included as categorical variables with three response options each, namely "Yes", "No" and "Unspecified". The health conditions included diagnoses of depression, HIV/AIDS, hypertension and any mental health conditions. Pregnancy is also included with categorical variable options of: "Yes", "No", "Do not know" and "Not applicable".

3.4.2 Exploratory data analysis on the 2018 GHS data

In the 2018 General Household Survey data, the number of diagnosed cases of diabetes are highest amongst the age bracket of 60 to 65 with a very low number of cases under the age of 20. This is shown in Figure 11. The number of diagnosed cases is a misleading number given that there are fewer respondents at older ages. Prevalence rate is therefore a better indicator of the cases of diabetes in the population. Figure 11 highlights the strong correlation of diabetes incidence and increasing age. This aligns with age being one of the main risk factors for diabetes, as identified in Section 2.3.

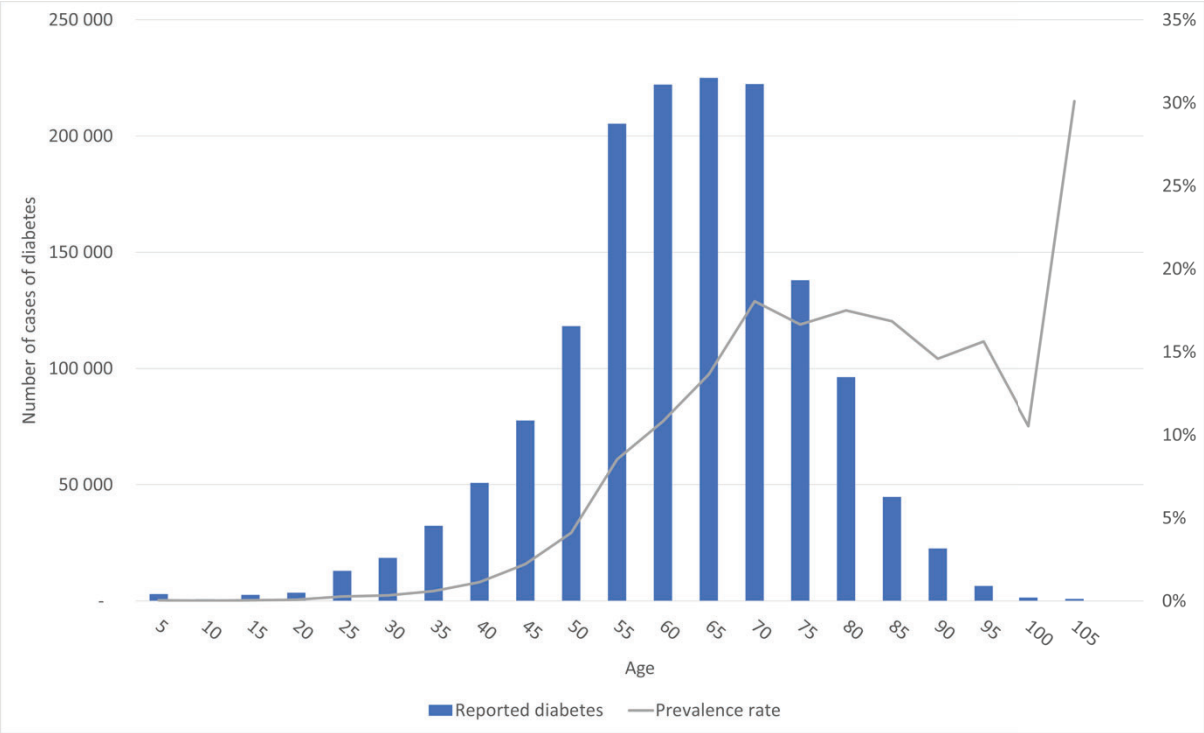


Figure 11: Number of cases of diabetes and diabetes prevalence rate per five-year age bands in the General Household Survey 2018

The prevalence of diabetes in Figure 11 appears to taper off after age 70 until it spikes again in the age groups of 100+. This is simply random variation as a result of the lower number of respondents in these age groups relative to the younger age groups.

The proportion of reported diabetes cases to survey respondents is highest in the Western Cape, at 3.9 per cent, followed closely by the Eastern Cape, at 3.3 per cent, and the Northern Cape, also at 3.3 per cent, as illustrated in Figure 12.

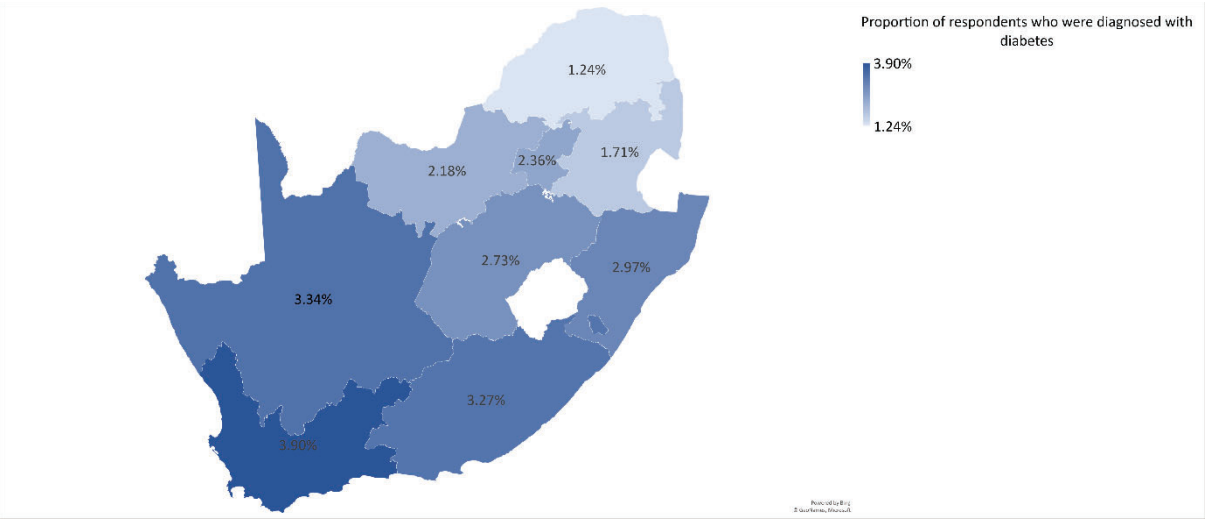


Figure 12: Proportion of respondents who declared that they had been diagnosed with diabetes in the General Household Survey, 2018

3.4.3 Reported cases of diabetes per metro area

The analysis of diabetes cases based on metro area status showed that roughly 41 per cent of all respondents are from metro areas and approximately 47 per cent of all reported diagnosed diabetes cases are from metro areas. Figure 13 shows that the main metro areas that have the highest proportion of reported diabetes cases are those in the Western Cape, KwaZulu-Natal and the Eastern Cape. On average, the proportion of reported cases of diabetes is higher in metro areas than in non-metro areas. Roughly three per cent of respondents reported being diagnosed with diabetes compared to the two per cent of respondents in non-metro areas.

A contributing factor, as outlined in Section 2.4.8, for the difference in diagnosis rate between metro and non-metro areas, could be due to differences in the access to testing. Non-metro areas do have a lower density of hospitals and clinics per person, as shown in Figure 3, in Section 2.4.3, which could be one of the contributing factors to the lower reported diagnosis rates. Furthermore, approximately 59 per cent of respondents reside in a non-metro area. There are key differences in lifestyles between metro and non-metro areas, namely a higher concentration of manual labour jobs which are performed in non-metro areas. As discussed in Section 2.3, the risk of developing diabetes significantly reduces when a person's occupation is exercise-intensive compared with the more office-centred occupations. This could be a further reason for the lower reported diabetes cases in non-metro areas.

3.4.4 Reported cases of diabetes per demographic group

Taking a closer look at the demographic profile of the respondents, the respondent population is approximately 64 per cent female and 36 per cent male. The respondent population is also approximately 81 per cent black, 9 per cent coloured, 8 per cent white and 2 per cent Indian / Asian. Figure 13 shows that the black population makes up a smaller proportion of the population in metro areas than in non-metro areas. In metro areas, 76 per cent of the population are black. This is 12 per cent lower when compared to the 88 per cent of the population are black in non-metro areas. Overall, 36 per cent of the black respondents reside in a metro area.

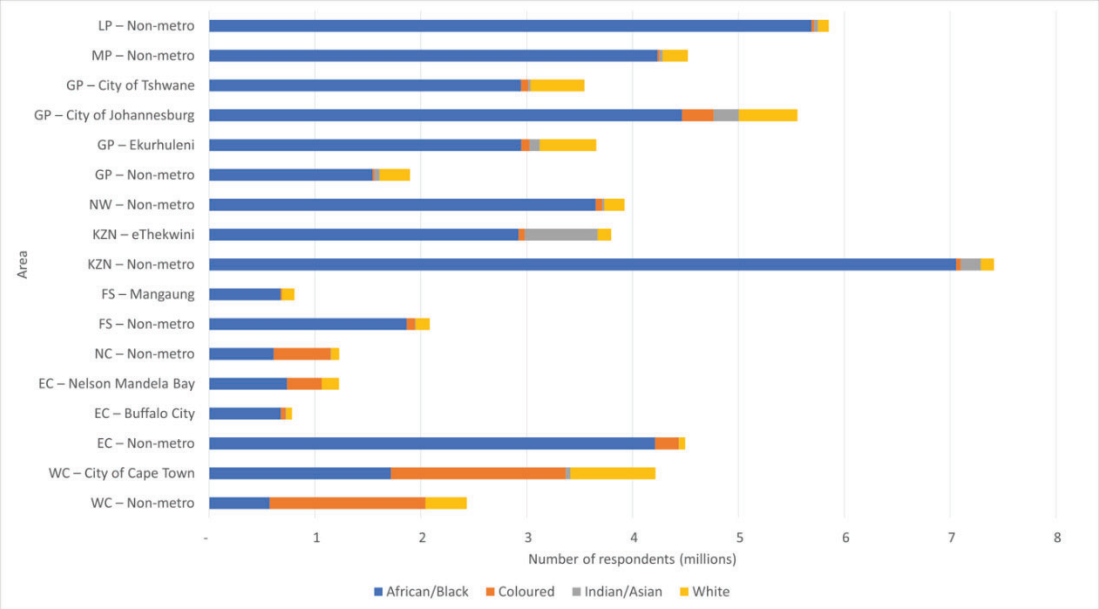


Figure 13: Number of respondents in each area in the General Household Survey, 2018

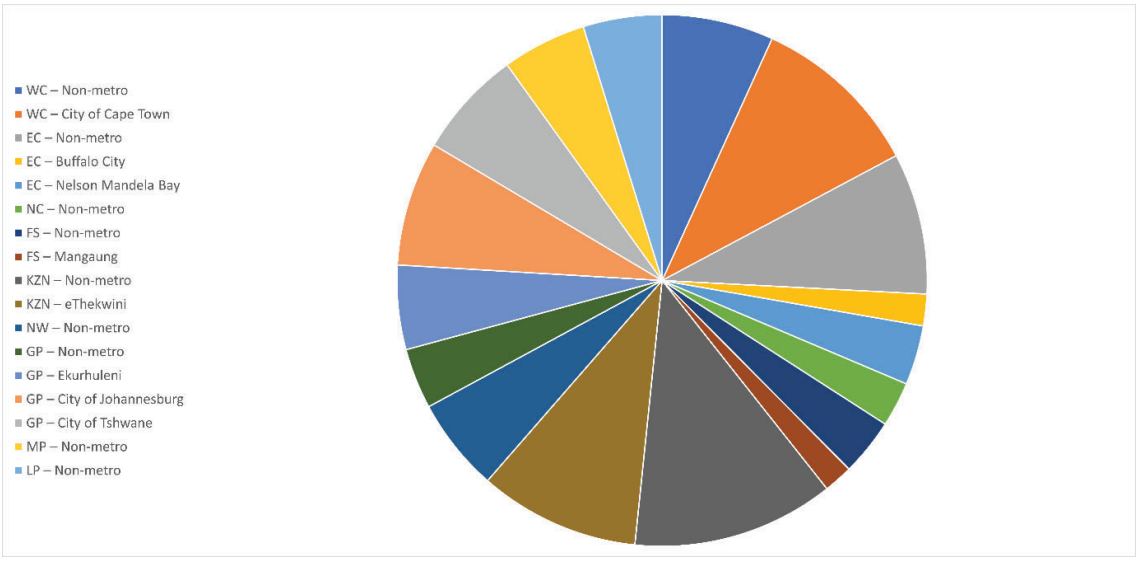


Figure 14: Proportion of diagnosed cases of diabetes per area in the General Household Survey, 2018

Table 3 shows that of the distribution of the reported cases of diabetes within the population groups and sexes, Indian / Asian female respondents have the highest prevalence of diabetes. Approximately 8.34 per cent of the Indian / Asian female respondent population report that they are diabetic. This is followed by 5.33 per cent of Indian / Asian males who are the second highest group, with white males who are the third highest group with 4.86 per cent, as shown by Table 3.

Table 3: Proportion of respondents per population group who reported having diabetes

Population group	Male	Female
Black	1,54%	2,62%
Coloured	3,89%	5,45%
Indian / Asian	5,33%	8,34%
White	4,86%	4,11%

Black respondents make up the highest proportion of survey respondents, as per Figure 13. However, this is the demographic group with the lowest prevalence of reported diabetes cases as shown in Table 3. There is no scientific evidence that the prevalence of diabetes in a population differs along racial lines and hence differences need to be attributed to other factors, for example, lifestyle (Akhuemonkhan and Lazo, 2017). As seen in Figure 13, more black survey respondents reside in non-metro areas as compared to other demographic groups. Non-metro areas, as discussed by Cois and Day (2015), have key lifestyle and diet differences when compared to metro areas. Specifically, a higher proportion of the population in non-metro areas perform manual labour jobs, resulting in more physical activity being engaged in on a daily basis, which correlates with the black survey respondents having the lowest prevalence of self-reported cases of diabetes.

3.4.5 Reported cases of other NCDs per demographic group

Table 4: Proportion of respondents with reported disease

Population group	Pregnancy	Mental illness	Hypertension	HIV	Depression	Severe disability
Black	2,5%	0,4%	6,4%	3,3%	0,2%	2,8%
Male	N/A	0,5%	3,9%	2,4%	0,1%	2,7%
Female	5,0%	0,2%	8,8%	4,0%	0,2%	2,8%
Coloured	2,5%	0,6%	12,1%	0,6%	0,3%	2,7%
Male	N/A	0,7%	8,2%	0,5%	0,2%	2,5%
Female	4,8%	0,5%	15,7%	0,6%	0,4%	2,8%
Indian / Asian	1,4%	0,4%	10,0%	0,1%	0,4%	1,6%
Male	N/A	0,5%	8,2%	0,2%	0,6%	1,7%
Female	2,8%	0,2%	11,8%	0,1%	0,3%	1,6%
White	1,0%	0,7%	14,5%	0,3%	0,7%	2,9%
Male	N/A	0,5%	13,8%	0,3%	0,6%	2,8%
Female	2,0%	0,9%	15,1%	0,2%	0,9%	3,0%
Grand Total	2,4%	0,4%	7,6%	2,7%	0,2%	2,7%

The white survey respondents have higher levels of self-reported cases of co-morbidity, as shown in Table 4. Roughly 14.5 per cent of white respondents are diagnosed with hypertension and roughly three per cent with some form of severe disability. A severe disability is defined as the survey respondent having “A lot of difficulty” or is “Unable to do” for one or more categories (StatsSA, 2021a). The categories include sight, hearing, exercise - either walking a kilometre or climbing a flight of stairs, concentration and remembering, the ability to take care of themselves, and communicating in their most spoken language (StatsSA, 2021a).

Amongst the black survey respondents, diagnosed cases of hypertension are higher amongst women than amongst men (hypertension is an established risk factor for diabetes, as highlighted in Section 2.3. In Table 4, roughly nine per cent of black female survey respondents reported having been diagnosed with a case of hypertension, whilst the corresponding prevalence of hypertension in black male survey respondents was only four per cent. In the white demographic group, the hypertension prevalence rates between male and female survey respondents are approximately equal. The vast majority of HIV/AIDS cases are also reported by black survey respondents - approximately three per cent, compared to less than one per cent reported by survey respondents in all other demographic groups. Similar to hypertension, cases are more prevalent amongst women than men, with approximately four per cent of all black female survey respondents reporting that they have HIV/AIDS, with the black male survey respondents reporting roughly half that rate. Reported rates for mental illnesses and depression

are low, with the highest proportion of cases occurring in the white demographic group. Less than one per cent of all white respondents reported a diagnosis for mental illness or depression, however, given the self-reported nature of the data, these figures may be misleading.

Overall, 7.6 per cent of all survey respondents have been diagnosed with hypertension and roughly 2.7 per cent of survey respondents reported a severe disability. These results need to be interpreted with caution, given the self-reported nature of the GHS. In order for the results of the survey to be reflective of the true underlying NCD rates, survey respondents need access to testing, which is beyond the scope of the GHS. As outlined in Section 2.4.4, there are clear improvements to be made in education and access to testing. There are differences in access to testing between the various demographic groups, provinces, regions and income brackets. Therefore, these NCD prevalence rates, shown in Table 4, are likely understating the true prevalence of these NCDs. The degree of understatement will vary between different population groups, different areas, different sexes, and is driven by a myriad of factors and their complex interactions.

3.4.6 Lifestyle features per demographic group

It is important to note that with these statistics, the focus is on the access to diabetes tests and the ability to pay for diabetes treatment and not a comparison or different demographic groups and their average incomes. These statistics do not include those who are unemployed; no adjustments are made for social grants, age, type of job performed and education level; and should not be used outside the aims of determining any potential hindrance to seeking healthcare in South Africa.

The overall average monthly salary of employed survey respondents is just under R11,000 per month with respondents in metro areas earning an average of roughly R13,000 per month. In the non-metro areas, the average salary of those employed is just under R,9000 per month. This is approximately 30 per cent lower than the average salary of those employed in metro areas. Considering the average salary of respondents who are employed in metro areas, females reported earning around 91 per cent of what males reported to earn. In non-metro areas, this difference is more striking, with females only earning around 72 per cent of what males earn. In a racial breakdown of average salaries, metro areas see the largest difference between the race groups with black survey respondents reporting that they earn, on average, around 46 per cent of what white survey respondents earn.

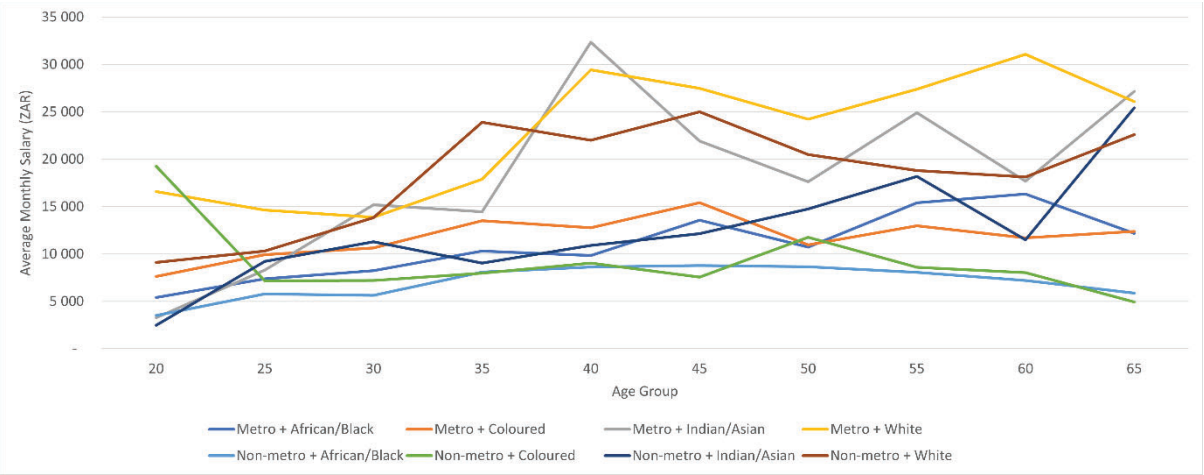


Figure 15: Average monthly salary per different demographic group

After adjusting for two outliers, there is a fairly consistent trend across all age ranges that white and Indian / Asian survey respondents report that they earn more, on average, per month than what their black or coloured counterparts report earning as shown in Figure 15.

In line with the results from the salary statistics, roughly 35 per cent of the survey respondents reported receiving some form of social grant. The black and coloured survey respondents reported the highest proportion of households receiving grants, with roughly 37 per cent and 32 per cent, respectively. Around 8 per cent of white survey respondents reported currently receiving some form of social grant. Similar trends are observed when analysing whether the survey respondents have medical scheme cover or other private health insurance cover. Overall, only 14 per cent of survey respondents are covered by such a scheme, with a large discrepancy of roughly 71 per cent of the white respondents who are part of at least one of these schemes compared with only 9 per cent of the black respondents.

On average, the white respondents of the survey reported a much higher level of education that was obtained than the other respondents of the survey. Eighty per cent of white survey respondents have passed Grade 10 and 70% have passed matric. This is shown in Figure 16. This is higher than for any other racial group. Compared to black and coloured survey respondents, roughly 40 per cent have passed Grade 10, and fewer than 30% have passed matric. Black and coloured racial groups also have the highest proportions of survey respondents who have had no schooling (including having no pre-schooling) - around 15 per cent. Higher education shows the largest discrepancy between the survey respondents - around 30 per cent of white respondents have completed a degree or diploma, compared to around 5 per cent of black and coloured survey respondents reporting having completed a degree or diploma.

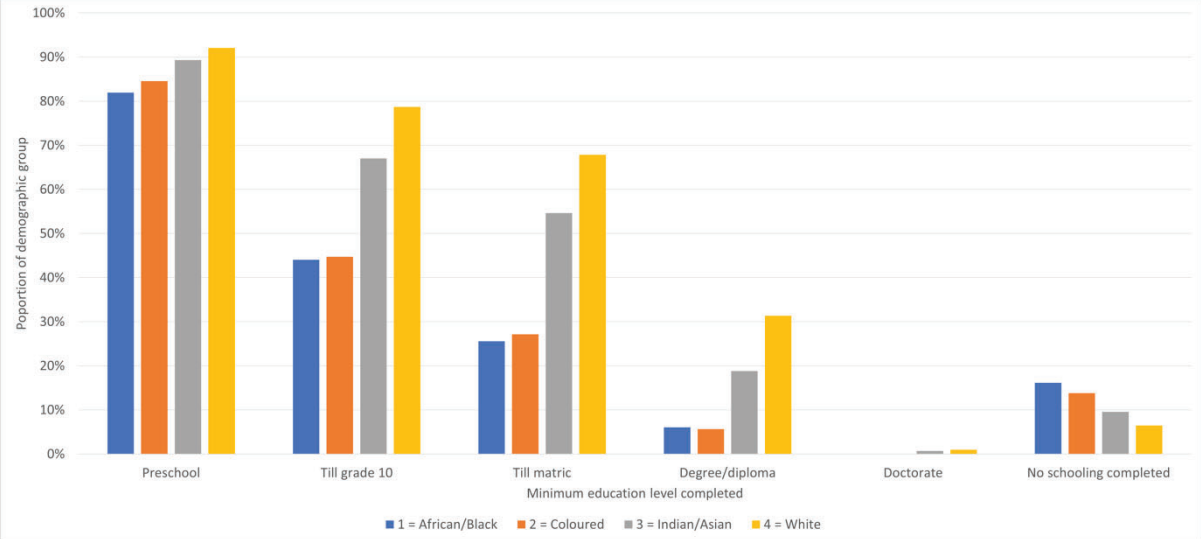


Figure 16: Proportion of racial group having completed education to the following education levels

Overall, around 55 per cent of respondents have achieved a pass for Grade 10 and that proportion drops to around 35 per cent when considering the proportion of respondents who have passed matric. It is observed that around 15 per cent of respondents had not completed any form of schooling, which is almost double the proportion of respondents who had completed a degree or diploma - around 8 per cent of survey respondents.

3.4.7 GLM definition of the model used

As noted in Section 3.1, a GLM is used to see how well explanatory variables from the GHS data can predict a self-reported case of diabetes. The model is constructed based on the model proposed by Schmittdiel *et al.* (2018) which is a log-odds regression model. This included a binomial generalised linear model (GLM) to be used in conjunction with a logit link function (Schmittdiel *et al.*, 2018). This GLM approach produced reasonable results (that is, achieved a goodness of fit "concordance" statistic of greater than 0.7). Hence it is used as the foundation of this exploratory model. Initially, the explanatory variables are assessed using correlations to determine the presence of any multi-collinearity. The model is constructed in RStudio 2023.12.0+369 "Ocean Storm" using R version 4.3.2 (2023-10-31 ucrt).

3.4.8 Generalised linear modelling process performed

The process of starting with a GLM containing every explanatory variable was outlined in Section 3.4.1. The GLM is first fitted with all the explanatory variables and an iterative algorithm called "stepAIC" was applied to remove the variables that did not have a significant

explanatory power of the response variable. This algorithm reduced the number of explanatory variables to identify the model with the lowest Akaike information criterion (AIC).

A second version of this model is performed with a GLM containing every explanatory variable as well as all possible interaction terms of the explanatory variables. The interaction terms are created based on a pair of explanatory variables which are multiplied together, thereby capturing any unique combinations. The various explanatory variables and interaction terms are removed iteratively until a GLM with the lowest deviance is found. Deviance is chosen as a measure over AIC because it contrasts the added accuracy of including more terms with the increase in the number of explainable variables. This allows for the resultant model to have as few variables as is necessary whilst still achieving a sufficient level of accuracy from the model.

After creating the models both with and without interaction terms, a final model is chosen based on a balance of AIC and simplicity. Whilst the finalised model including interaction terms has a lower AIC, additional interaction variables did not significantly improve the deviance. This resulted in the model without the interaction terms to be favoured because of the better simplicity and the added complexity of the interaction terms not resulting in a sufficient enough improvement in accuracy. The final GLM contained the following explanatory variables:

- PSU number to identify unique households
- Metro code of where the household resides
- Sex of the occupant (male or female)
- Age of occupant
- Population group
- Education level
- Medical aid status
- Individual's annual salary
- Whether the individual is on a social grant or not
- Whether the individual has been diagnosed with HIV/AIDS
- Whether the individual has been diagnosed with hypertension or high blood pressure
- Whether the individual is pregnant or not

The residuals of the final chosen model are assessed for any outliers or significant points. This is performed by plotting a normal Q-Q plot, a plot of the residuals against their predicted

values and the square root of the standardised Pearson residuals to the predicted values. The normal Q-Q plot is displayed in Figure 17.

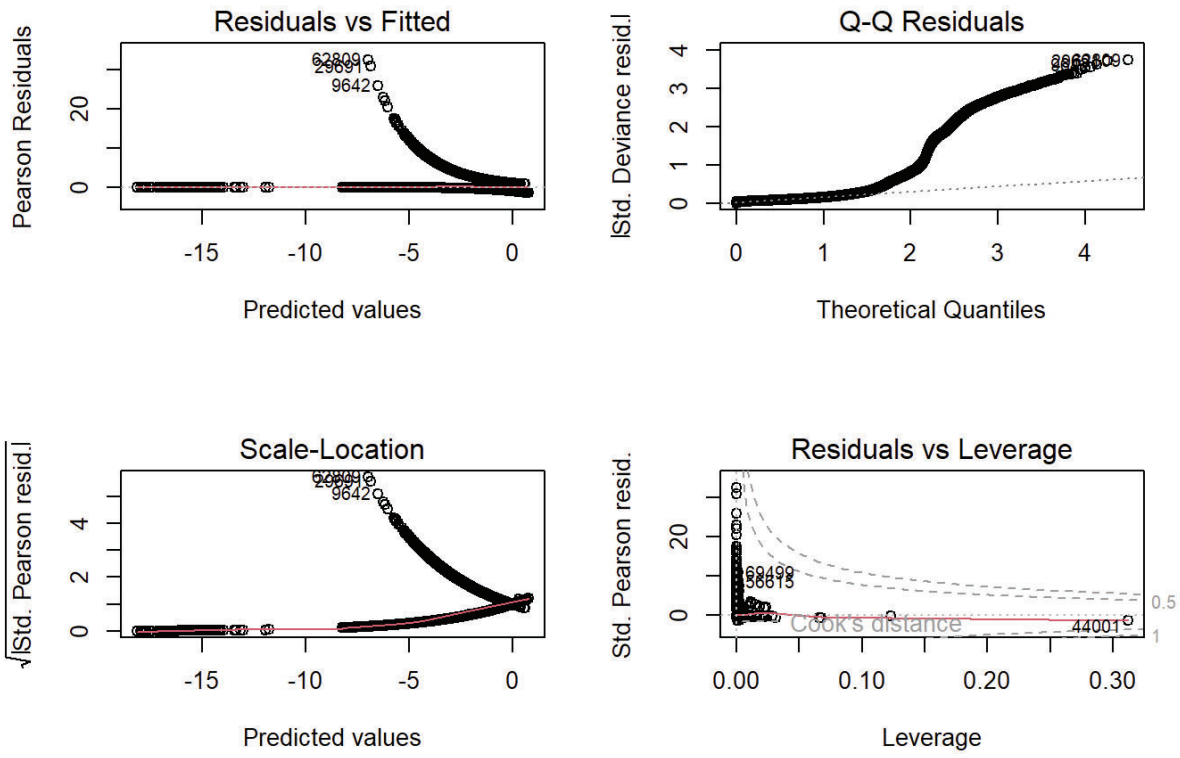


Figure 17: Outlier analysis of the final GLM

The Pearson residuals calculated in Figure 17 were calculated as:

$$r_i = \frac{o_i - e_i}{\sqrt{e_i}}$$

where r_i is the raw Pearson residual for the *i*th observation

o_i is the observed value of the *i*th observation

e_i is the expected value of the *i*th observation

Cook's distance, calculated in Figure 17, was then assessed to determine whether any of the outliers had any significant statistical influence on the model's results. The Cook's distance was calculated as:

$$D_i = \frac{\sum_{j=1}^{n}\left(\hat{y}_j - \hat{y}_{j(i)}\right)^2}{p \times MSE}$$

where D_i is the Cook's distance of the *i*th observation

$\hat{y}_j$ is the *j*th fitted response

$\hat{y}_{j(i)}$ is the *j*th fitted response, excluding the *i*th observation

p is the number of coefficients in the regression model

MSE is the mean squared error

From Figure 17, the Pearson residuals plotted against the predicted values show several outliers above the horizontal red line. These residuals all appear less than the -10 predicted value. The presence of outliers continues in the Scale-Location plot in Figure 17 with data points occurring above the red line. The red line in the Scale-Location plot in Figure 17 does not remain straight and increases as the predicted value increases. Most of the residuals are closely aligned along the respective red line in Figure 17. Therefore, many of the residuals do appear to follow the GLM assumption of the residuals following a linear trend.

The assumption of the residuals following a standard normal distribution is displayed in the Q-Q plot of residuals in Figure 17. The residuals deviate from the dotted black line after quartile 2. Most of the residuals follow the normal distribution. The outliers identified in Figure 17 are shown to have little leverage in the residuals vs leverage graph in Figure 17. The outliers all have very low leverage with the residuals displaying a high leverage all sticking close to the red line. Therefore, the residuals identified in Figure 17 do not significantly impact the ability of the model to predict self-reported diabetes cases.

3.4.9 GLM accuracy testing

The chosen GLM, which is calibrated on the 2018 GHS, is run on the 2019 GHS results and an actual versus expected analysis was performed. This is used to test the effective predictability of the GLM year-on-year. The model resulted in correctly predicting 97 per cent of the reported diabetes cases. A prediction accuracy per metro code as well as the final predicted proportion of the population reporting diabetes is outlined in Table 5. The prediction accuracy is measured by calculating the proportion of predicted outcomes (either a self-reported case of diabetes or not) that are the same as the actual respondent's answer.

Table 5: Prediction accuracy of the finalised GLM to reported cases of diabetes

Metro Area	Correct identification of diabetes case	False positive cases of diabetes being predicted
WC – Non-metro	93%	0.42%
WC – City of Cape Town	95%	0.24%
EC – Non-metro	96%	0.35%
EC – Buffalo City	95%	0.25%
EC – Nelson Mandela Bay	95%	0.45%
NC – Non-metro	97%	0.10%
FS – Non-metro	97%	0.14%
FS – Mangaung	96%	0%
KZN – Non-metro	97%	0.09%
KZN – eThekwini	96%	0.08%
NW – Non-metro	97%	0.09%
GP – Non-metro	96%	0.05%
GP – Ekurhuleni	98%	0.07%
GP – City of	98%	0%
GP - City of Tshwane	97%	0.06%
MP – Non-metro	98%	0.10%
LP – Non-metro	98%	0.01%

3.5 Indian Diabetes Risk Score model

3.5.1 IDRS data definition

The General Household Survey of 2021's data are used for the IDRS model. This dataset is chosen as it was the latest available GHS data. GHS dataset consists of 90 variables with 35,265 individuals' responses to the questions asked in the survey. Each response is pre-coded as a categorical variable. The data are filtered for the variables that were most applicable for the study, based on which variables would best identify the respondent (for example, metro code, sex, age). Other questions of the questionnaire are removed as there is currently no identified scientific correlation with diabetes that has been identified from the literature review. The final explanatory variables chosen for the study were:

- Reported case of diabetes
- Province of the household
- PSU number to identify unique households
- Metro code of where the household resides
- Sex of the occupant (male or female)
- Age of occupant
- Population group
- Unique number used to identify the respondent
- Person weight calculated as an exposure measure for the General Household Survey

All variables included in the above list are selected to provide unique insights into the simulations, both as a sense check and to be used for the results. From the GLM, sex, age, population group, and PSU are used, as they are identified to be significant in explaining the reported diabetes prevalence rate once the simulations are completed. Person weight is included to be used as an exposure measure. The reported diabetes prevalence rate is included as a sense check to see how close the simulated results related to the reported diabetes rate. Province and metro code were included to provide more broad geographic results instead of just using the PSU.

This same dataset variables and data cleaning approach is performed on all the General Household Survey datasets from 2013 to 2020 to produce a scenario estimation of the diabetes rate over time.

3.5.2 IDRS definition of the model used

The IDRS model is simulated to assess the potential undiagnosed diabetes cases. The IDRS is used as a proxy for the undiagnosed cases. The model is constructed in RStudio 2023.12.0+369 "Ocean Storm" using R version 4.3.2 (2023-10-31 ucrt). The General Household Survey between 2008 and 2021 does not contain any questions asking the respondents waist circumference, exercise frequency or family history of diabetes. As these are necessary to calculate a diabetes risk score, these variables are simulated with assumptions made for this missing information. A definition of a risk score threshold is set to represent that a person likely had a high risk of diabetes, to align with the findings from the literature review (Dudeja *et al.*, 2017).

3.5.3 Waist circumference assumption in South Africa

The mean waist circumference statistics are sourced from the 1998 South African National Demographic Health survey and is broken down by sex and age group (Puoane *et al.*, 2002). These age groups include the ages 15 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and those 65 or older. The Demographic Health Survey from 2016 provided a similar breakdown of waist circumference (DHS, 2016). A linear trend is assumed, per sex and age group, over time between the two survey dates. In the absence of more up-to-date data being available, the waist circumference after 2016 is assumed to be equal to the sizes reported in the Demographic Health Survey from 2016. The final mean waist circumference per sex and age group is outlined in Tables 6 and 7.

Table 6: Waist Circumference (cm) over time assumption – Female

Female						
Year	**Ages 15-24**	**Ages 25-34**	**Ages 35-44**	**Ages 45-54**	**Ages 55-64**	**Ages 65+**
1998	74.7	83.3	89.1	92.1	93.6	91.2
2016	75.8	85.6	90.5	93.1	93.9	93.9

Table 7: Waist Circumference (cm) over time assumption - Male

Male						
Year	**Ages 15-24**	**Ages 25-34**	**Ages 35-44**	**Ages 45-54**	**Ages 55-64**	**Ages 65+**
1998	73.4	80.7	85.5	89.4	89	89.6
2016	73.8	80.2	84.7	88	91.9	93

In Tables 6 and 7, the rows are the actual waist circumference means found in the South African Demographic Health Surveys (DHS, 1998; DHS, 2016). In 1998, a national sample of 13,089 adults was chosen to participate in this survey (DHS, 1998). This increased to 15,292 with the 2016 national sample information (DHS, 2016).

This final population waist circumference distribution is assumed to follow an independent normal distribution as a simplifying assumption with a mean outlined in Tables 6 and 7 and a standard deviation of four centimetres. The standard deviation is assumed from the deviation in waist sizes between age groups. A waist circumference per respondent is then simulated using this normal distribution to be used in the Indian Diabetes Risk Score calculation.

3.5.4 Family history of diabetes assumption in South Africa

Both the 1998 and the 2016 South African Demographic Health Surveys (SADHS) give the proportion of the sample group who reported having diabetes (DHS, 1998; DHS, 2016). Furthermore, they both report the proportion of the sample group who, when tested, had sufficiently high blood glucose levels to be classified as having diabetes (DHS, 1998; DHS, 2016). However, only the 1998 SADHS included questions around how many parents have been diagnosed with diabetes (DHS, 1998). The DHS (1998) reported that 12 per cent of men and 13 per cent of women had one or more parents who reported having a family history of diabetes.

With the absence of this information in the 2016 SADHS, the change in this proportion of the population was required to set the assumption for the number of biological parents who have been diagnosed with diabetes. Additionally, the modelling approach for these IDRS simulations required the number of parents with a family history of diabetes rather than whether the population reported diabetes within the family.

Three simplifying assumptions are made to model the family history of diabetes in South Africa. The first assumption is to assume that there is a linear trend between the proportions of diabetes per subsection of sex and age group in Tables 8 and 9. Secondly, it is assumed that this linear trend was set to increase at the same rate as the actual diabetes rate over time. These two assumptions result in the probability of each parent having diabetes will increase in line with the actual increase in diabetes cases. The final assumption is that the probability of each parent having diabetes is equal to the proportion people who reported having a history of diabetes in their family.

Table 8: Diabetes Family History Assumption – Females

Female						
Year	**Ages 15-24**	**Ages 25-34**	**Ages 35-44**	**Ages 45-54**	**Ages 55-64**	**Ages 65+**
1998	9%	13%	16%	17%	12%	12%

Table 9: Diabetes Family History Assumption – Males

Male						
Year	**Ages 15-24**	**Ages 25-34**	**Ages 35-44**	**Ages 45-54**	**Ages 55-64**	**Ages 65+**
1998	9%	13%	16%	17%	12%	12%

In Tables 8 and 9, the row is the actual proportion of the population group with a family history of diabetes that was reported in the SADHS of 1998.

A further simplifying assumption is made that the proportion reported in Tables 8 and 9 is representative of only one parent having diabetes rather than, as it is currently reported, either or both parents having diabetes. This is a necessary assumption to calculate whether a person has one, or both parents having diabetes and applying the appropriate IDRS. The assumption is required because the IDRS differs based on the number of parents with a family history of diabetes (Dudeja *et al.*, 2017). For example, one parent with a family history of diabetes scores 10 points, whilst in the case of both parents having a family history of diabetes, a score of 20 points is awarded.

To calculate the simulated IDRS for family history for each person, two independent and identically distributed standard random numbers per respondent are calculated to simulate each of the respondent's parents. Based on respondent's age group and sex, the corresponding proportion from Tables 8 and 9 will be used to calculate the simulated number of parents with a family history of diabetes that the respondent has.

For example, from the 2006 survey, if the respondent is female and aged 37, if one of the random numbers is below the assumption in Table 8 (which is 16 per cent) then one of that

respondent's parents is assumed to have diabetes. If both random numbers are below the assumed 17 per cent, then is it assumed that both the respondent's parents have diabetes.

3.5.5 Exercise frequency assumption in South Africa

The SADHSs contain no information on the South African population's exercise frequency, so other population studies are used to infer the assumption. Therefore, the exercise frequency assumption is set using results extracted from a 2012 South African population-based survey (Mlangeni *et al.*, 2018). This survey interviewed 26,339 nationally representative South Africans investigating different lifestyles of the population and how they relate to HIV/AIDS (Mlangeni *et al.*, 2018). One of the questions related to exercise frequency, which was used to inform the assumption for the IDRS model (Mlangeni *et al.*, 2018).

The exercise proportions were broken down into three groups: not physically active; moderately physically active; and vigorously active (Mlangeni *et al*., 2018). A simplifying assumption that half of the population that is "moderately physically active" were "mildly active" and the remaining half are moderately active was made. This aligned the reported population proportions to each IDRS category, as outlined in Section 2.5.

Table 10: Exercise frequency assumption – Females

Female		
No exercise	**Mild/regular exercise**	**Strenuous exercise**
0.67	0.15	0.18

Table 11: Exercise frequency assumption - Males

Male		
No exercise	**Mild/regular exercise**	**Strenuous exercise**
0.47	0.14	0.39

The exercise frequency in the sub-Saharan Africa region remains relatively constant over time at a population level (Guthold *et al.*, 2018). As such, a further simplifying assumption is made for the IDRS simulation that the exercise proportions remained constant over time from 2008 to 2021. The final proportions of the population are outlined in Tables 10 and 11.

To calculate the IDRS for exercise frequency, an independent random number between 0 and 1 is generated per respondent. The value of the random number will inform the assumption of how active that respondent is on a weekly basis. If the random number is below the strenuous exercise proportion, then a score of 0 is given. If the random number is greater than the strenuous exercise proportion but less than the sum of the strenuous exercise proportion and the regular exercise proportion, then a score of 10 is given. This pattern

continues for the mild exercise and no exercise proportions with scores of 10 and 20 given respectively.

For example, if the individual is female and an independent random number is generated as 0.2. Since the random number is greater than the assumed “Exercise strenuous” assumption of 0.178 from Table 10. Then, a check is performed if this number is less than the sum of “Exercise strenuous” and “Exercise regular”, which results in a value of 0.2535. Since the random number is less than the resultant value of 0.2535, the respondent is assumed to exercise regularly and a IDRS of 10 is assumed.

3.5.6 IDRS modelling process

The risk score is calculated as per the IDRS requirements outlined in Section 2.5. That is, the risk scores for the age, waist circumference, family history and exercise frequency are added to derive a final diabetes risk score. A Monte Carlo simulation approach is performed consisting of 10,000 simulations. The average risk score per respondent across the 10,000 simulations is then calculated. This is performed to allow for the generation of random numbers to stabilise the estimate of risk scores and significantly reduce the effect of outlier estimates. For the simulation performed over time from 2013 to 2021, again with 10,000 simulations per year.

This simulation process is repeated, whilst varying the assumptions outlined in the previous section to create three scenarios. These scenarios are a base scenario followed by a lower and an upper scenario. The three scenarios are created to check how sensitive the simulations were to a change in the assumptions. The base scenario used the assumptions displayed in Sections 3.5.3, 3.5.4 and 3.5.5. The upper scenario is determined by multiplicatively increasing the waist circumference assumption by one per cent (this changes the average waist circumference by 7 to 10 per cent). Further changes include the exercise frequency assumption to reduce each of the “active” probabilities by ten per cent of its initial probability and increasing the probability of a case of family history by ten per cent of its initial probability. For the lower scenario, the inverse operation is performed on each of these assumptions (for example, the waist circumference assumption is increased by one per cent of its initial average value). These scenarios are termed the best estimate, upper scenario and lower scenario respectively.

A simplification is made to adjust the IDRS risk categories for the differences in population between India and South Africa. This is an adjustment to the risk score used to identify a case of diabetes. Instead of using the risk score threshold to determine a significant

risk of diabetes of 60 points, as recommended by Dudeja *et al.* (2017), a new risk score threshold is calculated for the South African population. This new risk score threshold is calculated by solving for the risk score on the 2016 GHS that will result in the proportion of the respondent population being made equal to that of SADHS 2016.

First, the IDRS is calculated on the 2016 GHS using the same assumptions as the base scenario outlined in Section 3.5.2. A risk score threshold of 60 is initially used and the proportion of the simulated IDRSs that are above this threshold is calculated on the 2016 GHS. The proportion is calculated separately for the male and female population. This proportion of the population is compared to the equivalent proportion of each population with adjusted HbA1c levels of 6.5 per cent or above from the 2016 SADHS. The DHS (2016) calculated these proportions to be 9.8 per cent for males and 14.5 per cent for females.

The risk score threshold of 60 is adjusted until the proportions of males and females in the 2016 GHS are equal 9.8 per cent for males and 14.5 per cent for females. A separate risk score threshold is calculated for males and females in order to adjust for differences in the assumptions made in Sections 3.5.3, 3.5.4 and 3.5.5. The final IDRS thresholds for which the proportions of the male and female population who have a significant risk of diabetes are equal between the simulated 2016 GHS and 2016 SADHS are calculated to be an IDRS of greater than 77 for the female population and 71 for the male population. This approach relies on the assumption that both the 2016 SADHS and the 2016 GHS are representative of the same population. The risk score thresholds of 77 for the female population and 71 for the male population are used in Sections 4.2 and 4.3 to determine the proportion of the GHS population who are at a significant risk of having diabetes.

3.5.7 IDRS model accuracy testing

Finally, the models from the simulated risk scores are compared to the actual reported cases in the 2021 GHS dataset. This is to compare, for the reported cases of diabetes in the 2021 GHS dataset, how accurate the IDRS simulations are at identifying these reported cases.

Table 12: The simulated IDRS comparison to actual reported cases

Sex	Correctly identified diabetes case
Female	80%
Male	73%
Grand Total	**78%**

For the best estimate scenario, 80 per cent of all reported cases for the female population has an average risk score of above 77, as shown in Table 12. For the male population in Table 12, 73 per cent of all reported cases have a risk score of above 71. Therefore, for all the respondents who self-report a case of diabetes in the 2021 GHS dataset, the IDRS model is able to correctly identify 78 per cent of them.

The model accuracy in identifying the respondents who have been diagnosed with diabetes across the various provinces of South Africa is displayed in Table 13. The Northern Cape province has the lowest proportion of reported diabetes respondents that are identified by the IDRS simulation. As shown in Table 13, 56 per cent of the reported cases of diabetes are also identified by the simulation. This is closely followed by the North West province with 65 per cent of the reported diabetes cases.

Table 13: The simulated IDRS comparison to actual reported cases

Province	Correctly identified diabetes case
Eastern Cape	80%
Free State	78%
Gauteng	70%
KwaZulu-Natal	88%
Limpopo	82%
Mpumalanga	77%
North West	65%
Northern Cape	56%
Western Cape	73%
Grand Total	**78%**

In Table 13, the accuracy of the North West and Northern Cape is significantly lower than the others and is driven by the lower number of cases of diabetes that are reported in those provinces. This is likely driven by the lower number of respondents from these provinces compared to the others as shown in Table 14.

The cases where the threshold risk scores of 77 and 71 for the male and female population respectively as defined in Section 3.5.6 are not exceeded, but there is a reported case of diabetes, are all cases below the age of 55. These cases are mainly distributed between the ages of 45 and 55, as shown in Figure 18.

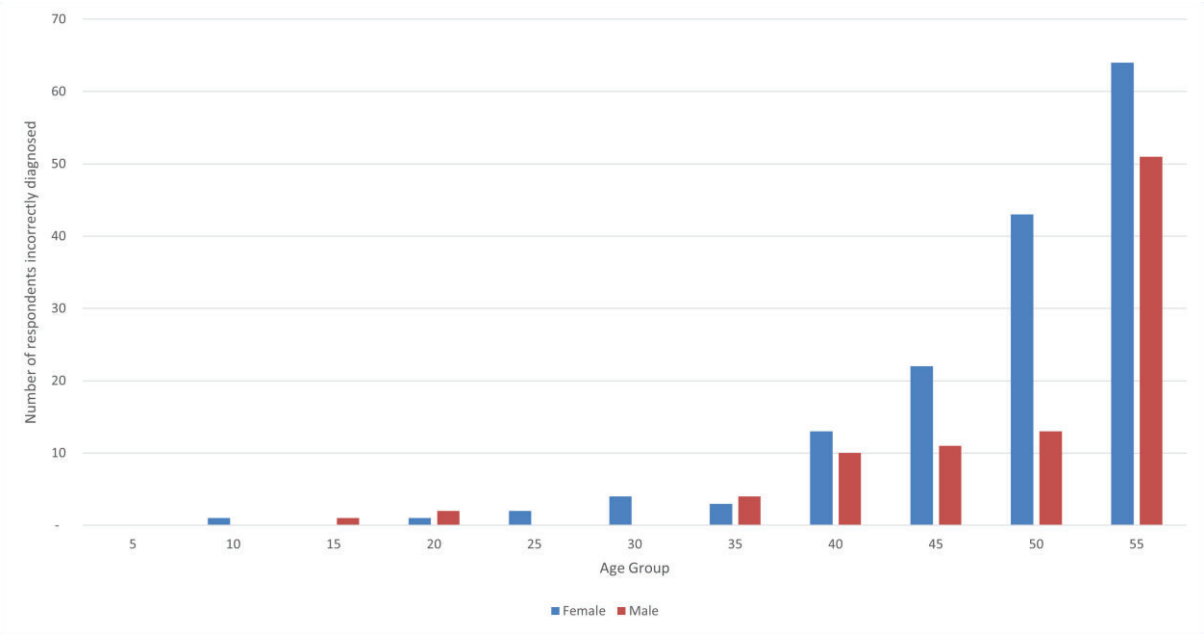


Figure 18: Number of reported cases of diabetes not identified by the risk score

Figure 18 shows that "age" has a significant impact on the accuracy of the model. As is outlined in Section 2.3, age is one of the main risk factors for diabetes. Since "age" has a large contribution to the overall IDRS, the older the respondent is, the higher the average risk score. Furthermore, the assumptions of the IDRS model are set based on age groups increasing the reliance on the respondent's age. This is a limitation of the IDRS model as shown in Figure 18, as there could be an overreliance on age as a predictor. However, this is required due to the lack of available information for each respondent for each of the other risk score contributors.

The model accuracy testing is limited to the event of a self-reported case of diabetes that is not correctly identified by the IDRS simulation. Without further information on the undiagnosed cases of diabetes in the 2021 GHS, the case of a the IDRS incorrectly identifying a respondent with a high risk of diabetes could not be tested.

Section 4. Results

4.1 Risk factor analysis of reported cases using the generalised linear model

The final identified GLM coefficients and *p*-values are shown in Table 14.

Table 14: Generalised Linear Model coefficients and p-value

Variable	Coefficient	Standard Deviation	*p*-value
Intercept	-3.157	0.404	<0.001
PSU	> -0.001	<0.001	0.002
Metro Code	0.094	0.046	0.021
Sex	0.0901	0.0528	0.088
Age	0.056	0.002	<0.001
Demographic Group	-0.065	0.029	0.022
Education Level	-0.005	<0.001	<0.001
Medical Aid Status	-0.141	0.043	0.004
Salary	<0.001	<0.001	0.040
Social Grant	0.113	0.061	0.063
HIV Status	0.211	0.148	0.154
Hypertension	-1.620	0.056	<0.001
Pregnancy	0.025	0.012	0.037

The most significant variables in predicting the reported diabetes cases were whether the respondent had already been diagnosed with hypertension, the age and their education level, as shown in Table 14. Hypertension and age are consistent with the significant risk factors identified by Fletcher *et al*. (2002). The model identified a positive correlation between whether a person self-reported that they had hypertension and a self-reported case of diabetes.

Therefore, the model calculates the respondent as having a higher risk of self-reporting as having diabetes than if they do not have self-report as having hypertension. Other significant variables included PSU area, metro code, demographic group, salary and whether the respondent reported having been pregnant in the previous six months. Education level, salary, metro code and PSU area could be used to link to the lifestyle risk factors of diabetes. These explanatory variables highlight the problems in healthcare facing South Africa. Whether the respondent reported being pregnant is likely due to the risk of gestational diabetes as outlined by Kerner and Brückel (2014).

The model uses a positive correlation for medical aid status. Therefore, a respondent who is on medical aid is more likely to report a case of diabetes. This could be due to the medical

aids encouraging or requiring regular testing. This is due to the increased awareness and the availability of these diabetes tests that a medical aid provides.

Another influence could be the barriers to these screening tests as outlined in Section 2.4.8. Despite the relatively insignificant *p*-value, the model assigns a negative correlation to whether someone is on a social grant or not. Therefore, if someone is receiving a social grant, they are less likely to be predicted to self-report a case of diabetes. Similarly, as salaries increase, the predicted risk of the respondent self-reporting a case of diabetes increases. This shows that the more money a respondent has access to, the more likely they are to report a case of diabetes.

The final GLM can achieve an accuracy of 97 per cent in predicting self-reported cases of diabetes. The GLM approach is an easy to calibrate and use tool for predicting self-reported diabetes cases. Whilst this does not account for the undiagnosed or non-reported cases of diabetes, the accuracy achieved allows for critical areas and demographic groups to be targeted.

4.2 Indian Diabetes Risk Score scenario analysis

The best estimate simulated diabetes rate was 12.2 per cent across the 2021 dataset, as shown in Table 15. The rate of diagnosed cases from the GHS 2021 dataset was 2.61 per cent. As per Table 15, the simulated diabetes proportions of the population for females are higher that of the male population in all scenarios besides the lower scenario.

The results of the 2021 GHS survey using the SADHS adjusted risk thresholds produce proportions that lie relatively close to the estimated 11.3 per cent (IDF, 2023), with the proportion of the population reporting they are diabetic as 2.6 per cent. As per Table 15, this is slightly above the lower scenario of 2.2 per cent.

Table 15: Exposure weighted proportion of population with diabetes

Sex	Lower Scenario	Best Estimate	Upper Scenario	Self-reported Diabetes rate
Female	4.2%	14.0%	18.4%	3.37%
Male	0.1%	10.4%	10.4%	1.81%
Grand Total	**2.2%**	**12.2%**	**14.5%**	**2.61%**

Across provinces, the Western Cape has the highest average simulated risk score for both females and males, with an average of 47 and 31 respectively. This is followed by the Free State province, with 45 for females and the Gauteng province, with 31 for males as per Figure 19. The respondents in metro areas have a higher average risk score than in non-metro areas.

This likely occurs because the average age for both males and females is higher in the metro areas than the non-metro areas.

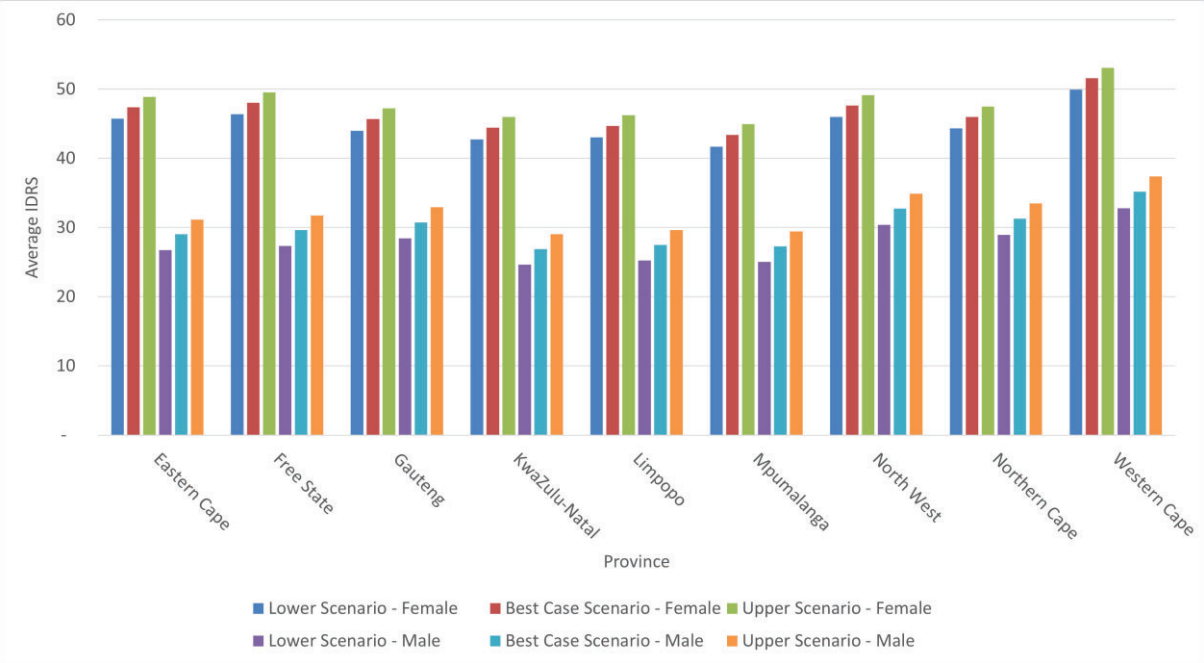


Figure 19: Average simulated IDRS per province

In Figure 19, the average risk score of females is higher than males. The average risk score for females is above the threshold outlined in Section 3.5.6 for all ages above 45 for all scenarios. The male population's average risk score is above the threshold outlined in Section 3.5.6 across all scenarios for all ages above 65. The average risk scores for females and males are shown in Figure 20.

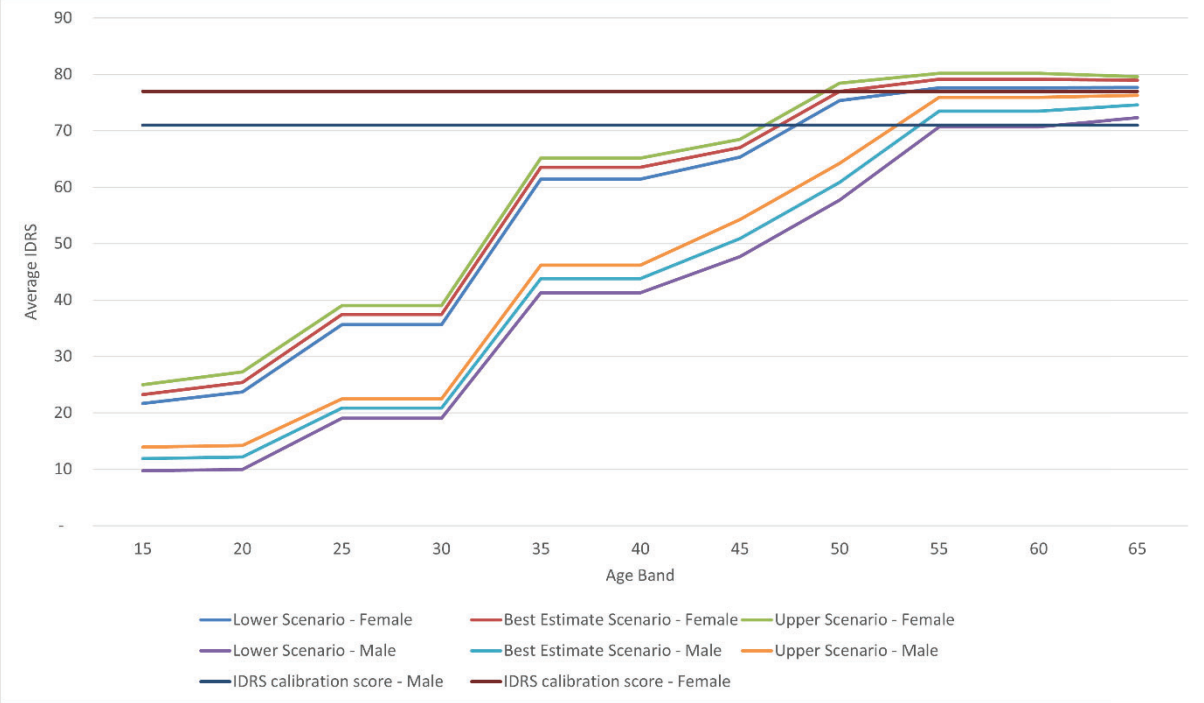


Figure 20: Average simulated IDRS per age

This is partially driven by the average waist circumference of females in South Africa being higher than the IDRS criteria for females in Tables 6 and 7 in Section 3.5.3. The female waist circumferences all increased, on average, between 0.3 per cent and 3 per cent between 1998 and 2016. The two most significant increases were the age groups of those aged older than 65 and the age group between the ages of 24 to 34, both with an increase of 3 per cent over the period of 1998 to 2016.

Contrast this with the average male waist circumference per age group and, in every age group, the average female waist circumference is higher than the average male waist circumference, both in 1998 and in 2016. Whilst the average male waist circumference per age group between the ages of 25 to 54 all decreased, the average male waist circumference per age group aged older than 55 saw a greater than 3 per cent increase over the period of 1998 to 2016, as is shown in Table 7 in Section 3.5.3. The average male waist circumference per age group between 15 and 24 also increased over the same period by roughly 1.5 per cent, as is shown in Table 7 in Section 3.5.3.

The average waist circumference of the South African population remains high relative to the suggested IDRS criteria (DHS, 2016). In 2016, the average waist circumference for all females aged 35 and older was greater than 89 (which is in the highest risk category of the IDRS). The male population is generally between the 80 centimetre to 90 centimetre range

(which is in the middle risk category for the IDRS). This is a large reason why, in Figure 20, the simulated average score rises faster for the female population than the male population. As the risk categories for waist circumference are based on the Indian population, the calibration in Section 3.5.6 was performed to bring the IDRS estimates to be in line with the South African undiagnosed diabetes prevalence rates. As these IDRS waist circumference scores in Table 1 in Section 2.5 are calibrated to the Indian population, a revision of the waist circumference sizes is recommended.

Another contributing factor is the assumption of almost double the proportion of the male population as performing strenuous exercise than the female population, as outlined in Section 3.5.5. The risk criteria to performing little to no exercise, as per Table 1 in Section 2.5, is 30 points. With almost double the proportion of the female population assumed to perform no exercise, the high weighting to exercise of the risk score results in the higher average risk score for females across the simulation. A further driver for the higher female risk score is that the average age of the female respondents was higher than the male respondents.

Between the period of 1998 and 2016 in the SADHS, there has been an increase in the proportion of the population with type 2 diabetes across both male and female age brackets, as shown in Tables 16 and 17.

Table 16: Proportion of the female population with HbA1c levels of greater than 6.5 per cent

Year	Ages 15 to 24	Ages 25 to 34	Ages 35 to 44	Ages 45 to 54	Ages 55 to 64	Ages 65+
1998	0,5%	1,6%	2,7%	7,2%	7,6%	8,9%
2016	1,0%	5,0%	12,0%	21,0%	29,0%	30,0%

Source: DHS (1998) and DHS (2016)

Table 17: Proportion of the male population with HbA1c levels of greater than 6.5 per cent

Year	Ages 15 to 24	Ages 25 to 34	Ages 35 to 44	Ages 45 to 54	Ages 55 to 64	Ages 65+
1998	0,1%	0,8%	2,5%	5,4%	7,9%	4,8%
2016	2.0%	3,0%	7,0%	12,0%	23,0%	21,0%

Source: DHS (1998) and DHS (2016)

This rise in the proportion of the population having diabetes reported by the DHS (1998) and (2016) is consistent with the results of Figure 21's results. There is a clear increasing trend in the best estimate simulated diabetes rate over time, starting from 3 per cent in 2013 to 15 per cent in 2020. If this trend in Figure 21 continues, the proportion of the population in South Africa with diabetes may be becoming significantly worse in the future (IDF, 2023).

The proportion of the population with blood sugar levels equivalent to those who are diagnosed with diabetes indicates an increase of two to four times what they were in 1998, across all age ranges. This coincides with the rise in waist circumference coupled with an increase in the average age.

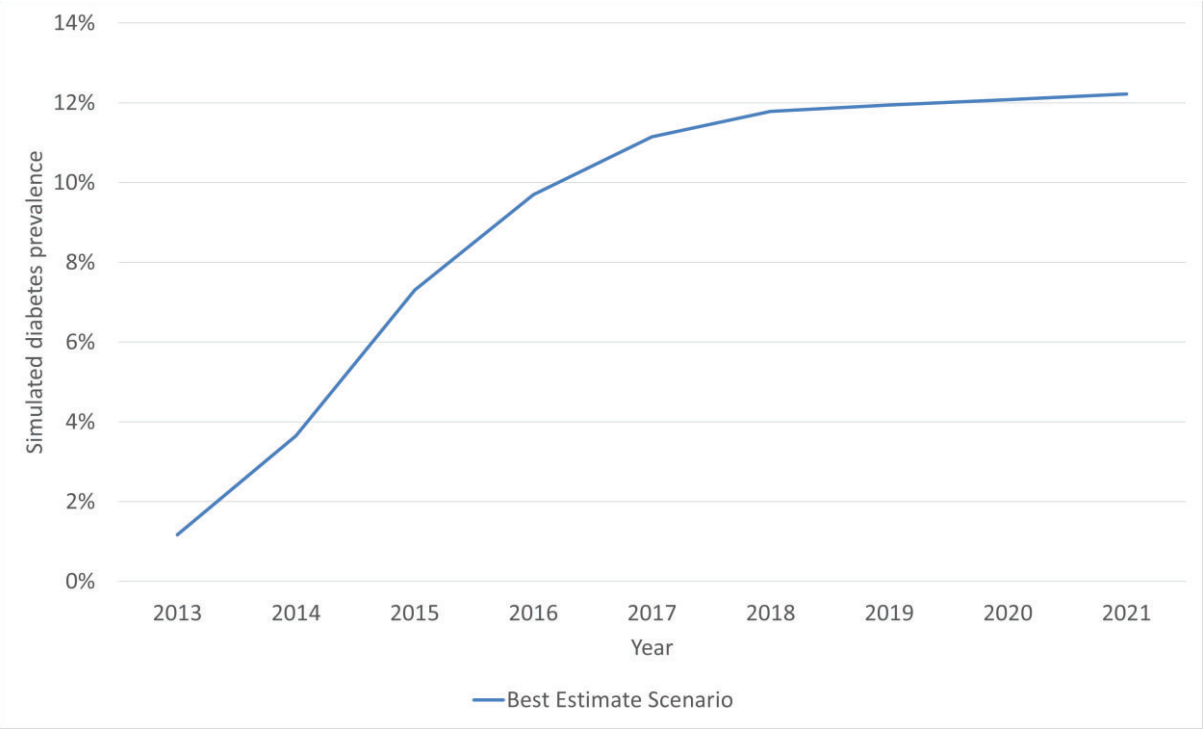


Figure 21: Simulated diabetes rate per year under the best estimate scenario

Section 5. Discussion

Diabetes in South Africa is a rising problem, with many cases of diabetes remaining undiagnosed due to issues with access to healthcare (DHS, 2016). Specifically, the issues of the cost in monetary terms, outlined in Section 2.4.4; travel times to a healthcare provider, as outlined in Section 2.4.3; trust in the healthcare system; and quality of treatment, as outlined in Section 2.4.6. These undiagnosed cases are estimated mainly from the results of the SADHS, the last of which was performed in 2016. The SADHS performs an HbA1c test to establish the blood sugar levels of the respondent as outlined in Section 3.2. This is compared to the response of the respondent as to whether they have been diagnosed with diabetes or not (DHS, 2016). Almost 15 per cent of females and almost 10 per cent of males report to either be diagnosed with diabetes or were tested as having HbA1c levels above the diabetes threshold of 6.5 per cent. To establish the prevalence of diabetes in South Africa, a regular estimation of the undiagnosed cases of diabetes is useful to monitor the rise in diabetes cases.

However, the SADHS is not regularly performed and was only conducted in 1998 and 2016. The 2016 dataset was used to calibrate the IDRS model. Therefore, reasonable assumptions were made to estimate the risk score assumptions outlined in Sections 3.5.3, 3.5.4 and 3.5.5. As these surveys are so far apart, a lot can change before, during and after that period. For example, the proportion of the population aged 15 or older who have a self-reported case of diabetes increased from four per cent to five per cent and from two per cent to four per cent over that period for the female and male populations respectively (DHS, 1998; DHS, 2016). The estimation of the undiagnosed cases of diabetes in South Africa can allow for more-informed policy decision-making. This would allow for a more cost-effective approach to be implemented in order to prevent significant medical costs in the future for the South African Government (Dudeja *et al.*, 2017).

Using diabetes risk factors to estimate the cases of undiagnosed diabetes allows for a more proactive approach to be taken with regards to the fight against this NCD in South Africa. By tracking these risk factors, it is possible to identify a high-risk individual in the population and ensure early testing and treatment before significant complications arise (Dudeja *et al.*, 2017).

Whilst this is most beneficial at a population level, insurers could benefit from lower underwriting costs if such a risk factor estimation could identify these high-risk individuals.

However, there are significant limitations to testing for biomarkers on a regular basis. For example, obtaining BMI in a survey performed every year requires additional training of

the survey staff in taking both height and weight measurements, as well as the cost of the equipment needed for scales and tape measures. Furthermore, there are practicality issues of transporting this equipment, storing the equipment and the potential for theft or loss of this equipment. If an estimation were to be made on the proportion of undiagnosed cases of diabetes in South Africa on a yearly basis using risk factors, the risk factors should be only as many as are necessary, are relevant to the South African population and easily measurable or obtainable.

The IDRS is a useful tool developed in India to use these risk factors as a proxy for the undiagnosed cases of type 2 diabetes in a country (Dudeja *et al.*, 2017). This low-cost approach to the prediction of type 2 diabetes over time has been used to effectively predict the risk of type 2 diabetes (Dudeja *et al.*, 2017). The accuracy of prediction that the risk of the IDRS on a South African population is, at least, comparable to the results published from the Indian population, is out of the scope of this paper and is a recommended follow-up study. However, a calibration of the IDRS simulation model as outlined in Section 3.5.6 shows promising results if the IDRS is calibrated to the South African population. This suggests that a South African-specific risk score threshold could be calculated to improve the accuracy of the estimates. This risk score threshold could be calibrated by the use of the SADHS dataset but further investigation into the viability of this suggestion is out of the scope of this paper. It is recommended that a full calibration of the different risk scores for the IDRS components in Section 2.5 be performed before the model is used.

Modelling the risk factors for diabetes in the South African population has three main benefits. The first benefit is that it allows for the earlier detection of high-risk segments of the population. By understanding how the risk factors are changing over time, it allows for these individuals to receive targeted screening and receive potential medical treatment earlier than would normally be the case. According to Li *et al.* (2010), targeted screening is more cost-effective than universal screening. Furthermore, the sooner a case of diabetes is identified, the more cost-effective the treatment and the lower the risk of downstream medical complications that could occur (Dudeja *et al.*, 2017).

The second benefit is the additional information that can be used from analysing the observed trends in the risk factors for type 2 diabetes in South Africa. Historical analysis of these risk factors, such as waist circumference and exercise frequency, allows for a more up-to-date view on the success of the various interventions applied in South Africa. A difficulty identified in assessing the implementation of interventions is that the effects are unlikely to be realised for a number of years and diabetes rates will likely be unaffected in the short term. However, trends in the waist circumference and exercise frequency (two modifiable risk

factors) are likely to change sooner than the diabetes rates in South Africa. This allows for stakeholders in South Africa (from insurers to government) to potentially identify the effects of the intervention on their relevant populations before a change in the type 2 diabetes is identified. Insurers such as Discovery have already started collecting detailed exercise and waist circumference data so that these metrics are already established and are used within the insurance industry (Lambert *et al.*, 2009).

The final benefit is that the risk factors, and specifically the ones used in the IDRS, are easily understandable and explainable by the various users and stakeholders of the results. The results of the predictions produced by modelling the IDRS are easy to interpret by the stakeholders using the analysis. If the general risk score has increased, the results can be explained by an increase either in the non-modifiable factors of age or family history, or modifiable factors such as waist circumference or exercise frequency. With this ease of interpretation, it is also easier to communicate how lifestyle changes can reduce the risk of type 2 diabetes for the population of South Africa.

The limitation, and difficulty, in application of reporting the results of these predictions, is that the IDRS is a simplification of a complicated non-communicable disease. With the full scope of treatment being an interplay between lifestyle, medication and emotional support, a medical professional is still required to both diagnose and treat a case of diabetes on a patient-by-patient basis (ADA, 2019).

To obtain these benefits whilst leveraging off existing survey infrastructure and keeping the information cost-effective to obtain, is how the IDRS could be incorporated in the South African GHS. As the South African GHS is performed every year, a regular snapshot of the reported risk factors and their changes over time could be achieved. The questions of family history of diabetes, waist circumference and exercise frequency are, at the time of writing this paper, not included in the GHS; therefore, assumptions are required for the modelling of the IDRS in South Africa on a population level.

The most accurate approach to achieving this risk factor snapshot for type 2 diabetes would be to include a question for waist circumference, exercise frequency and number of parents with a family history of diabetes to the GHS. This may be expensive and could take time to implement. However, there is an increasing trend in diabetes rates, as shown by the IDRS estimations diabetes rates over time, as seen in Section 4.2, as well as the SADHS (DHS, 1998; DHS, 2016) and the IDF (World Bank, 2024). Therefore, it may be more cost-effective in the long term to add these questions in order to have more information to be used for policy formation and monitoring.

The increasing trend in diabetes is higher amongst the female population in South Africa (DHS, 2016). This warrants earlier and more targeted interventions for that population group if effective management of diabetes is to be achieved by the government. Specifically, females or males who are older, overweight and have a direct family member who has had diabetes should be screened.

The results from Section 4.3 indicate that there are high levels of undiagnosed diabetes cases in South Africa. With little nation-wide testing, data that can be used to identify these undiagnosed cases are sparse. The data available, such as the GHS, often lack information on key risk factors such as waist circumference, BMI and exercise frequency. This adds further complexity to identifying these cases, often resulting in assumptions needing to be made, such as those made in Section 3.5.

Even within datasets such as the GHS, due to the lack of testing, reliance is placed on the respondent reporting a case of diabetes. This requires an individual to have access to a testing facility, make use of it, be diagnosed with diabetes and report it in the survey. The multiple points where information can become lost can occur in the quantification of a diabetes rate that includes both diagnosed and undiagnosed cases across South Africa.

The results in Section 4.3 as well as the SADHS (DHS, 2016) and the IDF (World Bank, 2024) motivate for increased screening efforts in both public and private healthcare settings. Increasing the screening efforts in those spheres would reduce the need for estimating undiagnosed cases using risk factor models such as the IDRS. However, as outlined in Section 2.4.10, the cost of this increase in screening can be expensive. It is recommended that a targeted screening approach using a risk factor model such as the IDRS, when calibrated to the South African population, be undertaken to address this increasing trend in diabetes. This approach could be particularly useful for the implementation of the NHI, which was outlined in Section 2.4.7. With a nation-wide insurance scheme being rolled out, the ability to identify and screen targeted individuals for diabetes could be a key cost-saving measure and could help mitigate many of the expensive medical costs outlined in Section 2.4.9 that can arise from many of the complications and treatments of diabetes.

Section 6. Conclusion

Diabetes in South Africa is a rising problem with estimates expected that the number of South Africans with diabetes will double over the next 23 years (IDF, 2023). Large surveys and testing for diabetes is an expensive approach and currently has only been undertaken in 1998 and 2016 by the South African Government. The changes in the risk factors over that period have been significant, with the proportions of diabetes rising by sometimes 20 per cent of the population over these 18 years. Significant increases in waist circumference result in the South African population largely falling into the riskier thresholds for diabetes, according to the IDRS specifications.

Yearly surveys provide information only on the self-reported cases and have no indication of the number of cases of diabetes that may be undiagnosed. From the SADHS 2016 results, more than double the estimated actual number of diabetes cases are undiagnosed cases (DHS, 2016). South Africa sees these large numbers of undiagnosed cases because of problems with access to healthcare experienced by many South Africans. These access problems can be due to a lack of time, money or the medical centres around them do not have the same quality of care as the private medical centres.

With a large number of cases of diabetes being undiagnosed, as well as the difficulties such as what thresholds to use for blood sugar levels for the black population, it makes targeted screening and other interventions difficult to assess. Without this information, distributing healthcare resources according to their need is challenging, as there could be bias in the most risky areas identified, due to the access problems in those areas. Furthermore, as many of the regulations are aimed at prevention, there is no clear way to consistently track the impacts these interventions may have and assess their results until the overall reported cases change or another large-scale survey is performed.

By focusing on the established risk factors of diabetes and using the IDRS, the general household survey may be able to be used as a proxy for identifying undiagnosed cases of diabetes in South Africa. By making assumptions on three of the outstanding risk factors (namely family history, exercise frequency and waist circumference), the risk scores are able to be estimated. These risk scores, when applied with the risk score thresholds of Section 3.5.6, result in an excess of between 5 per cent and 21 per cent of the population that is at significant risk of being diabetic. The results appear to align with the 11.3 per cent estimation of the actual South African diabetes rate.

However, these results are heavily dependent on the assumptions that are made, especially the age assumption. In order for useable results to be created, these three questions of exercise frequency, family history and waist circumference would need to be added to the GHS. Further developments would need to be investigated, including the risk score threshold and what would be appropriate to be used for the South African population. This study is also based on self-reported cases which, as Mutyambizi *et al.* (2019) point out, may result in some bias for the accuracy of the prediction of diabetes unless clinical data are included. Whilst this is beyond the scope of this paper, a follow-up study could be undertaken where a clinical study is performed, and the model is calibrated to include clinical data. This would result in a more accurate prediction of the annual diabetes rates in South Africa as the new census results are being released.

With further investigation and the addition of the three questions to the GHS, it could help to allow for a better tracking of undiagnosed cases of type 2 diabetes in South Africa. The results produced by the simulations look reasonable with the diabetes rate rising over time, in line with the actual diabetes proportions of the population (SADHS comparison), and, once the risk score threshold is calibrated, the model could result in a powerful tool that South Africa could use in the allocation of medical resources (playing a critical role in the NHI roll-out), as well as sooner estimating the effect of various interventions on the population.

Section 7. References

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