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To Go or To Not Go?

Structure Equation Modelling of Healthcare Utilisation among Older Adults in Mpumalanga, South Africa

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Abstract

Providing healthcare services for the older rural population in South Africa is a matter of availability and accessibility. This study aims to analyse the factors influencing healthcare utilisation among rural older adults in South Africa using Andersen's behavioural model of health services use. Structural equation modelling (SEM) with confirmatory factor analysis (CFA) technique will be used to examine which factors significantly influence healthcare utilisation. Data from the HAALSI study, specifically the second wave, were used (N = 4176). The findings show that the enabling and need factors significantly influence healthcare utilisation, with the former having the biggest influence. Vehicle ownership and wealth asset index are found to have a huge impact within the enabling factor, unlike medical coverage. Meanwhile, for need factors, the present self-rated health status was found to have a bigger impact than health compared to the previous year. Contrary to some previous studies, the predisposing factor is found to have little impact on healthcare utilisation. Even so, age, education level, and employment status are found to have a big influence on predisposing factors. After the removal of sex and marital status from the predisposing factors, model fit indices show that Andersen's model is a good fit.

Keywords: healthcare utilisation, need factors, predisposing factor, enabling factors, rural older adults

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1. Introduction

1.1 Background

Population growth has always been the main focus of demographic trends. However, another demographic trend, population ageing, has been gaining much concern lately. It is the result of longer life expectancies and lower birthrates, which causes an increase in the average age of populations (Haddock, Leahy and Engelman, 2008). Initially, it was seen as a positive social and environmental development, but its potential to become extreme average age is worrisome (Haddock, Leahy and Engelman, 2008). When the proportion of older people in society increases, it will heavily impact society, from the decline of productivity to the need to reorganise healthcare and social security structures (United Nations Economic Commission for Europe, 2007). This phenomenon can be observed in numerous countries around the world, though in high-fertility countries, it becomes a double burden since they will have to manage both high fertility and population ageing (Bloom and Zucker, 2023).

The main challenges of population ageing for governments are declining revenues from the decreasing productivity, as well as increasing expenditures, especially in the healthcare sector, for example, for long-term care needs (Cristea *et al.*, 2020). Such cases can be seen in Italy, where almost 90% of older adults have one chronic disease, and about 60% have more than one (Atella *et al.*, 2019). Likewise, this trend can also be observed in South Africa, where multimorbidity – the coexistence of more than one chronic disease – is increasingly prevalent among older adults (Roomaney, van Wyk and Pillay-van Wyk, 2023). However, this trend is even more challenging for low- and middle-income countries (LMICs). LMICs face a double burden of diseases, where infectious diseases and undernutrition are still major issues while facing increasing prevalence of obesity and non-communicable diseases (NCDs) (Basto-Abreu *et al.*, 2022). Furthermore, the health systems in LMICs are not prepared to face the challenges of multimorbidity due to the limited resources and infrastructure of the health systems (Basto-Abreu *et al.*, 2022).

In the case of South Africa, increasing life expectancy is one of the aims of the National Development Plan (NDP) 2030. It also relates to the aim of Sustainable Development Goals (SGDs) 3, which is to ensure healthy lives and promote well-being for all at all ages (United Nations, no date). However, the demographic change will increase government spending on

healthcare and pension provisions, and the working-age population may be struggling to bear the cost with no clear strategies to meet these challenges (Roomaney, van Wyk and Pillay-van Wyk, 2023). Also, the health disparities between urban and rural populations remain an issue, where older rural populations reported significantly lower overall health status and quality of life than their urban counterparts (Peltzer, Phaswana-Mafuya and Pengpid, 2019). There is also a persistent concern over disparities in healthcare access between urban and rural populations, which have been ongoing for decades (Weisgrau, 1995; Reid, 2006). Providing healthcare services in rural areas is not only a matter of availability but also accessibility (Vergunst *et al.*, 2017). In order to make health policies that can ensure accessibility for the whole population, it is important to understand the factors that predict the use of health services. It is also important to ensure the effectiveness and efficiency of health services delivery (Andersen and Davidson, 2007).

Various studies have shown that many different factors influence healthcare utilisation, such as age, education level, and medical coverage (Taffa and Chepngeno, 2005; Ataguba, Akazili and McIntyre, 2011; Zayas *et al.*, 2016). However, studies have found inconsistent results on how much these factors influence healthcare utilisation across different populations (Zhang, Chen and Zhang, 2019; Brandão, Paúl and Ribeiro, 2022). Understanding the characteristics and important predictors of healthcare utilisation among specific demographics, as well as how the factors interact together, is an important step to providing accessible healthcare services for all.

1.2 Purpose and Aim

The utilisation of healthcare services has been the focus of many studies in the past. It has also been found that the availability of healthcare services is not the only factor influencing healthcare utilisation. Aside from the need for the service itself, the healthcare service must also be accessible to the people, in which the biological and environmental factors will influence the utilisation (National Academies of Sciences *et al.*, 2018). In order to understand the use of health services, Andersen's behavioural model of health services use has been extensively used across different contexts. Although some studies analysed the model using multivariate analysis, such as structural equation modelling, the majority of the studies using this framework utilise univariate analysis, such as regression analysis, focusing on certain similar variables while doing secondary data analysis (Babitsch, Gohl and von Lengerke,

2012). Therefore, to better understand the associations between the main factors in Andersen's behavioural model, primary studies that use complex statistical analysis, such as multivariate analysis, are needed (Babitsch, Gohl and von Lengerke, 2012). The complexity of the model is shown in a study that found both age and health status matter when it comes to adherence and trust in healthcare providers. However, age and health status do not necessarily matter together (Petrovic and Blank, 2015). This study aims to contribute to a better understanding of the factors that influence healthcare utilisation among rural older adults in South Africa while also utilising structural equation modelling to unveil the complexity of the factors in Andersen's behavioural model of health services use.

1.3 Research Questions

Healthcare services must be not only available but also accessible to the population. In order to design health policies that ensure accessibility, especially for rural older adults, it is important to understand the factors that influence healthcare utilisation. Andersen's behavioural model of health services use has been widely implemented to understand the factors influencing healthcare utilisation. To contribute to a better understanding of the important predictors of healthcare utilisation among rural older adults, as well as illustrating the complexity of Andersen's health behavioural model, the research questions that direct the study are:

- What factors influence healthcare utilisation among rural older adults in South Africa?
    - Which variable significantly affects the need factor for healthcare utilisation?
    - Which variable significantly affects the enabling factor for healthcare utilisation?
    - Which variable significantly affects the predisposing factor for healthcare utilisation?

2. Literature Review

This chapter will provide information about relevant preliminary studies related to the study. It will elaborate on the concept of healthcare utilisation and map out relevant related studies.

2.1 Healthcare Utilisation

Healthcare utilisation has been the focus of many studies in various fields. Carrasquillo (2013) defined it as "the quantification or description of the use of services by persons for the purpose of preventing and curing health problems, promoting maintenance of health and well-being, or obtaining information about one's health status and prognosis". Simply put, healthcare utilisation is the use of healthcare services.

Healthcare utilisation has a significant impact on population health outcomes (Wang *et al.*, 2012). The increase in the ageing population and increase in healthcare expenditures require a better understanding of the risk factors and social characteristics related to the use of health services to ensure the sustainability of the system (Goel *et al.*, 2018).

The concept of healthcare utilisation is closely related to the concept of access to care. Access to care itself is complex and has many different notions (Nguyen, 2023). Some defined it as a set of dimensions to describe how to fit the patient's needs and the system, while others defined it as the ability to obtain health services (Khan and Bhardwaj, 1994). Some also believe that healthcare utilisation is an indicator to measure health policies related to access to care (Ngwakongnwi, 2017).

Regarding access and healthcare utilisation, the theoretical framework can be divided into system-centred and patient-centred (Nguyen, 2023). System-centred approaches normally focus on the barriers to healthcare utilisation, while patient-centred approaches focus on the ability of individuals to identify, seek, and obtain health services (Nguyen, 2023). In the system-centred approaches, the barrier-focused model of Penchansky and Thomas' is commonly used. The framework of access focuses on the fit between the patient's needs and the system's ability to meet those needs, where access is characterised by affordability, availability, accessibility, accommodation, and acceptability (Wyszewianski, 2002; Ngwakongnwi, 2017). Penchansky and Thomas (1981) defined each dimension as follows: (1)

availability, the adequacy of supply of health providers and services; (2) accessibility, the relationship between the location of the services and the patients, such as the availability of transportation; (3) accommodation, the ease of patients to access the care they need, such as the clinic hour and the waiting time for appointments; (4) affordability, the financial ability of patients to use the care, including the coverage of health insurance; and (5) acceptability, the patients' attitudes towards healthcare providers.

On the other hand, concerning the patient-centred category, one of the earliest models is Andersen's health behaviour model. The framework focuses on individual behaviours, recognising the three determinants of the behaviour (Andersen and Newman, 1973; Ngwakongnwi, 2017; Nguyen, 2023). First, the health delivery system focuses on resource factors, such as the type of health services, purpose, and unit of analysis. Then, the population factor focused on the three factors that characterised the population, which are predisposing factors, need factors, and enabling factors. Finally, the external environment focuses on the economic and political conditions, as well as the norms of society.

Although both frameworks explain the concept of access and healthcare utilisation, this study will use Andersen's behavioural model for healthcare services as the theoretical foundation. Andersen's behavioural model for health services use has been used plenty of times to identify individual factors related to healthcare utilisation across different populations, which is the aim of this study.

2.1.1 Healthcare Utilisation in Low-Middle Income Countries

The right to a standard of living adequate for health has been acknowledged as part of human rights, which calls for universal health coverage (Sachs, 2012). However, there are many difficulties for LMICs to provide quality healthcare compared to high-income countries (HICs), affected by both internal and external factors (Braithwaite *et al.*, 2012). Externally, LMICs have difficulties in ensuring water and sanitation quality, as well as nutritional adequacy, to name a few (Sachs, 2012). On the other hand, inside the healthcare system, the lack of health financing and basic healthcare system infrastructure, as well as the lack of supportive policies, are some of the challenges (Braithwaite *et al.*, 2012; Sachs, 2012).

The inequalities in healthcare services do not only happen between LMICs and HICs but also between urban and rural areas within the same countries. Healthcare services in rural areas lack basic infrastructure and resources, such as the scarcity of clinics and healthcare providers, to provide equal healthcare services to its residents (Weisgrau, 1995). Furthermore, in the case of South Africa, the majority of its poor residents live in rural areas, making access to quality healthcare services even more difficult (Reid, 2006).

2.1.2 Healthcare Services in South Africa

South Africa is the wealthiest country in the sub-Saharan Africa region, though it also has the highest income inequality, especially between people with different racial groups (Chavez-Lindell, 2022). The disparities also translate to inequality in accessing healthcare services.

After the end of apartheid, the South African government prioritised healthcare reform to the country's development agenda. It aims to promote accessible and affordable healthcare services, especially among the poorest and most marginalised, through expanding the healthcare system network and eliminating the fees of primary healthcare (Burger and Christian, 2020). However, the policies are not backed by good leadership and management by the government that they fail to meet their purpose (Coovadia *et al.*, 2009). In the end, the poor black residents are the ones who majorly carry the heavy burden of disease within the country (Burger and Christian, 2020).

The healthcare system in South Africa can be divided into two categories, the private sector and the public sector, where the latter provides up to 40% subsidy of medical cost (Dauncey, 2023). About 80% of the population normally uses public healthcare, while the wealthiest ones use private healthcare (Buswell, 2024). However, the public healthcare system suffers from underfunding, mismanagement, and neglect, which impact the quality of the healthcare, as well as causing a long waiting list of patients (Mayosi Bongani M. and Benatar Solomon R., 2014; Buswell, 2024). Even so, as part of its attempt to achieve universal health coverage, the government has passed the National Health Insurance (NHI) Bill that aims to provide universal and free healthcare to all South Africans by 2026 (Dauncey, 2023).

There are different levels to the public healthcare system, which are: (1) clinics, or primary healthcare, which treats common health needs and is run by trained nurses; (2) community

health centres, which are larger clinics and are run by doctors and nurses; and lastly (3) hospitals, which are for surgery and treatments that are not available at clinics (Sonke Gender Justice, no date). In regards to the location of the study, the data collection was conducted in the Agincourt sub-district in Mpumalanga Province, South Africa. There are 31 villages in the area, where the available healthcare system consists of six clinics, two health centres, and three district hospitals (Gómez-Olivé *et al.*, 2018).

2.2 Predictors of Healthcare Utilisation

Healthcare utilisation is a complex issue that is influenced by a variety of factors. This part will elaborate on existing knowledge regarding the factors influencing healthcare utilisation. The factors will be organised following Andersen's behavioural model of health services use.

2.2.1 Need Factors

The need factor is one of the important predictors of healthcare utilisation. It is an important predictor towards visits to the emergency department by older adults (Chavez-Lindell, 2022). Need factors focus on the health condition of the individuals, which can either be self-reported or evaluated by the healthcare providers. Due to the lack of available data, self-reported health (SRH) is normally used for traditional health measurement (Kapteyn and Meijer, 2014). Regardless, various studies have found SRH to be as reliable measurement as various other objective health measurements (Bourne, 2009; Short *et al.*, 2009; Kapteyn and Meijer, 2014). In fact, self-reported health has also been found to be a predictor of healthcare utilisation (Gómez-Olivé *et al.*, 2013).

2.2.2 Enabling Factors

The enabling factor is related to the resources available to individuals to use health services (Aday and Andersen, 1974). Low-income households and lack of insurance coverage are some of the enabling factors that are related to the under-utilisation of health services (Chavez-Lindell, 2022). The enabling factors consist of the financing aspect and the organisational aspect. Regarding the financial aspect, socio-economic status (SES) is one of the important factors influencing healthcare utilisation. Several studies have found a significant correlation between SES and healthcare utilisation, where people from low SES show significantly lower healthcare utilisation (Kevany *et al.*, 2012; Agerholm *et al.*, 2013; Frølich *et al.*, 2019; Gordon, Booysen and Mbonigaba, 2020). The incident can be observed in both LMICs and HICs.

People from low SES have difficulties accessing healthcare services, especially regarding their ability to afford healthcare services (Gordon, Booysen and Mbonigaba, 2020). Not only the cost of healthcare services, but poor people often cannot afford the transportation expenses to access healthcare services, especially those who live in rural areas (Kevany *et al.*, 2012). Though SES is hard to measure, it has been found that the wealth index, based on household expenditure and consumption, is more reliable compared to household income, especially in the context of developing countries (Ataguba, Akazili and McIntyre, 2011).

Another part of the financial aspect is the health insurance coverage, which has been found to have a direct impact on healthcare utilisation (Ataguba and Goudge, 2012; Tilahun *et al.*, 2018; Wang *et al.*, 2018; Zhou *et al.*, 2020). Even when controlling their health status, patients without health insurance coverage use fewer healthcare services, especially among older adults (Wang *et al.*, 2018). However, some studies have also found that the type of healthcare services matters. In South Africa, for example, insurance coverage increases the use of private health services while it has no significant impact on the use of public health services (Ataguba and Goudge, 2012).

On the other hand, the organisational aspect within the enabling factor is concerned with the availability of care to individuals, including transportation and the travel time to the healthcare services (Andersen and Davidson, 2007). The availability of transportation is an important predictor of healthcare utilisation, even where free healthcare is available (Goudge *et al.*, 2009; Neely and Ponshunmugam, 2019). For older people, those who live in urban or rural areas, transportation and travel time to the healthcare services heavily impact the frequency and satisfaction of healthcare service use, especially since transportation cost places huge burdens on rural older adults (Kullanit, 2016; Jang, Seon and Oh, 2020; Li *et al.*, 2020).

2.2.3 Predisposing Factors

Individual characteristics are crucial factors in healthcare utilisation. Studies have found that various socio-demographic factors, such as age, gender, education level, and employment status, have an impact on healthcare utilisation (Abera Abaerei, Ncayiyana and Levin, 2017; Singh *et al.*, 2018; Tilahun *et al.*, 2018; Chavez-Lindell, 2022). First, age is a strong predictor of healthcare utilisation (Rennemark *et al.*, 2009; Zayas *et al.*, 2016). For example, age is strongly related to chronic diseases, which implies that older people are at higher risk of chronic

diseases (Atella *et al.*, 2019). In relation to that, the various health conditions that older people have explained why older people use healthcare services more frequently (Rennemark *et al.*, 2009). However, gender and cultural situations also play a role in the age factor since older women in rural Bangladesh are less likely to seek healthcare services than young ones. In contrast, elderly men are more likely to seek healthcare services than younger ones (Young *et al.*, 2006). One of the possible explanations for this phenomenon is the attempt of the Bangladesh government to promote education for women, which is why younger women have high education levels and are more likely to seek healthcare services (Young *et al.*, 2006).

Another important predictor of healthcare utilisation is sex. It is one of the most commonly studied socio-demographic factors. Research has revealed that females are significantly more likely to seek healthcare services than males (Dias *et al.*, 2011; Otwombe *et al.*, 2015; Abera Abaerei, Ncayiyana and Levin, 2017). However, cultural differences also have to be considered, such as the case in Vietnam, where males are more likely to seek healthcare services (Thorson, Hoa and Long, 2000).

Then, marital status is another significant predictor of healthcare utilisation (Goodman, 2010). When it comes to preventive healthcare services and primary healthcare services, married people are found to utilise them more than unmarried ones (Hanske *et al.*, 2016; Bjørnelv *et al.*, 2020). However, another study found that widowed and divorced people use healthcare services more frequently than married ones when it comes to curative treatment like hospitalisations, but the ones that are never married utilised healthcare services less (Joung, Van der Meer and Mackenbach, 1995).

In relation to the social aspect of healthcare utilisation, some important predictors are education level and employment status. Education level is an important predictor of healthcare utilisation, where a higher level of education is associated with higher utilisation of healthcare services (Taffa and Chepngeno, 2005; Chakrabarti *et al.*, 2013; Muriithi, 2013). Education level is related to various other factors that are related to healthcare utilisation, such as income level and poorer self-reported health (Feinstein *et al.*, 2006; Raghupathi and Raghupathi, 2020). However, the relationship between education level and healthcare utilisation is quite complex. On the one hand, education positively impacts positive health behaviours, decreasing the need for healthcare services (Feinstein *et al.*, 2006). At the same time, higher education levels also positively correlate with seeking preventive healthcare services (Sabates and Feinstein, 2006).

Then, when it comes to employment status, it has been found that employed people are more likely to use healthcare services (Abera Abaerei, Ncayiyana and Levin, 2017). On the other hand, retirement actually decreases the use of healthcare services (Frimmel and Pruckner, 2020). Employment status is also related to other factors in healthcare utilisation since employed people are more likely to be covered by insurance (Abera Abaerei, Ncayiyana and Levin, 2017). However, external factors will also affect the impact of employment status on the healthcare situation, such as the case in Sweden, where during an economic recession, unemployed people utilise healthcare services more than employed people (Macassa *et al.*, 2014).

Another critical aspect of the predisposing factor is health beliefs. It is the "attitudes, values, and knowledge people have about health and health services" (Andersen and Davidson, 2007). Health beliefs are a strong predictor of healthcare utilisation (Strain, 1991). Even after controlling the socio-demographic and health-related variables, health beliefs still show a strong influence on healthcare utilisation (Agyemang-Duah and Rosenberg, 2023).

The various predisposing factors have been found to impact healthcare utilisation based on various studies. However, a majority of these studies use regression analysis, which focuses on how each factor influences healthcare utilisation (Babitsch, Gohl and von Lengerke, 2012). Further research on how these factors will affect healthcare utilisation when put together is vital to provide a deeper understanding of the crucial factors that influence healthcare utilisation in real-life settings.

3. Theoretical Framework

This chapter focuses on the theoretical framework which will guide the research approach, data analysis, and discussion of this study. Two frameworks are mainly used when discussing healthcare utilisation, which are Penchansky and Thomas' access framework and Andersen's health behaviour model. Penchansky and Thomas' framework of access focuses on the fit between the patient's needs and the system's ability to meet those needs, where access is characterised by affordability, availability, accessibility, accommodation, and acceptability (Wyszewianski, 2002; Ngwakongnwi, 2017). On the other hand, Andersen's health behaviour model focuses on individual behaviours, recognising the three determinants for the behaviour: (1) characteristics of the health delivery system, (2) population, and (3) external environment (Andersen and Newman, 1973; Ngwakongnwi, 2017). Therefore, in relation to the research question of this study, Andersen's health behavioural model will be used as the framework.

Andersen's behavioural model for health services utilisation has undergone several revisions since its initial conception in the 1960s. The first phase of the model focuses on trying to understand people's use of health services based on their predisposition, the factors that enable them to use the health services and the need for care (Goodman, 2010). The original model emphasised the importance of the family unit, where variations in the use of healthcare services can mainly be explained by the need factor, measured by families' perception of illness and their response to it (Andersen, 1968). Andersen (1968) also noted that the need factor is crucial where family discretion is less important, such as inpatient healthcare services. On the other hand, when it comes to services that require more family discretion, such as dental services, the predisposing components – family composition, social structure, and health beliefs – as well as the enabling components – family and community resources – are more important (Andersen, 1968). The initial model of the behavioural model is illustrated in Figure 1 below.

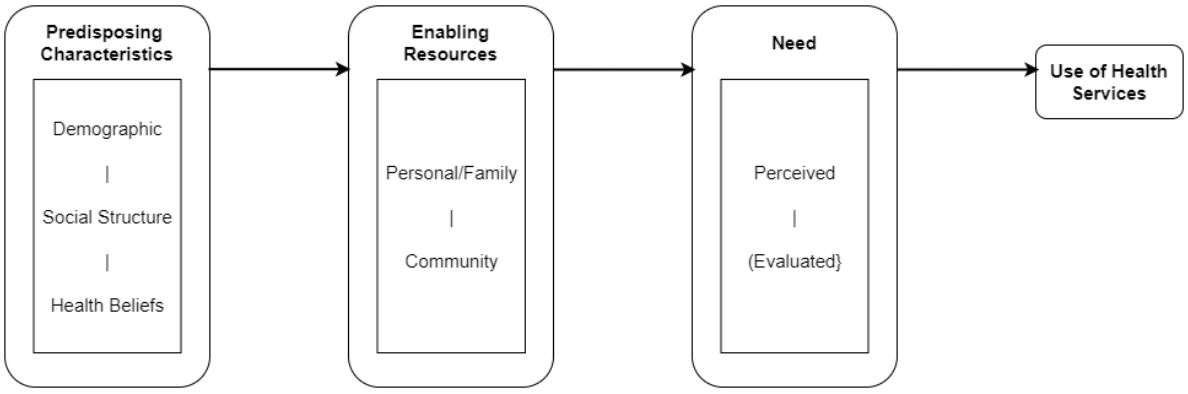

Figure 1: Phase 1 of Andersen's Behavioural Mode – 1960s (Andersen, 1995)

The second phase of the model was developed after the topic of access gained more attention among healthcare services policymakers and consumers in the 1970s. Aday and Andersen (1974) stressed that accessibility is more than the availability of healthcare services; it is also the willingness of individuals to seek care. Instead of using family as the analysis unit, the new model emphasised the use of individual as the analysis unit (Chen and Gu, 2020). Furthermore, the healthcare system was explicitly included to highlight the importance of national health policy and healthcare services organisation, as proven by the addition of organisation as part of the enabling factor (Andersen, 1995). The second model also incorporated the customer satisfaction component as the outcome beyond healthcare utilisation, which is measured through service convenience, availability, quality, and provider's characteristic (Aday and Andersen, 1974; Andersen, 1995; Chen and Gu, 2020). Finally, the new model elaborated on the use of the health services component, explaining that it is measured through its type, site, purpose, and time interval (Aday and Andersen, 1974). The model developed during this second phase can be seen in Figure 2 below.

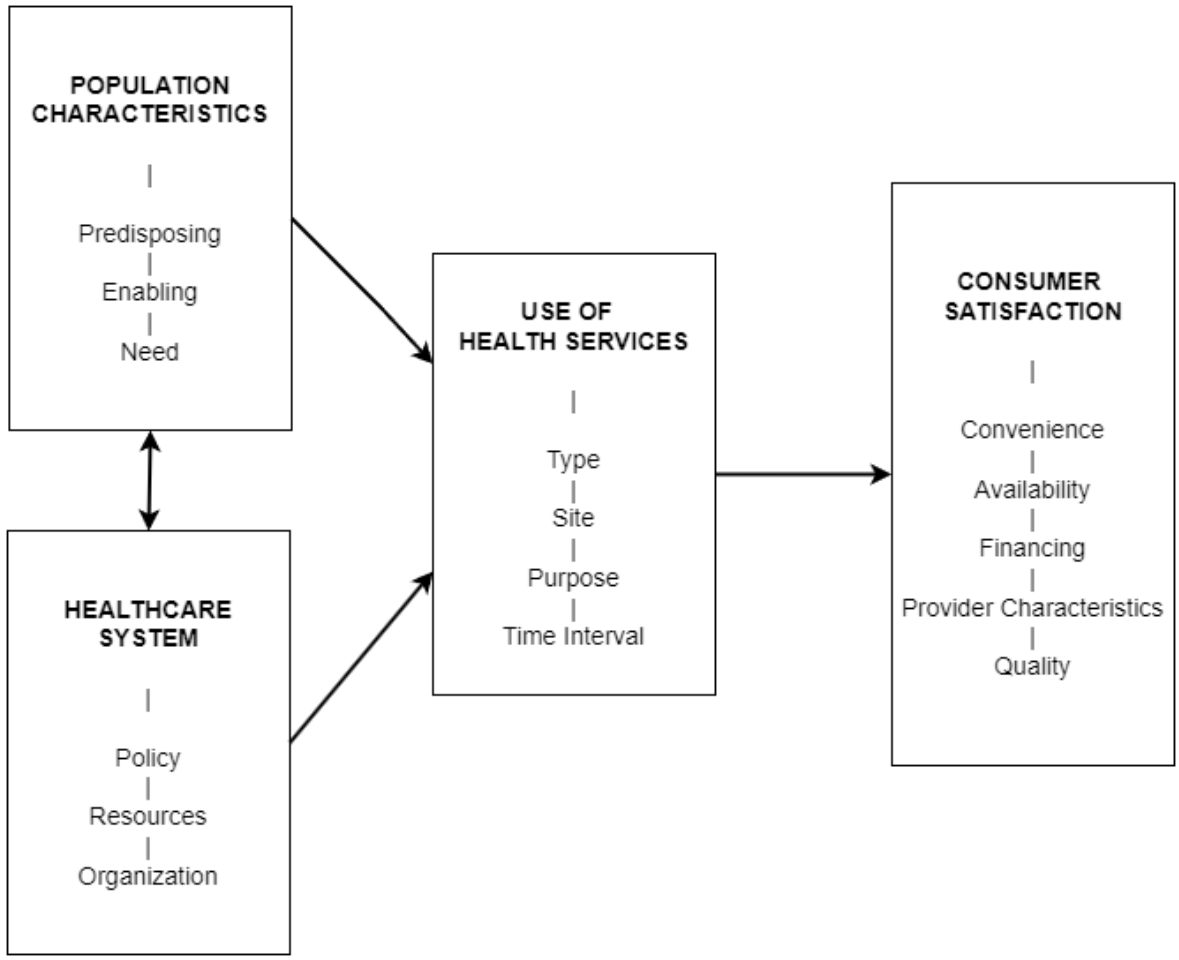

Figure 2: Phase 2 of Andersen's behavioural model – 1970s (Aday and Andersen, 1974; Andersen, 1995)

The third phase of the model, which evolved in the 1980s and early 1990s, was developed in regards to the explicit recognition of the role of health services in maintaining and improving the population's health status (Andersen, 1995; Chen and Gu, 2020). Figure 3 below portrays the third phase of the model. It restructured the model into three main components, which are primary determinants of health behaviour, health behaviour, and health outcomes (Andersen, 1995). Primary determinants of health behaviour comprise population characteristics, the healthcare system, and the external environment (Andersen, 1995). The external environment was added to the model to highlight the importance of contextual factors, such as physical, political, and economic factors (Chen and Gu, 2020). Then, the model recognised that healthcare services are part of the health behaviour component, which also includes personal health practices (Chen and Gu, 2020). Finally, the model acknowledged the influence of health behaviour on health outcomes, which was expanded to include perceived and evaluated health

status while also including consumer satisfaction (Andersen, 1995). These changes allow the inclusion of the measurement of access, which are effective access – measured by consumer satisfaction – and efficient access – measured by health status and the amount of healthcare utilisation (Andersen, 1995).

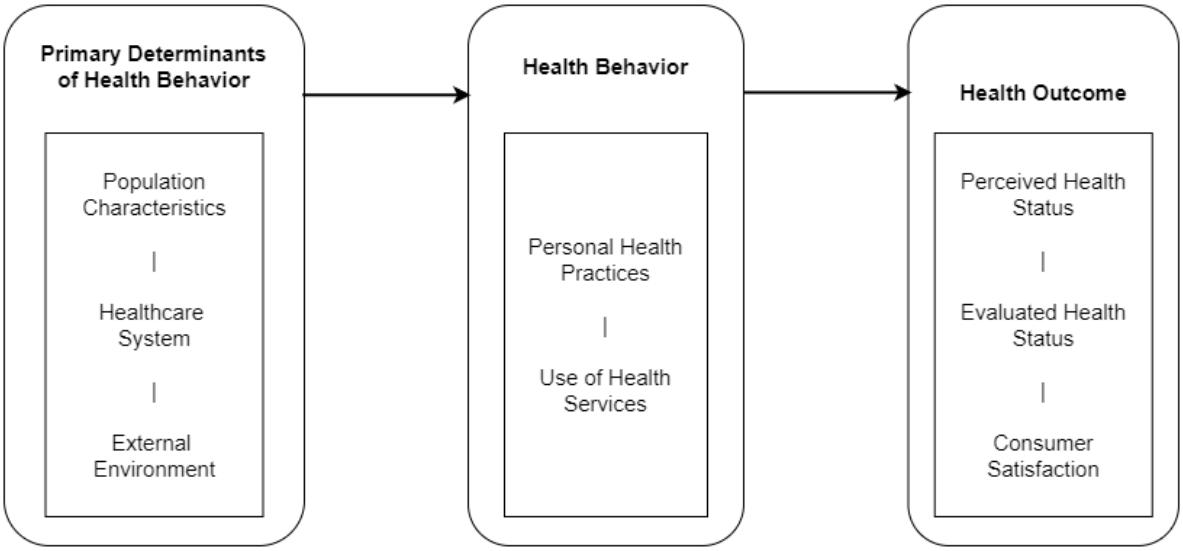

Figure 3: Phase 3 of Andersen's behavioural model – 1980s-1990s (Andersen, 1995)

Recognising the dynamic and recursive nature of the use of healthcare services, Andersen revised the model again in the late 1990s. The fourth phase of the model went back into a four-component model consisting of environment, population characteristics, health behaviour, and health outcomes, with the addition of a feedback loop to show that health outcomes will affect population characteristics (Andersen, 1995). Furthermore, the direct influence of the environment and population characteristics component is shown (Chen and Gu, 2020). The complexity of the fourth phase of the model is illustrated in Figure 4 below. As can be seen in the model, the three components of the initial model – predisposing characteristics, enabling resources, and need – are part of the population characteristics.

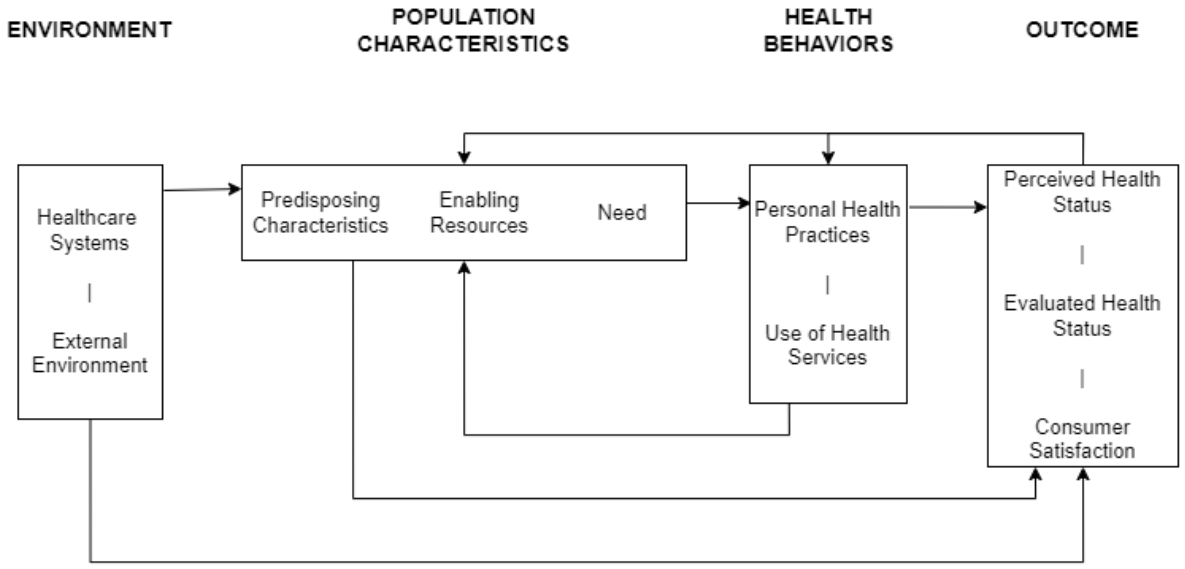

Figure 4: Phase 4 of Andersen's behavioural model – 1995 (Andersen, 1995)

In the 2000s, Andersen would once again revise his behavioural model. The fifth phase of the model analysed the three components – predisposing, enabling, and need – into two-level, contextual and individual determinants (Andersen and Davidson, 2007). Contextual determinants are measured at an aggregate level, from the level of the family unit to the national health care system. It emphasises the importance of community, structure, the process of providing care, and the realities of the care environment (Chen and Gu, 2020). On the other hand, the individual determinants are measured at an individual level. Both contextual and individual determinants have the same factors to measure access, similar to the initial model, which is: (1) predispose conditions that influence people to use or not use services; (2) enabling conditions that facilitate health services use; and (3) need or conditions that are recognised as requiring medical treatment (Andersen, 1995; Andersen and Davidson, 2007) . Another important addition to the model is the inclusion of the medical care process as part of health behaviour to explain how consumer satisfaction and healthcare utilisation affect healthcare providers' interaction with patients. The illustration of the behavioural model of health services use can be seen in Figure 5.

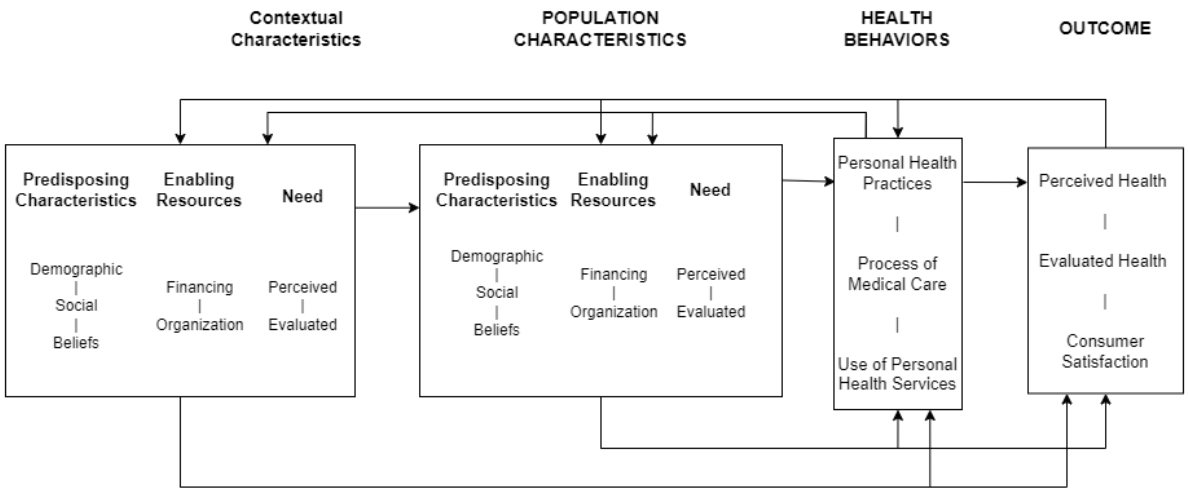

Figure 5: Phase 5 of Andersen's behavioural model – 2000s (Andersen and Davidson, 2007)

The contextual determinants may affect health behaviours and outcomes in various ways, including their influence on the individual determinants. The three components of contextual determinants are contextual predisposing characteristics, contextual enabling characteristics, and contextual need (Chen and Gu, 2020). When it comes to contextual predisposing characteristics, the focus is on demographic and social characteristics at a community level. Andersen and Davidson (2007) further stressed that the demographic of a community, e.g. age, gender, and marital status, may influence the type of health services and facilities that are available in the area where the community resides. Then, the social characteristics explain how beneficial or detrimental people's living and working environment is to their health and ability to access health services, which includes educational level, ethnicity composition, crime rate, etc. Aside from the two characteristics, the fundamental values and norms within the community also determine how health services are organised, financed, and accessed by the population.

Another important contextual determinant is contextual enabling characteristics (Chen and Gu, 2020). It refers to health policies related to the pursuit of health, which include the financial aspect and organisation of health services (Andersen and Davidson, 2007). The financial characteristics depend on the available resources to pay for health services. On the other hand, the organisational aspect depends on the number of health services facilities and personnel and how the health system is structured.

Finally, regarding contextual determinants, there is a contextual need characteristic. It refers to the health-related measure of the physical environment of a community, including the quality of housing, water, and air (Andersen and Davidson, 2007). Aside from the physical environment, population health indices are also used as a general indicator of community health, such as infant mortality and the prevalence of a specific disease (Andersen and Davidson, 2007).

Aside from the contextual determinants, individual determinants are also as important. Similar to contextual determinants, individual determinants also consist of three factors, which are individual predisposing characteristics, individual enabling characteristics, and individual need characteristics (Chen and Gu, 2020). Individual predisposing characteristics are concerned with demographic factors, social factors, and health beliefs of an individual (Andersen and Davidson, 2007). Andersen and Davidson (2007) explained that demographic factors include age, gender, and other biological imperatives that affect one's likelihood of needing health services. Then, the social factors affect an individual status in a community and one's ability to cope with a particular problem. It is not only an individual education and occupation but also encompasses people's social networks and interactions. Finally, health beliefs are the attitudes, values, and knowledge about health that influence the perception of needing health services.

Another important part of the individual determinants is individual enabling characteristics. Just like in the contextual determinants, the individual enabling characteristics focus on the financing aspect and organisation of health services (Andersen and Davidson, 2007). At the individual level, the financial aspect refers to the individual income and wealth, and the organisation of health services refer to the availability of health services, including the means of transportation to access health services.

Finally, individual need characteristics are also included in the model. The individual need characteristics focus on evaluated need and perceived need for health services (Andersen and Davidson, 2007). The evaluated need is the professional judgement and objective measurement of one's physical status and needs for medical care. On the other hand, perceived need is the people's view of their general health and functional state, including their experience and responses to symptoms of illness or health problems.

Andersen and Davidson (2007) further described three components of health behaviours, which are personal health practices, the use of personal health services, and the process of medical care. Personal health practices are behaviours of an individual that will impact their health status, including diet and nutrition, exercise, alcohol and tobacco use, and many more. Then, the process of medical care is defined as the behaviours of providers when interacting with patients when delivering care, such as patient counselling and education. Finally, personal health services refer to health behaviours in a comprehensive model of access to care, such as the number of health services visits. In fact, the original behavioural model is designed to predict the use of personal health services.

The last part of the behavioural model framework is health outcome, which is affected by individual health behaviours, as well as their contextual and individual characteristics. It evaluates both perceived and evaluated health status, as well as customer satisfaction. Perceived health status measures an individual's capability to live a functional and pain-free life. The evaluated health status depends on the professional judgment of individual health status, both their diagnosis and prognosis. Both perceived and evaluated health statuses are measured the same way as the need characteristics. Finally, customer satisfaction refers to how individuals feel about the health care that they receive.

The final model – the sixth version – was developed in the 2010s and is believed to be the most comprehensive model (Chen and Gu, 2020). The new model adds genetic factors as part of the individual predisposing characteristics, as well as quality of life as part of the health outcomes (Chen and Gu, 2020).

Over the years, Andersen's behavioural model for health services use has undergone several revisions to accommodate newly discovered information. However, the model also contains some limitations. Some of the unaccounted variables that are understudied and may have huge implications in the healthcare utilisation model, such as the decreasing influence of the resources factors, are technological advancement, mass media campaigns, and improved universal healthcare system (Chen and Gu, 2020; Liu *et al.*, 2020). For example, regarding technological advancement, better medicines may reduce healthcare utilisation, but chemotherapy and radiotherapy for cancer may increase healthcare utilisation. Then, when it comes to older adults, another factor that may impact healthcare utilisation is the emergence of loss and changes (Travers, Hirschman and Naylor, 2020). It can disrupt their way of life and

resources, which later may result in the loss of hope and identity, as well as decrease their well-being (Bergin and Walsh, 2005; Olsen, 2013; Travers, Hirschman and Naylor, 2020). The integration of this factor when studying older adults using the Andersen behavioural model can be a key point.

Another criticism of Andersen's model is the measurement of access to healthcare services itself. Some argued that instead of the actual utilisation, subjectively rated access to healthcare is more informative in measuring access to care and health outcomes (Zhang *et al.*, 2017; Chen and Gu, 2020). Subjectively rated access to healthcare contains information on whether the healthcare services meet the patient's need, whether the patient got timely treatment, the barriers in access to care, the satisfaction of the care, and other perceived dimensions (Hao *et al.*, 2020).

Finally, Andersen's model has also been noted for its lack of studies focusing on various populations and subpopulations (Chen and Gu, 2020). For example, when it comes to healthcare utilisation for severe conditions, the need factor will play an important role. However, when it comes to the least severe conditions, the enabling factor will play an important role (Chen and Gu, 2020). The issue with these patterns is that the model has not been actively validated across different demographics. However, such understanding is believed to be crucial in understanding the mechanism and patterns of healthcare utilisation (Chen and Gu, 2020).

All in all, Andersen's behavioural model of health services use has been through many changes and revisions to explain healthcare utilisation better. Each revision considers the criticisms and newly discovered knowledge that adds to the complexity of the model. In order to examine the factors that influence healthcare utilisation among rural older adults in South Africa, the fifth version of the model will be used. In particular, this study will focus on individual determinants, examining the influence of individual predisposing characteristics, individual enabling characteristics, and individual need characteristics on the use of personal health services.

4. Methodology

This section focuses on the methodological process applied in this study. The research design, participants criteria, and sampling will be elaborated here. Then, the information about the variables used in this study and the process of coding will be explained. Finally, this chapter will also contain the ethical considerations and limitations of this study, as well as the author's positionality concerning the topic.

4.1 Research Design

This study utilises a quantitative research approach with a survey design by doing a secondary analysis of an existing dataset. Quantitative research aims to objectively test theories by examining the relationships between variables (Creswell and Creswell, 2018). Quantitative research provides several benefits in the development field. Some of the strengths of quantitative research are: (1) greater accuracy of results by using pre-established statistical results; (2) greater generalisability by studying large sample size; (3) ability to compare data over time and across different populations; and (4) ability to provide an objective standpoint (Wilson, 2019). By using quantitative research, the result gained from analysing the sample population can be generalised to the general population (Wilson, 2019). Despite the benefits, some limitations of using quantitative research are the inability to provide context and behavioural aspects of the result, and using a survey with preset answers may not be reflective of the actual conditions and lead to bias (Wilson, 2019).

Quantitative research can be divided into two categories, which are experimental research and descriptive or survey-based design (Creswell and Creswell, 2018; Wilson, 2019). Experiments focus on determining whether a specific treatment affects an outcome, while surveys focus on quantitative description of trends within a population by studying a sample of the population (Creswell and Creswell, 2018). Survey-based design involves a wide range of types, from national census data to small-scale project-based surveys (Hammett, Twyman and Graham, 2015). The ability to collect reliable, valid, and unbiased data from a sample population is one of the objectives of using a survey-based design (Wilson, 2019).

Surveys can be categorised by traditional surveys, such as face-to-face, mail, or telephone surveys, and online surveys (Mutepfa and Tapera, 2019). Traditional surveys are suitable for

collecting data in rural and remote areas since not everyone has internet access, which causes sample selection bias (Mutepfa and Tapera, 2019). However, conducting a traditional survey with a large sample size can be expensive and time-consuming, which may not be feasible for everyone (Smith *et al.*, 2011). In such cases, using an existing dataset can be the solution to conduct high-quality studies that address high-impact questions (Smith *et al.*, 2011).

The rapidly growing existing datasets in development research have driven the increase of secondary analysis of existing datasets since it is a cost-efficient way to use data that are already collected to address new research questions (Cheng and Phillips, 2014; Hammett, Twyman and Graham, 2015). Aside from the advantage of it being low cost and being collected by professional staff members, researchers must also be aware of its disadvantages, such as the lack of availability of important third variables and the unawareness of study-specific nuances in the data collection process that may influence the interpretation of specific variables (Cheng and Phillips, 2014). Furthermore, the observational nature of an existing dataset makes it hard to assess causality (Smith *et al.*, 2011).

When it comes to quantitative research, regardless of the research designs, the emphasis on objective measurement signifies the importance of reliability and validity (Creswell and Creswell, 2018). Reliability is concerned with measurement consistency, while validity is concerned with whether a concept truly measures what it says it does (Bryman, 2016). There are three types of reliability: test-retest reliability, internal reliability (or internal consistency), and inter-observer consistency. The test-retest reliability implies that the test result will remain the same even if the test is re-taken later, while inter-observer consistency implies that the test result will remain the same even if different observers are doing the judgement (Chiang, Jhangiani and Price, 2015). Then, internal reliability is achieved when multiple measures that are administered at the same time are consistent and are usually measured using Cronbach's alpha coefficient (Bryman, 2016). Then, regarding validity, there are also several types of validity, which are face validity, concurrent validity, and construct validity (Bryman, 2016). Face validity is established when the measurement reflects the content of the concept and can be fulfilled by asking the judgement of an expert in the field, while concurrent validity is established when one's score on the measurement is correlated with the score on other variables that are expected to correlate with (Chiang, Jhangiani and Price, 2015). Finally, content validity is established when the concepts in the research are related to one another in the way the theory predicts it to be (Bryman, 2016).

4.2 Data Source

This study uses the data from Health and Aging in Africa: A Longitudinal Study of an INDEPTH Community in South Africa (HAALSI) conducted by Lisa F. Berkman (2023) with funding from the United States Department of Health and Human Services, the National Institute of Health, and the National Institute of Aging. The project is part of the Harvard Center for Population and Development Studies, in partnership with the MRC/Wits Rural Public Health and Health Transitions Research Unit (Agincourt) of the University of Witwatersrand (*HAALSA Data*, no date). Further information about the data sources is explained below.

4.2.1 Study Design, Participants Criteria, and Sampling

The HAALSI study aims to examine and characterise a population of older men and women in rural South Africa regarding health, physical and cognitive functioning, ageing, and well-being, in regard to other Health and Retirement Studies. It is a longitudinal study that aims to monitor social, economic, and biological risks for chronic health conditions, both infectious and non-infectious (Gómez-Olivé *et al.*, 2018).

The study was conducted in the Agincourt sub-district in Mpumalanga Province, South Africa (Gómez-Olivé *et al.*, 2018). The participants in this HAALSI study were sampled from the existing framework of the Agincourt Health and Socio-Demographic Surveillance System (AHDSS) in Mpumalanga province, South Africa. The study area consists of 31 villages and covers an area of 450 km2, with a total population of 116.000 people (Gómez-Olivé *et al.*, 2018). People above 40 years old and have been permanently living in the study site for the previous 12 months were eligible for the study. Using the 2013 census data, 8.974 women and 3.091 men above 40 years old who met the residence criteria were identified. Using the power calculations for key health outcomes, the target sample size was approximately 5.000 completed interviews, divided equally between men and women. The data is collected through traditional methods, which are telephone surveys and face-to-face surveys. In the end, a total of 6.281 people were randomly selected for the longitudinal study at 3-year intervals. Out of the people selected for the study, a response rate of 85,9% is reported, meaning there are 5.095 completed surveys.

The data collected for the second wave of the data collection, conducted between 2018 and 2019, will be used for this study. From the original 5.095 respondents, a total of 4.176 individuals responded to the second wave of the data collection. The main reason for individuals not following up on the second round is deaths (Riumallo Herl *et al.*, 2022).

4.3 Structural Equation Modelling (SEM)

Structural Equation Modelling (SEM) is a multivariate statistic used for describing relationships between observed variables which seeks to understand the structure of interrelationships (Hair *et al.*, 2019; Jitesh J. Thakkar, 2020). The primary advantage of SEM is that it estimates the relationships between latent variables and observed variables (Jitesh J. Thakkar, 2020). Latent variables (LV) are variables that cannot be measured directly, such as happiness or intelligence, while observed variables (OV) are variables that can be measured directly and can be used to estimate latent variables, such as age and income (Jitesh J. Thakkar, 2020).

SEM has some advantages and disadvantages in comparison to regression analysis. The advantages are (1) the ability to analyse the influence of independent variables on several dependent variables, (2) the ability to test the entire theoretical model instead of focusing on individual relationships, and (3) the ability to take measurement error into account when doing the analysis (Schumacker and Lomax, 2015; Collier, 2020). Measurement error happens when there is a miscalculation in measuring the 'true' value of variables due to the imperfect tools (Hair *et al.*, 2019). However, one of the main limitations of SEM is the requirement of a large sample size, especially if the data does not meet the assumption of multivariate normality and if there is more than 10% missing data (Hair *et al.*, 2019). It is also important to note that SEM does not explain causalities between the variables but rather explains the correlations between variables and how they influence one another (Collier, 2020).

There are several techniques for doing SEM, one of which is factor analysis. Factor analysis is divided into exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Jitesh J. Thakkar, 2020). EFA is employed to determine whether the observed variables measure the latent variables and whether the latent variables are correlated; thus, it does not have a specific theoretical foundation (Schumacker and Lomax, 2015; Hair *et al.*, 2019). On the contrary, CFA

requires a solid theoretical foundation and is used to examine whether the measurement model fits the empirical data (Schumacker and Lomax, 2015; Hair *et al.*, 2019).

In order to understand the factors that influence healthcare utilisation among rural older adults in South Africa, this study is implementing Andersen's behavioural model of health services use. It becomes the theoretical foundation of this study. This study will employ CFA to test whether Andersen's behavioural model fits the empirical data from rural older adults in South Africa regarding the use of healthcare services.

4.3.1 Variables and Factor Loadings

In CFA, ideally, latent variables must be measured by at least three observed variables, and each observed variable only loads on one latent variable (Hair *et al.*, 2019). The latent variables can either be exogenous variables – variables that are not influenced by other variables in the model – or endogenous variables – variables that are influenced by other variables in the model (Jitesh J. Thakkar, 2020). In other words, exogenous variables are independent variables, while endogenous variables are dependent variables.

The correlation between the latent variables and its observed variables can be estimated through factor loadings (Bowen and Guo, 2011). Factor loading is the direct effect estimation of observed variables to latent variables or exogenous variables to endogenous variables (Collier, 2020). A high factor loading implies a strong relationship between observed variables and latent variables, which means the observed variables are a good indicator of the latent variables (Hair *et al.*, 2019). Factor loadings also depend on sample size, where a larger sample size allows for lower factor loadings to be accepted (Hair *et al.*, 2019). For example, for a sample that exceeds 350 cases, factor loading with a value of 0.30 is considered significant (Hair *et al.*, 2019). Overall, factor loading in the range of 0.30 to 0.40 is considered the minimal level for interpretation, whereas loadings exceeding 0.50 are considered significant (Hair *et al.*, 2019). However, loadings above 0.70 are the goal of factor analysis since it signifies that it is a well-defined structure (Hair *et al.*, 2019).

In this study that examines Andersen’s behavioural model of health services use, four latent variables are examined: the predisposing factor, need factor, enabling factor, and healthcare utilisation. Among these latent variables, healthcare utilisation is the endogenous variable,

while the exogenous variables are the predisposing factors, need factors, and enabling factors. The observed variables in this study will be elaborated below.

4.3.2 Reliability and Validity

As mentioned above, reliability and validity are key points in quantitative research. Therefore, when doing CFA, reliability must first be established (Hair *et al.*, 2019). Reliability is important since it shows the consistency of the variables being measured, where high reliability is associated with low measurement errors (Hair *et al.*, 2019). Although Cronbach's Alpha is commonly used for measuring reliability, composite reliability is believed to be more suitable when doing CFA since it considers the factor loadings of each item (Cheung *et al.*, 2023). Therefore, this study will use composite reliability.

Validity is just as important as reliability when it comes to quantitative research. One of the validity measurement types is content validity, which shows that the variables are related to the way the theory predicts it (Bryman, 2016). In this case, content validity is reflected in the CFA result since CFA reflects how well the fit between the empirical data and theoretical model. Therefore, a good fit based on the CFA result indicates good content validity, meaning that the variables relate to how the theory predicts it.

4.3.3 Measurement Model

Another key aspect of the CFA technique is specifying the measurement model or path diagram. The measurement model is built based on the theory used for the CFA. Due to its foundation on a theoretical model, it is ideal to do a pretest using pilot data to ensure that the empirical test fits the measurement model (Hair *et al.*, 2019). However, this study will skip this step since it uses an existing dataset. Figure 6 displays the measurement model in this study, based on Andersen's behavioural model of health services use. Several symbols can be seen in the model. The ellipses represent the latent variable, while the rectangles represent the observed variables. The arrows describe the relationships of the variables. For example, the need, enabling, and predisposing factors have arrows pointing to healthcare utilisation, signifying that these factors influence healthcare utilisation. Finally, there is a circle pointing to each observed variable on the figure, portraying each variable's measurement error or residual. This measurement model will be used to examine the factors that influence healthcare utilisation among rural older adults in South Africa.

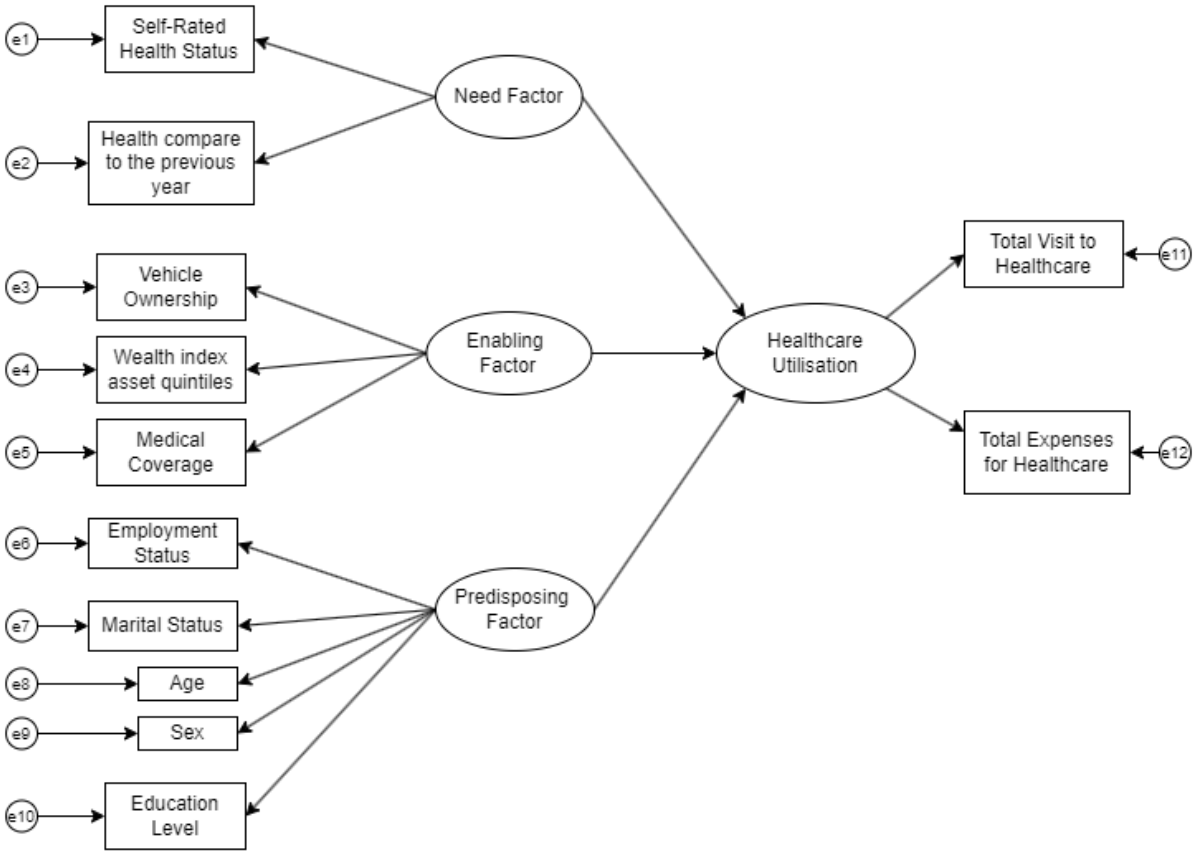

Figure 6: CFA Measurement Model based on Andersen's Behavioural Model

4.3.4 Missing Values

Missing value is a common occurrence in almost all types of research and can be defined as data value that is not available in the observation data (Kang, 2013). Missing data must be dealt with since it may reduce the statistical power and cause bias in the analysis (Kang, 2013). There are several types of missing data, such as missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Both MCAR and MAR mean that there is randomness in the missing data. However, MCAR indicates that the missingness is unrelated to any variables, while MAR indicates that the missingness is related to observed variables (Hair *et al.*, 2019). On the other hand, MNAR implies a non-random pattern of missing data that depends on unobserved data (Hair *et al.*, 2019). Identifying the type of missing data is crucial in deciding how to handle the missing data. Some procedures in handling missing data are listwise or case deletion – omitting the cases with missing data and using the remaining data for analysis and full information maximum likelihood (FMIL) imputation – using information in a dataset to substitute for the missing data points (Kang, 2013; Hair *et al.*, 2019).

Listwise deletion is the most commonly used method and is considered ideal when the missing data is MCAR, and there is a large enough sample so that power is not an issue (Kang, 2013). On the other hand, FMIL is considered to produce less bias than other missing data procedures (Hair *et al.*, 2019). However, some studies prove otherwise, where listwise deletion produces less bias on MNAR (Pepinsky, 2018). In the end, the researcher must decide which missing data procedures work best in the study.

4.4 Variables

This part will elaborate on the four latent variables that will be the focus of this study following Andersen's behavioural model, which are healthcare utilisation, need factor, enabling factor, and predisposing factor.

4.4.1 Healthcare Utilisation

Healthcare utilisation represents the use of healthcare services by the study participants. Aday and Andersen (1974) discuss that healthcare utilisation can be categorised by type, site, purpose, and time interval. However, in this study, the measurement for healthcare utilisation will be based on the study by Beidelman *et al.* (2023), who also use the HAALSI data, where the healthcare utilisation variable is measured through two observed variables, which are the total visit to healthcare services in the past three months and the total spending for healthcare services. The healthcare services measured in this study include public clinics and hospitals, as well as private clinics, doctors, hospitals, and pharmacists. Both variables are based on self-reported by the study participants, as self-reported healthcare utilisation data in the past year is as accurate as the data based on medical records (Roberts *et al.*, 1996; Dalen *et al.*, 2014).

4.4.2 Need Factor

The need factor consists of evaluated and perceived health status (Andersen and Davidson, 2007). Only perceived health status, or self-rated health status, will be used in this study, as it is as reliable as evaluated health status (Short *et al.*, 2009; Kapteyn and Meijer, 2014). To provide a comprehensive picture of perceived health status, the self-rated current health status and the health comparison to the previous year are used as observed variables for the need factor.

4.4.3 Enabling Factor

There are two categories of enabling factors: the financing and organisation of health services (Andersen and Davidson, 2007). The financing aspect includes the wealth available to the individual, as well as the effective price of healthcare services, such as health insurance. In this study, the financing aspect is measured through information on the participants' wealth asset index quintiles and medical coverage. The wealth index was created from principal component analysis of household characteristics and ownerships of items, vehicles, and livestock (Gómez-Olivé *et al.*, 2018). Then, regarding the organisational aspect, due to the lack of available data on the healthcare services location, it is solely measured through vehicle ownership, which represents the transportation needed to access the healthcare services.

4.4.4 Predisposing Factor

Andersen and Davidson (2007) elaborated three factors that are part of the predisposing factor, which are demographic factors, social factors, and health beliefs. In relation to the demographic factor, the variables of age, sex, and marital status will be used in this study. Each of these variables has been proven to be a predictor of healthcare utilisation (Rennemark *et al.*, 2009; Goodman, 2010; Abera Abaerei, Ncayiyana and Levin, 2017). Then, social factors, the representation of a person's status in the community, will be measured by education level and employment status (Andersen and Davidson, 2007). Health beliefs will not be used in this study due to the lack of available data in the dataset.

4.5 Data Analysis Process

Two statistical analysis software used for the data analysis in this study are IBM SPSS version 29 and AMOS version 29. The original dataset is processed in the SPSS to be cleaned and organised. Since this study uses the second wave of the data collection, only respondents whose data are available for the second wave of the data collection were selected. Each variable will undergo initial checking to determine whether the missing value contains information. At the same time, the recorded data of “do not know”, “refused to answer”, and “empty” will be recoded as missing values. After the data is organised, descriptive analysis will be done. Then, the pattern of the missing value will be analysed. The missing values among the variables in this study indicate a non-random pattern, which means that it is an MNAR. The FMIL and listwise deletion methods are applied to compare the results of each method. The CFA results

show that the results are similar, whether using FMIL or listwise deletion to deal with the missing values, indicating no particular bias regardless of the missing value treatment method. However, listwise deletion will be used in this study since it supports the adjustment of modification indices in CFA. After listwise deletion, the data will be analysed with confirmatory factor analysis. The procedure is as follows:

4.5.1 Descriptive Analysis

The descriptive analysis of this study will be done using IBM SPSS version 29. It will provide information about the overall characteristics of the study population. Out of all the variables, age, total visits to healthcare, and total healthcare expenses will be presented using the variables' mean, median, mode, minimum, and maximum values. On the other hand, the rest of the variables will be presented in frequency tables.

4.5.2 Confirmatory Factor Analysis

The second analysis of this study is the confirmatory factor analysis. In this part, the measurement model, or path diagram, will first be constructed based on Andersen's behavioural model. Figure 6 above is the illustrated measurement model. After that, a composite reliability test will be conducted to gain information on the internal consistency of the data.

The measurement model will be analysed once the reliability data has been collected. There will be several model fit indices to evaluate the model fit. Depending on the result of the model fit indices, some adjustments to the model can be considered. For example, the factor loading estimation of each variable can be evaluated. Variables with extremely low factor loadings can be eliminated from the model since it indicates that the variables barely influence the corresponding factor.

Aside from that, additional model diagnostics can also be obtained for suggestions on how to adjust the model so that the fitness can be improved, such as with modification indices (Hair *et al.*, 2019). Modification indices show the potential paths between variables that, if it is correlated, will improve the model fit (Collier, 2020). The modification indices of 4.0 or higher suggest the variables that may be related, and by acknowledging the correlation between these variables, the model fit indices can be improved (Hair *et al.*, 2019). However, modification indices should be done carefully and with good justifications (Collier, 2020).

4.6 Ethical Consideration

The HAALSI study is part of the Health and Retirement Study (HRS) conducted by the Harvard Center for Population and Development Studies in partnership with the MRC/Withs Rural Public Health and Health Transitions Research Unit (Agincourt) team from the University of Witwatersrand in South Africa. The HAALSI study collected personal data on the participant's health condition, which has received ethical approval from the University of the Witwatersrand Human Research Ethics Committee; the Harvard T.H. Chan School of Public Health, Office of Human Research Administration; and the Mpumalanga Provincial Research and Ethics Committee (Gómez-Olivé *et al.*, 2018). The data is also collected by trained local fieldworkers, either face-to-face or by telephone, which ensures that the data collection is easily understood by the participants. Participants were asked for consent for each part of the study, such as the questionnaire and the blood test. Furthermore, the study commits to do no harm to any participants so that all potentially identifying information has been removed. Finally, the study is funded by the National Institute of Aging.

This study also commits do no harm to the participants regarding confidentiality. All the data is processed following the ethical guidelines of Lumid. The researcher also further ensures that there will be no identifiable personal information about the participants.

Another consideration to be addressed is positionality, reflecting on the researcher’s position that may impact the study. As someone who studied psychology as an undergraduate, I tend to focus on psychological variables initially, such as subjective well-being. The awareness of the potential bias, added with my supervisor's guidance, helped me focus on variables that matter to the study. Furthermore, even though I also come from a middle-income country, since the study is using an existing dataset, I have not had a chance to visit the site of the study, making me unaware of other factors that may otherwise be important in the study site.

4.7 Limitations

Research limitations are common occurrences and are usually caused by the decisions of the researchers. Likewise, several limitations can be identified in this study. First of all, the use of secondary analysis on an existing dataset method causes the unavailability of certain variables that are part of the theoretical model, such as the health beliefs variable or the incomplete

information on the healthcare utilisation variable. Furthermore, regardless of how much the researcher tries to understand the dataset, the researcher may be unaware of study-specific nuances that are part of the data, which may cause certain biases in the analysis results.

The limitations of this study are also related to the choice of statistical analysis, SEM with CFA technique. When doing CFA, it is ideal to do a pilot test to ensure that the test or survey fits the measurement model. However, since this study uses an existing dataset, the pilot test is skipped, and there is no check of how well the test fits the model. In relation to the decision to do CFA, the result of the study is only able to show how the variables are related to one another. However, it does not explain causalities in the study. Not only that, but the use of quantitative research design causes the missing of context-specific information that may otherwise be available in a qualitative study.

In relation to the limitation based on the data itself, the existence of missing values also has the possibility of causing bias in the result, even after the researcher has tested different methods to deal with the missing values. The missing values in the dataset also cause bias in the researcher when choosing the variables to work with. For example, when analysing the enabling factor, instead of using the income variable, the researcher chose to use the wealth asset index quintiles since it has more complete data.

5. Result

This section presents the findings of this study, both the descriptive analysis and the confirmatory factor analysis. The descriptive analysis will inform about the distributions of the study population in regard to their need, enabling, and predisposing factors. Then, the confirmatory factor analysis will inform about the fitness between the theoretical and empirical models, as well as the factor loading estimations.

As part of the data analysis process, this study compares the use of FMIL and listwise deletion to see whether using either will introduce bias to the analysis that causes a significantly different analysis result. It turns out that the results of using FMIL and listwise deletion are similar. Therefore, this study uses listwise deletion as part of the missing value treatment since it allows for checking modification indices on the CFA result.

5.1 Descriptive Analysis

This section will present the descriptive statistics of the sample population to convey to the readers the background and characteristics of the study population. The information provided will focus on the socio-demographic background of the sample and data related to the need factor, enabling factor, and predisposing factor.

5.1.1 Predisposing Factor (Demographic Data)

Detailed information about the demographic distribution of the sample is presented in Table 1. It will include information on the study participants regarding their age, sex, marital status, employment status, and education level. The total sample of 4176 participants consists of 2314 female participants (55.4%) and 1862 male participants (44.6%). In terms of age, since the study is focused on older adults, the youngest participant is 43 years old, and the oldest participant is 115 years old, with the average age of the participants around 65.12 years old, though the mode age is 56.

The table below also presents other important demographic data. Regarding marital status, most study participants are currently married or living with a partner, accounting for 44.8% of the sample. Then, about 35% of the participants are widowed, and around 12% are separated

or divorced. Finally, 325 participants, or 7.8%, are never married. On the other hand, regarding employment status, more than half of the participants are not working, and only about 16% are employed, either full-time or part-time. Another information that is presented is regarding the education level of the participants. Most participants have no formal education (44.4%) or only received primary education (34.5%). However, about 12% of participants have secondary level education, and 9% have more than secondary level or more than 12 years of study.

The post-apartheid Agincourt population shows high unemployment rates, low education level, and low access to basic infrastructure, such as electricity, water, and good road conditions, compared to the general population in South Africa (Beidelman *et al.*, 2023; Mutola, Gómez-Olivé and Ng, 2023). However, it actually represents the typical rural South African adults (Gómez-Olivé *et al.*, 2018).

Table 1: Frequency Table of Socio-Demographic Factors of the Sample Participants

Demographic Information		**Number**	**Percentage**	**Cumulative Percentage**
Sex	Male	1862	44.6%	44.6%
	Female	2314	55.4%	100%
	Total	4176	100%	
Marital Status	Never Married	325	7.8%	7.8%
	Separated or divorced	518	12.4%	20.3%
	Widowed	1449	34.7%	55.1%
	Currently married or living with partner	1869	44.8%	100%
	Total	4161	99.6%	
Employment Status	No	3477	83.9%	83.9%
	Yes	669	16.1%	100%
	Total	4176		
Education Level	No formal education	1855	44.4%	44.5%
	Some primary (1-7 years)	1439	34.5%	79.1%
	Some secondary (8-11 years)	497	11.9%	91%
	Secondary or more (12+ years)	375	9.0%	100%
	Total	4166	99.8%	

Table 1: Descriptive Analysis Result of Age variable from the sample population

Age	**Numbers**
Mean	65.12
Median	64
Mode	56
Minimum	43
Maximum	115

5.1.2 Need Factor

This part will inform about the need factors of the study population, with a focus on self-rated health status. The participants were asked to rate their health condition on that day, depending on five levels: very good, good, moderate, bad, and very bad. The detailed information can be seen in Table 3 below. Most participants rated their health condition as good, while a very small percentage, about 2.2%, rated it as very bad. About 23% of participants believed their health condition was moderate. From here, it can be inferred that the majority of the participants perceived themselves as being in relatively good health.

Table 2: Frequency Table on Need Factors from the Sample Population

Need Factor		**Number**	**Percent (%)**	**Cumulative Percent (%)**
Self-Rated Health Status	Very Good	416	10.0	10.0
	Good	2041	49.1	59.1
	Moderate	965	23.2	82.3
	Bad	645	15.5	97.8
	Very Bad	92	2.2	100.0
	Total	4159	100.0	
Health compared to 1 year ago	Much Better	89	2.1	2.1
	Better	645	15.5	17.6
	Same	2664	64.1	81.7
	Worse	599	14.4	96.1
	Much Worse	162	3.9	100
	Total	4159	99.6	

5.1.3 Enabling Factor

Table 4 below illustrates the enabling factor related to healthcare utilisation of the sample population. It contains information regarding vehicle ownership, medical coverage, and the wealth index quintiles. Out of all the participants, most of the sample (89.9%) have no medical coverage. A similar trend can also be seen regarding vehicle ownership, with up to 84.1% of

participants not having any functional vehicles in the form of motor vehicles or motorcycles. In regards to the participants' wealth, the index quintiles, based on household spending, are used, where participants are divided almost equally between the five quintiles. Although the wealth asset index is put into quintiles, the unavailability of vehicle ownership and medical coverage confirms that the Agincourt population is experiencing a low level of SES (Mutola, Gómez-Olivé and Ng, 2023).

Table 3: Frequency Table on Enabling Factors of the sample participants

Enabling Factor		**Number**	**Percent (%)**	**Cumulative Percent (%)**
Medical Coverage	No	3737	89.9	89.9
	Yes	418	10.1	100
	Total	4155	100	
Vehicle Ownership	No	3513	84.1	84.1
	Yes	663	15.9	100
	Total	4176	100	
Wealth Asset Index Quintiles	1	844	20.2	20.2
	2	821	19.7	39.9
	3	822	19.7	59.6
	4	830	19.9	79.4
	5	859	20.6	100
	Total	4176	100	100

5.1.4 Healthcare Utilisation

This study focuses on healthcare utilisation as the dependent variable. It is measured by total visits to healthcare services in the last three months and total spending for healthcare services through self-reporting. When it comes to the number of times that participants visit healthcare, the average number is 1.15 times in the last 3 months, with a maximum visit of 102 times. On the other hand, the maximum spending for healthcare services is 6000 Rand, while the average spending of the participants is 31.437 Rand. It is also important to note that most of the participants did not visit any healthcare services or spend any expenses on healthcare services. The data showed us that there are huge disparities in healthcare utilisation, where a particular

group of people have high access to healthcare services. At the same time, most of the sample population does not utilise healthcare services.

Table 4: Frequency Table on Healthcare Utilisation of the sample participants

Total Visit to Healthcare Services in the last 3 months	Mean	1.154
	Median	1
	Mode	0
	Minimum	0
	Maximum	102
Total Spending for Healthcare Services in the last 3 months (in Rand)	Mean	31.437
	Median	0
	Mode	0
	Minimum	0
	Maximum	6000

5.2 Structural Equation Modelling (Confirmatory Factor Analysis)

This section is focused on answering the main research question of the study about the factors that influence healthcare utilisation and which factors have the strongest influence on healthcare utilisation. In order to answer the research question, confirmatory factor analysis is done to evaluate the model fit of Andersen's behavioural model for health services use, as well as the strength of each factor in influencing the use of healthcare services. After the listwise deletion, the total sample becomes 4122 participants. Before doing the CFA, reliability analysis is done to measure the internal consistency of the observed variables. Afterwards, the measurement model is created to measure the model fit analysis. Finally, the factor loadings estimation will be presented to evaluate the strength of each factor in influencing healthcare utilisation.

5.2.1 Reliability Analysis

Before testing the measurement model, reliability must first be established. One way to measure reliability is by internal consistency, where individual items are believed to measure the same construct and thus will be highly intercorrelated (Jitesh J. Thakkar, 2020).

Reliability values range from 0 to 1. However, there is no definite number for the cut-off value. Some argue that the acceptable reliability value is above 0.5, where above 0.9 is excellent reliability (Koo and Li, 2016). Then, some argue that 0.45 is an acceptable value (Taber, 2018). Finally, there are also some arguments that insist there is no specific value that determines whether some measurements are acceptable or not and that measurements with low reliability may also be useful (Schmitt, 1996).

In relation to the measurement in this study, Table 6 presents the composite reliability values. Out of the four constructs, the predisposing, enabling, and need factors have values above 0.4. On the other hand, the healthcare utilisation construct has a value of 0.1. Although the situation is not ideal, studies with good model fit and low reliability exist, especially with a very broad construct with a large sample size, such as healthcare utilisation (Stanley and Edwards, 2016).

The measurement of healthcare utilisation combines the use of public and private healthcare. However, in South Africa, public healthcare provides medical subsidies, which means that the expenses do not accumulate like in private healthcare. This is the reason for the low reliability level. When comparing the CFA results for both public and private healthcare and only private healthcare, it shows that the model fit indices are similar. On the other hand, the reliability value of private healthcare utilisation is 0.5815. This means that the low-reliability value of healthcare utilisation does not affect the CFA much, which allows for the use of the healthcare utilisation construct.

Table 5: Composite Reliability Result

Constructs	**Composite Reliability Values**
Healthcare Utilisation	0.10566
Predisposing Factor	0.65301
Enabling Factor	0.464952
Need Factor	0.440394

5.2.2 Measurement Model and Factor Loadings

Specifying a measurement model is one of the key aspects of confirmatory factor analysis. The measurement model is important because it is the specification of the theoretical model that illustrates how the constructs, or latent variables, are operationalised through a set of observed variables (Hair *et al.*, 2019). The system of the model, such as the identification of which

observed variables are connected to which latent variables, must be established based on the theoretical foundation. The extent of how well the measurement model fits the pattern of the empirical data is reflected by the model fit, which also means the construct validity (Jitesh J. Thakkar, 2020). There is no single way to measure model fit, as there are several fit indices to be considered (Hair *et al.*, 2019). Hooper *et al.* (2008) compiles several varieties of fit indices that can be used. This study will use two of them: (1) absolute fit indices, which determine how well the model fits the sample data and does not rely on the comparison model, and (2) incremental fit indices, which compare the performance of the measurement model to its baseline model, where it assumes no correlation between variables. Table 7 presents the fit indices of the measurement model in this study.

The significant chi-square result means that the model differs significantly from the empirical data. However, chi-square statistic is sensitive to sample size, where a large sample size almost always produces significant result (Hooper, Coughlan and Mullen, 2008). RMSEA and SRMR are other fit indices that are also commonly used, where they measure the misfit of the model, though SRMR is found to be more powerful in measuring the model fit, especially ones that contain ordinal data (Shi, Maydeu-Olivares and Rosseel, 2020). In RMSEA, a value below 0.08 is considered a good fit, while 0.08 to 0.1 is a mediocre fit (Hooper, Coughlan and Mullen, 2008; Jitesh J. Thakkar, 2020). On the other hand, in SRMR, a value below 0.05 is considered a good fit, while below 0.08 is still acceptable (Hooper, Coughlan and Mullen, 2008; Jitesh J. Thakkar, 2020). Then, aside from the ones mentioned before, other fit indices that are also commonly used are CFI, GFI, and NFI. For these indexes, the cut-off of 0.90 is deemed a good fit (Hooper, Coughlan and Mullen, 2008; Jitesh J. Thakkar, 2020).

There are a couple of ways to report the fit indices. Some suggested using Chi-square, RMSEA, CFI, and SRMR, while others suggested the combination of RMSEA and SRMR, where the SRMR is lower than 0.09, and RMSEA is lower than 0.06 (Hooper, Coughlan and Mullen, 2008). Based on the value of fit indices in Table 7, the measurement model fits the data moderately to some extent but not good enough.

Table 6: Model fit indices of the first measurement model

	Fit Indices	**Value**
Absolute fit indices	Chi-square	758.262 (df = 49; p-value = 0.000)
	RMSEA	0.059

	SRMR	0.0442
Incremental fit indices	NFI	0.817
	CFI	0.826

Table 7: Factor loading estimation of the first measurement model

Variables			**Factor Loadings**
Healthcare Utilisation	←	Need Factor	0.602
Healthcare Utilisation	←	Enabling Factor	0.914
Healthcare Utilisation	←	Predisposing Factor	-0.320
Total Visit to Healthcare	←	Healthcare Utilisation	0.143
Total Expenses for Healthcare	←	Healthcare Utilisation	0.149
Self-Rated Health	←	Need Factor	0.697
Health Comparison 1 year ago	←	Need Factor	0.347
Vehicle Ownership	←	Enabling Factor	0.561
Wealth Asset Index Quintiles	←	Enabling Factor	0.654
Medical Coverage	←	Enabling Factor	0.172
Education Level	←	Predisposing Factor	0.669
Employment Status	←	Predisposing Factor	0.502
Age	←	Predisposing Factor	-0.684
Sex	←	Predisposing Factor	-0.069
Marital Status	←	Predisposing Factor	0.011

Another benefit of doing CFA is factor loading estimations. Factor loadings are the correlation between the variables and the factors, where above 0.30 is considered acceptable, above 0.50 is practically significant, and loadings above 0.70 are considered a well-defined structure (Hair *et al.*, 2019). Table 8 shows the initial factor loading estimation of the measurement model. Out of all the variables, sex and marital status stand out due to their really low factor loadings, below 0.1, which shows that they have little to no effect towards predisposing factors. Therefore, this study proposes deleting the two variables from the measurement model.

After modifying the measurement model based on the initial CFA result, the CFA is run again. The model fit indices of the new measurement model are shown in Table 9. Based on the cut-off criteria of RMSEA and SRMR, it can be concluded that the measurement model is a good fit.

Table 8: Model fit indices of after modifying the measurement model (removal of sex and marital status)

	Fit Indices	**Value**
Absolute fit indices	Chi-square	448.441 (df = 30; p-value = 0.000)
	RMSEA	0.058
	SRMR	0.0383
Incremental fit indices	NFI	0.882
	CFI	0.889

Furthermore, the CFA also supported modification indices to improve the model fit. After correlating between the residual of wealth asset index quintiles and education level, the fit indices obtained can be seen in table 10, signifying an improvement of the model fit. The new diagram has a good fit based on various fit indices. Then, the information on the factor loadings of the latest measurement model can be found in Table 11. Finally, figure 7 shows the final measurement model, including the factor loadings based on CFA result.

Table 9: Model fit indices after modification indices between residuals of wealth index quintiles and education level

	Fit Indices	**Value**
Absolute fit indices	Chi-square	248.460 (df = 29; p-value = 0.000)
	RMSEA	0.043
	SRMR	0.0305
Incremental fit indices	NFI	0.935
	CFI	0.942

Table 10: Factor loading estimations of the variables and factors after the modification indices

Variables			**Factor Loadings**
Healthcare Utilisation	←	Need Factor	0.689
Healthcare Utilisation	←	Enabling Factor	0.865
Healthcare Utilisation	←	Predisposing Factor	-0.221
Total Visit to Healthcare	←	Healthcare Utilisation	0.145
Total Expenses for Healthcare	←	Healthcare Utilisation	0.141
Self-Rated Health	←	Need Factor	0.704
Health Comparison 1 year ago	←	Need Factor	0.343
Vehicle Ownership	←	Enabling Factor	0.616
Wealth Asset Index Quintiles	←	Enabling Factor	0.554
Medical Coverage	←	Enabling Factor	0.182
Education Level	←	Predisposing Factor	0.612
Employment Status	←	Predisposing Factor	0.498
Age	←	Predisposing Factor	-0.704

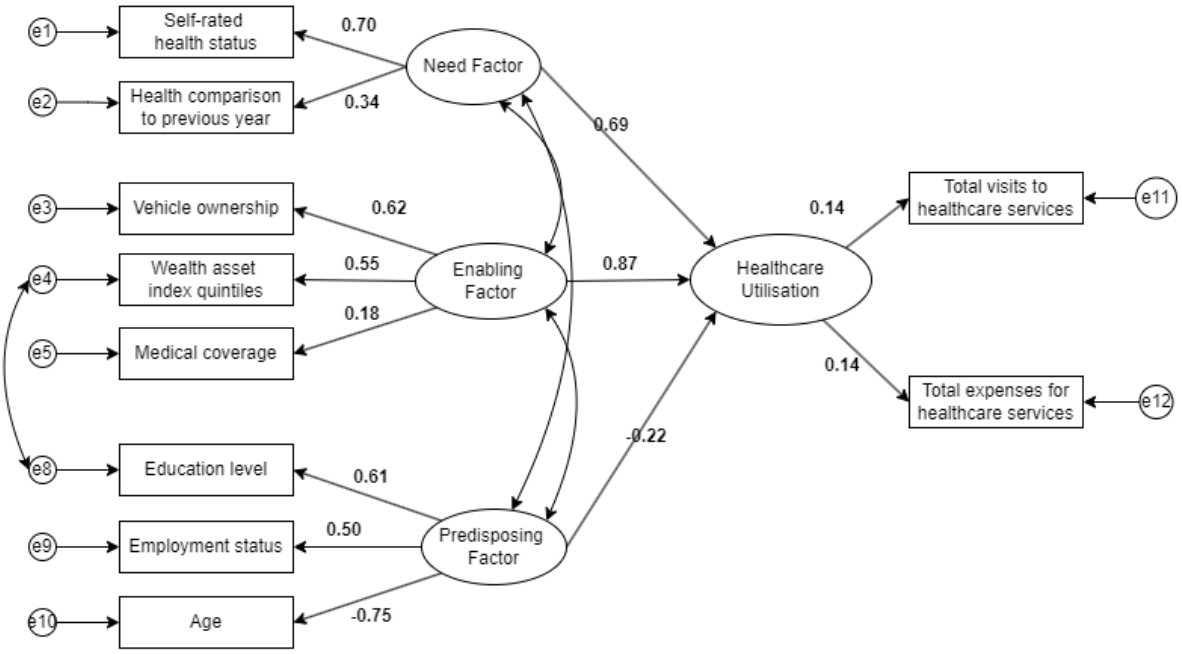

Figure 7: Final CFA result displaying the measurement model and factor loadings of each variable

6. Analysis and Discussion

The model fit indices and factor loadings result indicate that Andersen's behavioural model of health services use is valid in representing healthcare utilisation among rural older adults in South Africa. The findings also answer the question of which factor has the highest influence on healthcare utilisation, which is the enabling factor. Based on the factor loadings estimations, both need and enabling factors greatly influence healthcare utilisation. In contrast, the predisposing factor does not have a huge influence on healthcare utilisation. The finding supports the study done in China, which found that the enabling factor has the highest influence on healthcare utilisation compared to the predisposing and need factor (Zhang, Chen and Zhang, 2019). On the other hand, some other studies found that predisposing factors and need factors have a more significant influence on healthcare utilisation than the enabling factor (Kim and Lee, 2016; Brandão, Paúl and Ribeiro, 2022). Finally, there are also studies that found all three factors have a significant impact on healthcare utilisation (SoleimanvandiAzar *et al.*, 2020). A systematic review of studies using Andersen's behavioural model of health services use revealed that although the model has been so commonly used, there are many variations in the way the variables are determined and categorised, which may explain the mixed findings on the enabling and predisposing factors (Babitsch, Gohl and von Lengerke, 2012). Furthermore, Andersen has also noted the importance of contextual factors for each population, which has rarely been examined in many studies (Zhang, Chen and Zhang, 2019).

Out of the three factors that influence healthcare utilisation based on Andersen's behavioural model, the enabling factor is found to have the highest impact on the use of healthcare services among older adults who live in rural areas. The enabling factor is divided into financing and organisational factors (Andersen and Davidson, 2007). Although the organisational factor was given less attention in the past, certain aspects of it determine whether an individual can receive the care needed (Andersen, 1995; Andersen and Davidson, 2007). Vehicle ownership, which represents the organisational factor of the enabling factor, is found to have the highest influence on the enabling factor. One of the reasons for its importance in healthcare access for older rural adults is that, in South Africa, the healthcare system is organised in a spatial hierarchy, where specialised care is concentrated in urban areas (Neely and Ponshunmugam, 2019). Furthermore, although there is no information on the location of the healthcare centres, the fact that there are 11 healthcare services for 31 villages in Mpumalanga province is evidence that

these services are not very accessible (Gómez-Olivé *et al.*, 2018). Even when free healthcare is available, the transport cost to access healthcare services often burdens the individual and family (Goudge *et al.*, 2009). The lack of reliable public transportation in rural South Africa due to its poor road conditions makes it even harder for rural older adults to utilise healthcare services (Morris-Paxton, Reid and Ewing, 2020). Therefore, in this situation where healthcare services are sparsely located, and public transportation is unreliable, vehicle ownership has a huge role in determining whether an individual will use healthcare services.

Aside from transportation, wealth, which is part of the financing factor, also has a significant impact. Countless studies have found that wealth, a part of socio-economic status, is an important determinant of the use of healthcare services, which in turn will affect health status (Kevany *et al.*, 2012; Agerholm *et al.*, 2013; Bonfrer *et al.*, 2014; Gordon, Booysen and Mbonigaba, 2020). People from poor households are less likely to perceive the need for healthcare services and are more likely to postpone seeking healthcare services due to their inability to afford healthcare services (Gordon, Booysen and Mbonigaba, 2020). In the case of Mpumalanga, specifically, where 50.8% of the population is living below the poverty line, this raises huge concerns (Operation Hunger, 2023). More than half the population of Mpumalanga Province may have difficulty seeking healthcare services because of their inability to afford care. The important role of the financing aspect also relates to medical coverage that protects the population. Although this study found that medical coverage has little to no impact on enabling factors, the fact that almost 90% of the sample population has no medical coverage may produce bias. Another possible reason for the low influence of the medical coverage variable is that this study uses the combination of public and private healthcare utilisation since previous studies found that medical coverage significantly influences the use of private healthcare and not the use of public healthcare (Ataguba and Goudge, 2012). Furthermore, the availability of medical coverage is highly related to SES since it lessens the burden of poor households who cannot afford healthcare services. Indeed, medical coverage provides financial protection for the people and increases healthcare utilisation, though the type of insurance also matters (Ataguba and Goudge, 2012; Kondo and Shigeoka, 2013; Suh *et al.*, 2014). The aim of the South African government to provide universal health coverage by 2026, combined with the commitment to increase the accessibility of healthcare services, is a promising step to lessen the concern about healthcare services' affordability. It may encourage rural older adults who need it to seek healthcare services. Overall, it can be concluded that healthcare utilisation increases with mobility and affluence among rural older adults.

The other substantial factor in healthcare utilisation is the need factors. Andersen has emphasised the importance of the need factor in his behavioural model, both the perceived need and evaluated health (Andersen and Davidson, 2007). Perceived need is crucial because it determines the way people see their general health and functional state, as well as their judgement on whether they need healthcare services (Andersen, 1995). Though the perceived need is a part of the need factor, it is a social phenomenon that is heavily influenced by one's predisposing and enabling factors, both the social structure, health beliefs, and biological condition (Andersen, 1995). At the same time, evaluated need, which is focused on an individual physical status based on a professional judgement, is also influenced by social factor (Andersen and Davidson, 2007). Studies have found how perceived need can be a reliable measurement like the objective or evaluated need since it portrays how one feels about one's health, which determines the judgement to seek healthcare services or not (Bourne, 2009; Kapteyn and Meijer, 2014). Both the self-rated health status and the health comparison to a year before are used to measure the perceived need in this study, though the present perceived health status has a stronger influence on healthcare utilisation. The fact that perceived health status is not only influenced by physical health but also social structure, mental well-being and cognitive functioning suggests that in order to increase healthcare utilisation, policymakers should also consider interventions which improve all aspects of well-being and functioning (Andersen, 1995; Caramenti and Castiglioni, 2022).

Finally, the last factor that is believed to have an impact on healthcare utilisation is the predisposing factor (Andersen and Davidson, 2007). The predisposing factors include demographic factors, social factors, and health beliefs. The demographic factors represent the biological aspect of an individual. Then, the social aspect represents the ability of an individual to cope and use resources to solve a problem. Finally, health beliefs determine an individual's attitudes and values, which influence the perceived need for healthcare utilisation. Based on the CFA result, the predisposing factor is found to have little impact on healthcare utilisation among rural older adults in South Africa. Initially, five variables were used to measure the predisposing factors: age, sex, and marital status as part of the demographic factor, and employment status and education level as part of the social factor. However, due to the poor effect of sex and marital status in the original model, the two variables were deleted in the newer model.

One of the possible reasons for the low impact of predisposing factors on healthcare utilisation is the lack of measurement concerning the health beliefs variable in this study. Health beliefs are a strong predictor of healthcare utilisation among older adults (Strain, 1991). Furthermore, as Andersen (1995) noted, the predisposing factor also heavily influences the need and enabling factors. Altogether, it may undermine the influence of predisposing factors on healthcare utilisation on the CFA result, though they have been found to have significant effects on other regression analysis (Rennemark *et al.*, 2009; Goodman, 2010). Nonetheless, the little impact of predisposing factors on healthcare utilisation may imply that regardless of the demographic factors of a population, it is more important to ensure that the enabling factors, both the financial and organisational aspects, are sufficiently provided.

In regards to the variables used as part of the predisposing factor in this study, age, education level, and employment status have been found to influence the predisposing factor significantly. Education has indeed been found to be a significant predictor of healthcare utilisation (Taffa and Chepngeno, 2005). In this study, after acknowledging the correlation between education and wealth assets in the measurement model, the model fit indices increase, highlighting that education and wealth asset index are highly connected. In fact, some other studies put education as part of the enabling factor (Kim and Lee, 2016; SoleimanvandiAzar *et al.*, 2020). When it comes to the employment factor, it corroborates previous studies that found employment status as an important healthcare utilisation predictor (Abera Abaerei, Ncayiyana and Levin, 2017).

An unexpected finding in this study is the negative influence age has on the predisposing factor, which means that among rural older adults, the older they get, the less likely they will use healthcare services. A systematic review of healthcare utilisation studies in China also found mixed results on age, where some studies found that people will reduce healthcare utilisation as they get older, while others found the opposite result (Zhang, Chen and Zhang, 2019). One possible explanation of this phenomenon is the increased barriers to healthcare access among rural older adults, such as transportation difficulties, limited healthcare supply, social isolation, lack of quality healthcare, and financial constraints (Goins *et al.*, 2005). Nevertheless, further research on how age interacts with other variables and impacts healthcare utilisation is certainly needed.

Finally, it is also important to remember that both contextual and individual characteristics influence healthcare utilisation. This study focuses more on individual characteristics since the sample population is from the same geographic location in Mpumalanga province. This is why this study assumes that the contextual characteristics are similar among the sample population. Regardless, healthcare utilisation is a complex issue, and it is hard to pinpoint which factors have the most significant impact on healthcare utilisation across different populations. However, in the context of South Africa, the government must provide better systems to increase access to healthcare services to the population, especially the rural older adults.

7. Conclusion

Healthcare utilisation has been the focus of many different studies, especially with the rising concern of population ageing. However, it is a complex matter and is impacted by various factors, both internal and external factors. This study implements Andersen's behavioural model of health services use to determine the factors that influence healthcare utilisation among rural older adults in South Africa. Due to its complexity and to find out how the factors interact, the CFA technique is used, which provides information on the model fit indices and factor loadings.

The findings of this study show that among rural older adults in South Africa, the enabling factor and the need factor have significant impacts on healthcare utilisation. In contrast, the predisposing factor has little impact on it. It corroborates some studies in China that found that enabling factors influence healthcare utilisation the most. Within the enabling factors, the organisational aspect, represented by vehicle ownership, has been proven to have the highest impact. Wealth, within the financing aspect of enabling factors, is also found to be significant. Interestingly, medical coverage is found to have very little influence. Future research incorporating the travel time to healthcare services will strengthen the findings related to the enabling factors. Then, regarding the need factors, perceived health status is used in this study by measuring how the participants feel on the day of the data collection and their health comparison to the previous year. Self-rated health status has been proven to be more influential in measuring the need factor.

Another interesting finding of this study is the little influence of predisposing factors on healthcare utilisation. One possible reason is the lack of measurement for health beliefs, which could be an important variable for the predisposing factor. Although education level and employment status both impact the predisposing factor, sex and marital status are found to have little to no impact. In fact, age is found to influence the predisposing factors negatively. The findings related to age, sex, and marital status contradict previous studies that found each to be strong predictors of healthcare utilisation. Further research is needed to determine the possible reasons for this finding, especially among rural older adults in South Africa. It is also important to remember that this study has limited information to measure healthcare utilisation, though it actually has many different aspects. Further research will provide more complete information

on the type and purpose of healthcare utilisation, which may provide more insights into this complex construct

The findings of this study regarding factors that influence healthcare utilisation among rural older adults in South Africa can add to the expanding knowledge of healthcare utilisation. A better understanding of these factors, such as the importance of the need factor, can be used as a foundation to create health policies that ensure equal healthcare access to all people, especially in South Africa. In turn, it can also contribute to fulfilling the South Africa NDP 2030 and SDG 3's objectives.

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Appendices

Appendix 1: Model Fit Indices for Private Healthcare Utilisation

Model fit indices for all variables

(Private HC Awa)	**Fit Indices**	**Value**
Absolute fit indices	Chi-square	909.637 (df = 49; p-value =0.000)
	RMSEA	0.065
	SRMR	0.0481
Incremental fit indices	NFI	0.813
	CFI	0.821

Final model fit indices – after the deletion of sex and marital status variables and modification indices

(Private HC)	**Fit Indices**	**Value**
Absolute fit indices	Chi-square	407.438 (df=29; p-value = 0.000)
	RMSEA	0.056
	SRMR	0.0382
Incremental fit indices	NFI	0.910
	CFI	0.916

Appendix 2: Variable List of the Study

Variables	Questions	Answer
Total visits to healthcare	How many visits to the [each healthcare centre] in the last 3 months?	[numbers]
Total expenses for healthcare	On your last visit to [healthcare centre], how much do you pay and/or donate out of pocket {including fees and medicine) at the point of care or afterwards?	[numbers]
Age	Respondent's calculated age	[numbers]
Sex	Respondent's sex	[numbers]
Employment status	Now I have some questions about work. What would be the best description of your current work status?	Employed (part or full-time), not working, homemaker
Education level	What is the highest level of school that you completed?	No formal education, some primary (1-7 years), some secondary (8-11 years), secondary or more (12+ years)
Marital status	What is your current marital status?	Never married, separated/divorced, widowed, currently married
Vehicle ownership	How many functional vehicles [motor vehicles/motorcycles] do you have?	[numbers]
Wealth asset index quintiles	PCA of household characteristics and ownership of household items, vehicles, and livestock	[numbers]
Medical coverage	Are you covered by any type of medical aid programme, medical benefit scheme, provident scheme, health insurance, or hospital plan?	Yes/No
Self-rated health status	In general, how would you rate your health today?	Very good, good, moderate, bad, very bad
Health compared to the previous year	Compared to one year ago, how would you rate your health today?	Much worse, worse, same, better, much better