INTERROGATING THE CONCEPTUALIZATION AND MEASUREMENT OF SOCIOECONOMIC STATUS: EXPLORING A NOVEL METHODOLOGY USING SOUTH AFRICAN DATA

A Dissertation

presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

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by

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MAY 2024

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ACKNOWLEDGEMENTS

I wish first and foremost to thank Dr. Stephen Whitney. Dr. Whitney, your belief in my potential, even during moments when I doubted myself, has motivated me to become a better scholar. I am eternally grateful for the opportunity you afforded me to pursue graduate studies abroad. I will miss our conversations, both intellectual and frivolous, over cups of *rooibos* tea and Wednesday lunches.

Dr. Matt Easter, thank you for your steadfast support. Your contribution to my growth, both academically and personally, cannot be measured. It is because of the quality of your instruction and the time that you invest into each one of your students that I can call myself a competent quantitative researcher. I am indebted to you for this, and so much more.

Dr. Sonja Winter, I am forever in awe of the patience and care with which you meet me during our every interaction. You are the kind of committee member one can only hope to have in one's corner. I am so grateful for your comprehensive feedback and the standard to which you held my work. I cannot thank you enough for the pivotal role you have played in my academic journey over the course of the last year.

Dr. Gabrielle Malfatti, your knowledge of education systems around the world is remarkable, and I am so grateful to have had your insights inform my work. Thank you for being an advocate for every single international student across the college. You make this journey infinitely easier for each one of us.

There are additional faculty and staff across the Department of Educational, School, and Counseling Psychology to whom I am most grateful. Dr. Wes Bonifay, thank

you for sustaining the conversations that formed the basis of this dissertation. You have taught me to be a more critical consumer of quantitative research and I am so grateful for your guidance over the last three years. Dr. Francis Huang, thank you for taking the time to entertain my every question and for your invaluable assistance with managing this large dataset. It has been a privilege to learn from you. Dr. Cheryl Offutt, thank you for the sound advice you have so willingly provided. You are the kind of leader I one day hope to be. To Alex Spears—whom I can only describe as the backbone of this department—thank you for all you do to ensure the success of every student. I am also grateful to have spent the last year with the team in the Prosocial Development and Education Research Lab. Thank you for being mentors, editors, and trusted confidants.

I would not be here without my people, both back in South Africa and in this place that has become home. Maria Stewart, you are the kindest and most generous person I know, and you brighten my every single day. To Kelsey Forqueran, with whom I made so many treasured memories at Mizzou, thank you for being a fiercely loyal friend. Jenna Conard, I am grateful for your only ever being a phone call away, and for sweet baby Cape who sat with me as I wrote so much of this. Thank you, too, to Josie Visser, who is my number one supporter.

I am immensely grateful for my extended family and their unwavering belief in me. To Dad, Mom, and Matt—thank you for the critical role you have played in getting me to this point. I appreciate your love and support more than I could ever express. Finally, I am eternally thankful for the love of my life and very best friend. Nelson de Bastos, I am who I am because of who you always believed I could be. Thank you for never leaving my side. I love you.

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INTERROGATING THE CONCEPTUALIZATION AND MEASUREMENT OF SOCIOECONOMIC STATUS: EXPLORING A NOVEL METHODOLOGY USING SOUTH AFRICAN DATA

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This study explores various approaches to modeling socioeconomic status (SES) and examines their implications for understanding well-being outcomes in South Africa. Three modeling techniques are compared: an asset index model derived from Multiple Correspondence Analysis (MCA), latent variable models with reflective and formative indicators for SES, and a network model revealing the interconnectedness of socioeconomic factors. Results suggest that the network model accounts for more of the variance in some components of well-being. Upon closer inspection of the network's centrality, it is clear that socioeconomic conditions are more nuanced and that adopting common modeling approaches risks overlooking these. This supports the case for examining socioeconomic conditions as opposed to socioeconomic status, suggesting that researchers must carefully consider how they operationalize and measure these constructs in light of their research objectives.

CHAPTER I. INTRODUCTION

Poverty, inequality, and stark socioeconomic differentials plague societies worldwide. In sub-Saharan Africa, for example, the richest 10% in the region control more than half of its total income (Chancel et al., 2022). South Africa, Botswana, Namibia, and Nigeria report the highest levels of inequality, respectively (Adesina, 2016). Other regions, including Latin America and The Caribbean are characterized by equally alarming patterns. These disparities translate into vastly different realities for citizens as access to healthcare, education, and other necessities often depend on socioeconomic status (SES). Thus, in recognizing its importance, researchers have sought to define and measure SES, since estimating an individual's or household's SES supposedly allows for the prediction of a wide range of outcomes.

Indeed, the relationship SES and health, educational, and psychosocial outcomes is well-documented across psychology literature (Diemer et al., 2013). The American Psychological Association purports that the relationship between low SES and negative health outcomes persists through the lifespan: In the United States, lower levels of SES are associated with increased infant mortality rates (Haider, 2014), higher likelihood of sedentary lifestyles (Newacheck et al., 2003), higher markers of chronic stress, including elevated serum cortisol levels (Chen & Paterson, 2006), and higher rates of cardiovascular disease (Steptoe & Marmot, 2004).

The same organization reports an established relationship between SES and educational trajectories: Low SES is associated with lower educational attainment (Sheridan & McLaughlin, 2016), lower math achievement (Hochschild, 2003), higher

rates of absenteeism (Zhang, 2003), and higher rates of school dropout (National Center for Educational Statistics [NCES], 2016).

Finally, the APA (2010) also provides evidence for the association between SES and psychological health outcomes. Lower SES is associated with higher rates of emotional dysregulation, including social problems and attention deficit/hyperactivity disorder (ADHD; DeCarlo et al., 2011, Russel et al., 2016). Lower SES is associated with higher rates of mood and substance abuse disorders (Newacheck et al., 2003), increased aggression (Molnar et al., 2008), Alzheimer's disease (Evans et al., 1997; Karp et al., 2004), and morbidity from chronic disease (Miller et al., 2011).

Yet conceptualizing SES remains elusive, and one need only assess a handful of the above-mentioned studies to illustrate this. Chen and Paterson (2006) operationalized SES at a neighborhood and family level, utilizing income, education, and occupation data. For the neighborhood-level SES variable, they used census data delineated by neighborhood blocks; for the family-level variable, they assessed the total number of years of education, parents' occupational titles, total family income before tax, and savings readily available (Chen & Paterson, 2006). DeCarlo and colleagues (2011) used parents' monthly income, their level of education, and their occupation on the Hollingshead's (1075) scale of occupational prestige. Meanwhile, Molnar and colleagues (2008) developed and refined family, peer, and mentoring scales as a proxy for socioeconomic resources.

In the studies assessing Alzheimer's disease, Evans and colleagues (1997) report using predictor variables including years of formal education, annual household income, and lifetime occupation as individual measures of socioeconomic status, while Karp and

colleagues (2003) used a dichotomous measure educational attainment (2-7 years of schooling or > 8 years) and the Swedish socioeconomic classification system, which divides people by blue- and white-collar professions. Finally, in their synthesis of the relationship between SES and exposure to stress—and subsequent development of their *Biological Embedding Model*—Miller and colleagues (2012) used evidence from studies in which SES was operationalized as poverty status (*in poverty* or *not in poverty*) (Bradley et al., 2001); an index of socioeconomic position (Dodge et al., 1994); and free and reduce priced lunch (Arata et al., 2007).

Indeed, several approaches to the conceptualization, operationalization, and measurement of SES have proliferated over the course of the last century. To further illustrate this point, consider Antonoplis's (2023) recent analysis of articles measuring SES published exclusively in APA journals between 2000 and 2019. He found that 79.6% of studies provided no theoretical definition of SES. Others operationalized SES as defined by indicators; SES as defined by material resources; SES as defined by perception of social class; SES as defined by objective social standing; and SES as a result of inequality (Antonoplis, 2023).

Historically, SES has been defined as resulting from different combinations of income, educational attainment, and occupational status (Bradley & Corwin, 2002), though the way in which these are transformed into a measure is often at the discretion of the researcher. Today, the APA defines SES as:

> Socioeconomic status (SES) encompasses not only income but also educational attainment, occupational prestige, and subjective perceptions of social status and social class. SES reflects quality-of-life attributes and opportunities afforded to

people within society and is a consistent predictor of a vast array of psychological outcomes (APA, 2023).

Indeed, the evolving definitions and measurements of SES underscore its complexity in shaping individuals' trajectories. Still, most of these measures endeavor to capture the stratification of society, or the idea that people are ranked by the amount of a desired good that they possess (Wohlfarth, 1997). This is consistent with a functionalist view of society, the likes of which have been largely influenced by prolific sociologists like Max Weber (1968). Put simply, functionalists purport that stratification emerges because of the difference positions in society that must be fulfilled by individuals, and that these positions differ in the abilities and talents required to fulfil them, which must be rewarded accordingly (Wohlfarth, 1997). Marxists criticize this functionalist view; they believe instead that the structure of society is determined by those with the power to decide how those rewards should be allocated (Wohlfarth, 1997). This conceptualization is more akin to social class, which reflect power relations among a society that determine who controls the means of production. Wohlfarth (1997) thus differentiates SES and social class by their respective roles in producing socioeconomic inequality: SES focuses on prestige, while social class emphasizes control.

Despite this distinction being made some decades ago, the APA Task Force on SES highlights how the terms social class, SES, socioeconomic position, and stratification are often used interchangeably when, indeed, each represents a nuanced approach to measuring various components of a more complex phenomenon (Saegert et al., 2007). They assert that social class describes “a major group or division of society having a common level of power and prestige on the basis of common socioeconomic

status" (APA, 2023, APA Dictionary). By this definition, SES is a quantitative measure of social class which determines ones position within a hierarchy (Diemer et al., 2013).

It is evident that each concept represents a unique and nuanced aspect of societal hierarchy. This tendency to conflate terms obscures the complexity of socioeconomic phenomena and undermines the reliability and the validity of research findings. The imperative to develop more precise and comprehensive frameworks that capture the multidimensional nature of socioeconomic factors is clear. By doing so, researchers and policy makers can better understand societal inequalities and develop more effective interventions to address them.

The Present Study

The present study examines several approaches to the conceptualization, operationalization, and measurement of SES that have proliferated in the past decades. I argue that these traditional measures fail to capture the dynamic interactions between different dimensions of capital, limiting their utility in informing policy and practice. Thus, this dissertation addresses these limitations by proposing a comprehensive framework for conceptualizing and measuring SES, drawing on insights from network analysis. Here, SES is presented a multifaceted concept encompassing individuals' economic, human, social, and cultural resources which, in turn, are associated with their accessing opportunities that promote socioeconomic mobility and improve health and well-being outcomes over the life course. I term these resources *socioeconomic conditions*.

I turn to South Africa as an illustrative example in which this new conceptualization is applied, especially since the enduring legacy of apartheid and its profound imprint on the country's socioeconomic landscape. The apartheid system, spanning from 1948 to 1994, institutionalized racial discrimination and segregation, severely limiting access to resources and opportunities for people of color in South Africa. Despite the abolition of apartheid and the establishment of democracy, South Africa continues to grapple with entrenched socioeconomic disparities, characterized by high levels of income inequality, unequal access to education and healthcare, and persistent unemployment, particularly among Black communities.

Conceptualizing and measuring SES poses significant challenges for researchers and policymakers, particularly in countries marked by historical injustices and structural inequalities where legacies of colonialism have perpetuated disparities in access to education, healthcare, and economic opportunities. By adopting a multidimensional perspective, this dissertation seeks to reveal SES and its determinants to understand differences that might be driving socio-economic inequalities. I present three distinct measurement approaches: an asset-index as a proxy for SES; SES as latent variable using income, education, and occupation as indicators; and a network model to highlight the interrelations between socioeconomic conditions of interest.

By leveraging these insights, this dissertation seeks to enhance the validity and reliability of SES measures, paving the way for more effective interventions aimed at addressing socioeconomic disparities and promoting inclusivity and equity. Despite focusing on South Africa as a case study, this study also aims to highlight the broader

applicability of the proposed framework, offering valuable insights for researchers and policymakers across diverse contexts.

Research Questions

The present study seeks to answer the following research questions:

1. What do different approaches to conceptualizing and measuring SES reveal about its relationship with outcomes measuring health and well-being?
    a. What are the merits and limitations of each conceptualization?
2. To what extent does network analysis enhance our understanding of the relationship between socioeconomic conditions and outcomes of interest?
    a. How might this understanding be leveraged to address socioeconomic inequalities in South Africa?

CHAPTER II. LITERATURE REVIEW

The Conceptualization of SES

Considerable debate surrounds the terminology employed in discussing individuals' social and economic status. The terms "social class," "stratification," "SES," and "socioeconomic position" are frequently used interchangeably, as noted by the American Psychological Association's (Saegert et al., 2007) special task force on SES. However, as Diemer and colleagues (2013) reiterate, each term represents a unique approach to capturing some aspect of a multifaceted and complex phenomenon. To anchor this concept in its sociological roots, within this section, "social class" serves as a higher-level construct denoting one's placement within a socioeconomic hierarchy, as gauged by SES (Broer et al., 2019; Diemer et al., 2013).

In the mid-20th century, sociologists first attempted to quantify the relative social standings of individuals within society, leading to the proliferation of unitary conceptions in the field of sociology. Two distinct approaches to conceptualizing SES emerged in the field: SES as a unitary concept, which is a single dimension that underlies social position and drives class analyses (Bollen et al., 2001); and SES measured by different components responsible for stratification, thereby acknowledging that these have potentially different consequences in determining social class (Bollen et al., 2001).

Unitary concepts draw on the work of conflict sociologists such as Karl Marx (1973) who argued that individuals' positions in society were defined by their relationship to the means of production, including ownership of land and infrastructure (Bollen & Bauldry, 2011; Galobardes et al., 2007). This perspective proposed that social class

hinged on the dynamics between the owners of the means of production and the workers, depending on whether individuals controlled these means or, alternatively, sold their labor to those who did. SES, then, was understood as the position in the socioeconomic hierarchy, reflecting access to resources and resultant economic inequality (Jackman & Jackman, 1973). This approach appeared reasonable during a period when individuals could be categorized as either owners or workers. However, with the emergence of the middle class, it became apparent that class divisions were based on factors beyond mere economic standing (Manstead, 2018).

Recognizing this, Weber (1968) purported that people are stratified along multiple dimensions in addition to social class, thus individuals' positions in society were influenced not only by their economic status, but also by other factors such as education, political power, and cultural capital. His approach captures the mechanisms through which people trade specific skill sets, often because of their education and other attributes, for social advantages in society. Weber (1968) suggested the inclusion of three indicators—including class, status, and power—for measuring such stratification. Class reflects Marx's earlier conceptualization, using income as a marker of ownership and control of resources (Liberatos et al., 1988). Status reflects prestige within a community, using family background, lifestyle, and social networks to classify people into groups whose members share similar "life possibilities" (Galobardes et al., 2007, p. 23). Power is the ability of individuals or groups to influence and control the decisions and actions of others, thus determining dynamics in groups, organizations, and governments (Weber, 1978). In fact, for Weber, socioeconomic position was shaped by factors of production that extended beyond Marx's traditional concept of class status.

Warner (1949) introduced one of the earliest methods that departed from the reliance on an individual's connection to the means of production. This pioneering approach involved the synthesis of assessments of occupation, sources of income, housing arrangements, and neighborhood, culminating in the assignment of class scores. Alternatively, social classes can be classified using discrete categories rather than continuous scales. Duncan's (1961) *Socioeconomic Index* (SEI) is common among sociologists in the United States, as is Hollingshead's (1975) *Index of Social Position* (ISP). These indices incorporate both education and occupation to establish a two-factor classification. However, these approaches are now considered somewhat outdated, primarily because they are rooted in an antiquated system of occupational classification and tend to obscure the specific socioeconomic components linked to variables of interest, a common criticism associated with composite SES variables like these (Diemer et al., 2013; Hauser & Warren, 1997). Consequently, scholars have advocated against the use of composite measures, favoring the adoption of individual indicators of SES (Diemer et al., 2013; Saegert et al., 2007).

Contemporary sociology has adopted a component-based perspective for assessing social class, employing a range of indicators, most notably occupation, education, and income (Bollen et al., 2001). Occupational standing remains rooted in the Marxist approach, purporting that the type of job one holds—and the prestige, autonomy, and income associated therewith—indicates one's social and economic standing. Educational attainment is key to measuring SES, as the level of education one achieves is associated with greater employment opportunities, income potential, and social mobility (Bartee & Brown, 2007). Finally, income—which represents the flow of money into

one's household over time—as well as wealth—a reflection of accumulated assets—are equally important components of SES. The distinction between, and utility of, income and wealth are discussed in the second part of this paper.

It is imperative to highlight that these nuanced SES conceptualizations, originating in sociology, extend their influence beyond this discipline, permeating various domains such as education and health research. In the next section, I explore this evolution and attempt to shed light on additional, potentially distinctive approaches that have been shaped by these historical foundations.

SES in Health and Well-Being Research

Socioeconomic inequality is a pressing problem in public health (Demakakos et al., 2008). As demonstrated, social stratification profoundly influences the distribution of economic, cultural, and social resources among individuals over time. These unequal distributions in various resources are linked to disparities in health outcomes (Demakakos et al., 2008; Galobardes et al., 2007). In this context, Galobardes et al. (2007) operationalize health outcomes as the consequences arising from exposure to factors that impact health states, including those resulting from both responsive and preventative interventions.

Earlier theories about relationship between SES and health outcomes purport the importance of understanding three key mechanisms in the field of health research: The first is materialist, where SES is conceptualized as the availability of financial resources to purchase quality food, live in safe housing, and support access to health care services, all of which are linked to improve health (Grundy, 2001). The second perspective is

behaviorist, linking educational attainment with lifestyle choices, including decisions about how individuals access health care, such as when and where they seek medical assistance and whether they follow prescribed treatment plans. Indeed, there is an association between higher education levels and increased awareness of the adverse outcomes associated with certain behaviors, and the ability to make informed decisions about their health (Grundy, 2001). The third mechanism is psycho-socially orientated, where SES is conceptualized as resulting in differences in sense of autonomy and empowerment, perceived relative social standing, and social integration, the absence of which may result in increased exposure to stressors (Grundy, 2001).

Like sociology and education, the field of public health has traditionally employed several SES indicators to determine an individual's position within a social hierarchy (Demakakos et al., 2008). The selection of these in empirical research is contingent upon the specific mechanisms linking SES to health outcomes. Researchers with a materialist viewpoint often utilize income-based measures, whereas those emphasizing behavioral factors may opt for educational indicators. Alternatively, those interested in psychosocial influences on health may consider occupation or relative social standing as pertinent indicators.

But in recent years, there has been a growing recognition of the significance of subjective socioeconomic status (SSS; Adler et al., 2000) in public health research. People's subjective assessments of their own SES have emerged as a crucial factor in understanding health outcomes (Demakakos et al., 2008). Deprivation, defined as the inability to engage in normal activities due to a lack of material resources, likely drives this (Grundy, 2001). In the case of empirical research, an objective measure of

deprivation does not always duly consider the resources that are normatively valued in a particular population. As a result, subjective indicators of SES are frequently favored in such studies (Grundy, 2001). This conceptualization of SES reflects individuals' perceptions of their own position within the social and socioeconomic hierarchy and aligns with objective SES in the sense that the socioeconomic resources individuals possess influence their subjective judgments about where they stand in their community (Demakakos et al., 2008).

The concept of relative deprivation is pivotal in understanding how these perceptions are linked to health. It suggests that even if individuals have modest objective SES, perceiving themselves as having a higher status relative to their reference groups can reduce their physiological stress, for example, thus potentially accounting for favorable health outcomes (Diemer et al., 2013). By conceptualizing SES as a subjective measure and acknowledging the importance of understanding participants' subjective determinations of their social standing, empirical researchers might better understand associations between SES and health outcomes.

A final conceptualization of SES in health emerged from the collection of data from the Inner-City Fund's (ICF) Demographic and Household Surveys (DHS). DHS do not contain measures of income or expenditure, though they do collect information about several household assets, including durable goods, housing characteristics, and access to basic services (Howe et al., 2012). This conceptualization of SES as material living standards theorizes a relationship between more assets and favorable health outcomes. There are several mechanisms through which this relationship might manifest. For instance, the presence of a television or radio in the home increases the likelihood of

households receiving public health messages (Wakefield et al., 2010), while access to running water supports sanitation practices and reduces the risk of waterborne illnesses (Hubbard et al., 2020).

Well-being is a key component of health (see Diener et al., 2017, for a comprehensive review of the literature) given its association with several physical health outcomes and increased longevity (Ruggeri et al., 2020). Indeed, At the turn of the 21st century, well-being was declared the number one public health priority in the United States of America (U.S. Department of Human and Health Services [HHS], 2000). Measures of life satisfaction—a key indicator of subjective well-being—has received increasingly more attention from health researchers worldwide. Physical health status is an important predictor thereof. Furthermore, adverse health is, on average, associated with a decline in life-satisfaction (Easterlin, 2003; Barger et al., 2008).

Social relationships are also robust in predicting life satisfaction. In his seminal work, *Bowling Alone*, Putnam (2000) suggests that people prosper in places with high social capital, often marked by high levels of trust and mutual assistance. However, social capital is declining in the United States (Putnam, 2000; Schwadel & Stout, 2012). Social capital is thus an important component of SES in health and well-being research (Oakes & Rossi, 2003). Indeed, findings suggest that the extent to which social capital is related to well-being may be different for low- and high-SES individuals, such that social capital might protect against the repercussions of declining health for individuals of low-SES (Uphoff et al., 2013). While this hypothesizes that social capital functions as a buffer, it is equally likely that low-SES individuals have lower social capital to begin with, such that this capital cannot be leveraged for the benefit of health (Uphoff et al., 2013). This has

repercussions for mental health, for example, as individuals facing socioeconomic adversity may already be vulnerable to feelings of isolation and lack of support.

In assessing racial and ethnic differences in life satisfaction and the relative contribution of SES, health, and social capital, Barger and colleagues (2008) reported that Black and Hispanic participants were less likely to report high levels of life satisfaction, however, these differences were null after adjusting for SES, health, and social relationships. Diener et al. (2017) agree that the relationship between well-being and health and longevity likely differs across various population groups and the conditions in which they live, though they reiterate the need for further research in this area, as there is scant research in studying the nature of the relationship amongst different ethnic groups. What is clear is the role SES plays in physical and mental health outcomes. Indeed, SES affects one's engagement in health-related activities, including accessing medical care, safe and secure housing, and managing stress (CDC, 2023).

Final Thoughts on Conceptualization

A common theme has emerged in exploring the conceptualization of SES across fields of research: That is, that there are mechanisms through which SES is associated with an outcome of interest. In sociology, SES is recognized as a lens through which we can better comprehend patterns of social stratification and disparities in access to resources and privileges. In education, researchers have identified mechanisms ranging from disparities in access to quality education, such as well-funded schools and experienced teachers (Duncan & Magnuson, 2005), to the impact of parental education on school achievement through the facilitation of cognitive development at home (Chesters & Daly, 2017). The mechanisms linking SES to health outcomes can be

multifaceted and include factors like access to health care services which ensures timely care (Adler et al., 1994), health behaviors influenced by socioeconomic resources (Adler & Stewart, 2010), and the psychosocial stressors associated with lower SES (Muscatell, 2018).

The Measurement of SES

Problems Associated with the Determination of Common Indicators

There are several approaches to measuring the triad of SES indicators—occupational prestige, educational attainment, and income—the most common of which were detailed in the previous section. For a comprehensive review on extensive list of instruments used to estimate SES indicators, as well as those used to create composite SES scores, see Diemer et al. (2013). It is, however, important to highlight problems associated with each of these three indicators briefly.

Measuring occupational status can be problematic due to the reliance on outdated scales developed by sociologists in the 1960s, which may not adequately reflect contemporary job roles. Similarly, assessing educational attainment presents challenges, including the use of categorical credentials that oversimplify the highest level of education, rather than employing a continuous measure of years of education completed (Sanzenbacher et al., 2019). In cases where continuous data are collected, complications concerning grade repetition—particularly in developing countries—arise (Kim et al., 2019). Finally, non-response rates pose a significant challenge in the collection of income data, often because of privacy concerns or social desirability biases (Diemer et al., 2013; Harwell & LeBeau, 2010). Moreover, quantifying and validating income measures in

informal economies proves complex due to the presence of irregular and unrecorded income sources (Howe et al., 2012).

To this end, Diemer et al. (2013) suggest measuring wealth instead of income. This is echoed by Alan Greenspan, former chair of the Federal Reserve Bank, who purports that, "we need to examine trends in the distribution of wealth, which, more fundamentally than earnings or income, represents a measure of the ability of households to consume" (Greenspan, 1998 as cited in The Federal Reserve Board, 1998). The ability of households to consume makes it easier to pay bills, own property, and secure decent employment among other aspects of financial stability, rendering wealth a more theoretically appropriate indicator of SES, too.

Wealth measures have thus been incorporated alongside income assessments more recently. In assessing differences in cognition between White and Black middle- and old-aged participants, Glei et al. (2022) found that wealth was more important than income in accounting for racial disparities in cognitive scores after controlling for differences in educational attainment. Even though the authors could not conclusively account for the relative contribution of wealth, it is plausible that greater wealth was associated with increased access to health care as well as increased social engagement, both of which protect against cognitive decline amongst the elderly (Glei et al., 2022).

Problems Associated with the Single, Proxy Measures of SES

Indeed, the measurement of household wealth—in addition to income—is a common feature across large multi-national assessments. Wealth can be estimated using an assets-based index (e.g., PISA). Measuring SES based on the number of household

assets is common in low- and middle-income settings because material assets are more sensitive and dynamic than traditional indicators, especially in areas undergoing social and economic transition (Kagura et al., 2016; Kim et al., 2019). In assessing the use of measures of SES in South-Asian populations (including those in India, Bangladesh, and Pakistan), Saif-Ur-Rahman et al. (2018) reviewed 256 studies and found that 54% (n = 142) used an asset-based wealth index. However, this measure is potentially problematic in cases where the component variables are artificially constructed, thus the discriminating power of each index depends on the nature of the variables included, as well as their applicability to the context in which they are collected (Vyas & Kumaranayake, 2006).

Consider the case of PISA, in which the same asset index produced coefficient alphas ranging from .55 in Iceland to .84 in Tunisia in the 2006 assessment. The observed variance in assets scores attributable to true variation in wealth is clearly inconsistent across nations. In response, Traynor and Raykov (2013) used confirmatory factor analysis (CFA) to assess the validity of assets-based indices as wealth measures in PISA assessments in Indonesia and Israel. They found positive correlations between asset scores and both parental education status and occupation status, which provide evidence for the validity of the measure. Yet they stress the fact that the assets scores in some populations are indeed imprecise and suggest the adoption of country-specific items in attempting to measure wealth (Traynor & Raykov, 2013). While this is indeed a mammoth task, it reiterates the idea that when assets-based indices fail to account for what is normatively valued across populations of interest, the validity of such a proxy variable is debatable.

FRPL is also a common proxy for SES in the United States as families of lower income are eligible and subsequently apply for the program. Yet the validity of the measure has also been scrutinized. FRPL data are not collected for research, thus sound data collection practices are not necessarily used in the gathering thereof. Additionally, each year, only a small sample of household income reports are verified, undermining the accuracy of the measure (Domina et al., 2018). Harwell and LeBeau (2018) reviewed FRPL verification studies between 1990 and 2005 and found evidence for the enrolment of children in FRPL that were not actually eligible. In contrast, the same authors reported that many eligible children did not participate in FRPL (Harwell & LeBeau, 2010). This is potentially attributable to several factors: First, the call for enrollment in FRPL is made at a school district level through local media, forms sent home with children, etc., thus producing inconsistencies in the extent to which information is made available to households (Cookson, 2020; Domina et al., 2018). Consequently, many families eligible for FRPL are not necessarily aware of the program.

Yet even among those who meet the eligibility criteria and are informed about free and reduced-price lunch (FRPL) programs, not all choose to enroll, often due to the associated social stigma linked with revealing sensitive financial information. Indeed, the USDA reports a negative correlation between FRPL enrollment and grade level (Harwell & LeBeau, 2010). While the precise causal mechanism remains inconclusive, this observation may be attributed to the reluctance of older students to disclose their financial status, fearing judgment from both school personnel and peers. This reluctance was evident in a qualitative study by Poppendieck (2010) who sampled high school students eligible for FRPL.

Problems Associated with Individual Indicator Approaches

A new recommendation for measuring SES in psychology and public health arose at the turn of the 21st century. Many abandoned the previously agreed-upon composite measure (e.g., Duncan's SEI, Hollingshead ISP) in favor of returning to the use of individual indicators for SES (Diemer et al., 2013; Saegert et al., 2007). This shift was driven by the desire to measure the constituents of SES based on specific theoretical relevance to the outcome of interest for any given study. This suggests the measurement of SES should be tailored according to the research question. By selecting individual indicators that are directly related to the specific outcome being studied, researchers aim to enhance the precision of their findings. Yet empirical research articles that estimated the 'effect' of SES on some outcome of interest—published across APA Journals between 2000 and 2015—revealed that 79.6% (n = 129) of the studies did not offer any kind of theoretical definition of SES (Antonoplis, 2023).

This approach raises concerns about the comparability and interchangeability of different SES indicators. The APA Task Force on SES describes the indicators of SES as "not interchangeable" (Saegert et al., 2007, p. 11), implying that each indicator uniquely captures aspects of individuals' SES. This lack of interchangeability poses a challenge in cases where different SES indicators yield contradictory results. Such findings may emerge if, for example, one study uses education as an SES indicator and finds a positive association with some specific outcome, while another study uses income and finds no significant association—or even a negative one—with that same outcome. For example, Antonoplis (2023) reports than Alexander and Link (2003) and Williams et al. (2018) found an association between individuals of higher income and the tendency to want to

distance themselves from those with mental illness. However, others found that people of higher SES desired less social distance from people affected by mental illness (Corrigan et al., 2001; Martin et al., 2007).

Similarly, if the same study uses two different SES indicators, and one shows a negative association with the outcome of interest while the other indicates a positive association, the findings may be more challenging to interpret. For example, in a study assessing the effectiveness of a community intervention intended to educate members on mental health issues, Girma et al. (2013) established a statistically significant relationship between higher income and increased stigmatization against individuals with mental illness. Additionally, they observed a significant inverse association between the level of education and stigmatization towards those with mental health issues (Girma et al., 2013). It is worthwhile noting that after standardizing the coefficients of the predictor variables, income-stigma relationship appeared weaker. Additionally, an interaction analysis showed a synergistic effect between lower education and higher income on stigma such that the effect of these two predictors together was greater than each taken individually. Importantly, the author did not purport any claims about SES or similar terms, strengthening the study's theoretical relevance. But this is not always the case.

Problems Associated with Subjective SES Measures

Considering the challenges posed by the interplay of single socioeconomic indicators and the controversies surrounding composite SES measures, an alternate approach to measuring SES is the collection of individuals' perceptions of their own subjective social and economic status.

SSS is typically measured by the MacArthur Scale of Subjective Social Scale (MacArthur SSS; Adler et al., 2000). It consists of a ladder or scale with rungs representing various positions in society. Respondents are asked to place themselves on this ladder based on where they feel they stand in relation to others in terms of income, education, occupation, and overall social status (Adler et al., 2000). This gives individuals an opportunity to aggregate circumstances they deem relevant in determining socioeconomic standing. In frequently cited epidemiological studies in the United States, the MacArthur SSS reliably predicted health outcomes independent of objective SES indicators (Adler et al., 2008; Demakakos et al., 2008; Singh-Manoux et al., 2003). Notably, Adler et al. (2008) and Singh-Manoux et al. (2003) used data from the Whitehall-II study, in which the sample was almost exclusively European-American, thus the generalizability of the findings could not be determined, though evidence exists for the scale's cross-cultural validation (e.g., Operario et al., 2004).

Additionally, it is often difficult to determine the extent to which SSS reflects objective SES measures. For example, Mistry and colleagues (2015), assessed the extent to which elementary school children's SSS ratings were indicative of objective measures of SES. Children's SSS was significantly correlated with household income (r = .64), mother's education (r = .23), and father's education (r = .29). There was also a significant, positive correlation between parents' SSS and family SES. Finally, children's SSS were significantly and positively correlated to parents' SSS (r = .56).

However, qualitative data revealed that 47% of children (n = 50) most often used what the authors termed *purchasing power*, or "money as a resource and how the money is used," to make their determinations (Mistry et al., 2015, p. 1661). Goodman et al.

(2000) also reported that family money and family lifestyle were important determinants in making SSS judgements in the case of children and adolescents. This is potentially problematic as children tend to rely on a single indicator of SSS to make their determination. Furthermore, while this sample included 5th and 6th grades, it is important to note that developmental changes in social cognition with age render older children better able to assess their socioeconomic standing relative to others, but such a measure may not necessarily be appropriate across the elementary school context (Kilford et al., 2016).

In addition, SSS may vary across demographic groups. While Mistry et al. (2015) reported a significant correlation between SSS and SES ever after controlling for race, this is not always the case. For example, Shaked et al. (2016) found that Black Americans rated themselves higher on SSS (using the MacArthur SSS) despite scoring lower on every objective indicator of SES. This may be better understood through the lens of social identity theory, which highlights the tendency to make in-group as opposed to out-group comparisons—i.e., when individuals compare themselves to those in their own groups, they are less likely to regard factors that affect the group as whole (Crocker & Major, 1989). This reinforces how the subjective nature of such a measure allows participants to aggregate information about their conditions in many ways.

Problems Associated with Formative and Reflective Models

Considering the complexities surrounding both objective and subjective measures of SES, an alternate has emerged: Perhaps SES, as a latent variable, is like the 'hidden factor' that affects one's social and economic standing. If this is the case, the choice of measurement models is of paramount importance.

In recent years, the latent variable approach has gained prominence in the study of SES. It theorizes that SES is not just composed of observable indicators like income or education; instead, it is a hidden or latent construct that influences—or is shaped by—various aspects of society due to the interplay of multiple indicators and the way in which they are modeled. *Latent* variables are thus random variables for which there is no sample realization—i.e., the variable forms part of a theory, but that variable itself is not available in the data (Bollen, 2007). *Observed* (or *manifest*) variables are thus used to measure latent variables as either effects or causes of said latent variable (Bollen, 2007). For a more comprehensive summary of this approach, see Bollen (2007).

Effect indicators are modeled reflectively. These models position SES as an underlying or latent construct influencing the observed indicators. This means that people vary on some unobserved SES variable that manifests as varying levels of income, education, and occupational prestige. Reflective models are common in psychological and educational research (Coltman et al., 2008). A working paper by Whitney et al. (2023) sampled 100 papers across several fields—including education, health, psychology, and criminology—that employed a structural equation approach to modeling SES. Concerningly, 55 of the papers failed to supply sufficient information to determine the model specification. Of the papers in which a determination could be made, 34 modeled SES indicators reflectively. This is in keeping with recommendations that reflective models be used for SES (Howell et al., 2007).

Bollen (2007) warns that this approach increases the risk for model misspecification as researchers may mis-specify formative indicators as reflective indicators in response to Howell et al.'s (2007) suggestion, thus risking interpretational

confounding. To reiterate this point, a reflective model fundamentally implies that a single-unit increase in SES would produce a corresponding change in every indicator—but it can be demonstrated that some change in SES does not always result in an increase in occupation status, housing type, and the sudden ownership of desirable assets. Furthermore, various conceptualizations highlighted earlier assume that SES results from its constituents rather than causes them, thus modeling in SES reflectively would not be valid in these cases.

Formative models, on the other hand, treat the observed indicators, such as income, education, and occupational status, as fundamental causes (or formative factors) contributing to the overall latent construct of SES. Theoretically, this model specification is likely more appropriate if SES is conceptualized as a product of its constituent parts (Edwards & Bagozzi, 2000). Yet formative models are controversial and, in fact, not common in modeling in SES (Bollen & Diamantopoulos, 2017). The same working paper by Whitney et al. (2023) found that only 11 of the 100 papers used formative models.

A fundamental drawback of formative models lies in their interpretation, which is complicated by the estimation of how indicators influence the latent variable (Cenfetelli & Bassellier, 2009). This complexity is exacerbated when there is a misalignment between the conceptualization and operationalization of a construct. These disparities can arise because the shared variance among the outcomes may not accurately represent how many social and economic resources one has (Antonoplis et al., 2023). As a result, different studies employing varying sets of observed variables, all labeled as SES, may yield different empirical interpretations of SES. This poses a significant threat to validity as it undermines the ability to establish consistent interpretations of SES across studies.

Offering an Alternate Conceptualization of Socioeconomic Status

Considering the previously identified concerns with the more traditional conceptualizations, the need for a new operationalization of SES is clear. Antonoplis (2023) argues that SES can be thought of as "represent[ing] individuals' perceptions of normatively valued social and economic resources" (p. 279). He offers the following breakdown of the definition into its constituent parts:

First, this definition implies that identifying an effect of or on SES refers to understanding how individuals' current possession of resources influences their socioeconomic status at the time of measurement. Moreover, *normatively valued* means that the components of SES must be specifically defined for the population under study. Valued resources, in this context, encompass the factors that contribute to individuals' material well-being and functioning within society (Antonoplis, 2023). Thus, normative value in relation to SES considers what these individuals perceive as beneficial for promoting their socioeconomic mobility within their unique time and place. Finally, it acknowledges that SES components are shaped by historical and societal factors. *Social resources* encompass human elements like educational prestige and supportive social connections that support adherence to cultural norms. *Economic resources*, including wealth and income, determine the extent to which one may lead fulfilling lives within the country's unique historical and economic context.

This definition is valuable as it allows for the distinction between the conceptualization and measurement of SES: By framing SES in this way, it is no longer just one's level of education, or income, or occupational status, etc. that represents it (Antonoplis, 2023). Because present conceptualizations position SES as solely based on

the measurement of these (or alternative) specific indicators or variables, then one might conclude that studies claiming to measure SES—but then omitting these components—would be inaccurate. Thus, merely equating SES with its measurement procedure does not provide a comprehensive understanding of what SES represents (Antonoplis, 2023). But the proposed operational definition enables the development of various measures of SES tailored to a unique population in a specific context.

Thus, under this conceptualization, SES is a set of "structural features" that guide participants' important decisions and behaviors, instead of some unitary property one might attempt to study the effects of (Antonoplis, 2023, p.284). It means that socioeconomic conditions are factors that, in turn, make upward social mobility more likely. Such flexibility acknowledges that these factors can vary across regions: Though SES shares common characteristics that warrant thorough consideration, it is crucial to recognize that these features may function differently in diverse contexts. This approach emphasizes the need to identify and focus on the relevant features of SES within a specific setting. Thus, by labeling the construct as a socioeconomic condition as opposed to socioeconomic status, it increases its interpretational value and underscores the importance of context. While this limitation contains the generalizability of a specific finding, it also makes the falsification of competing theories more meaningful, thus increasing confidence in the utility of said conceptualization (Lucas, 2003).

To demonstrate this alternate conceptualization, I turn to the examination of socioeconomic conditions of South Africans as an illustrative example.

Socioeconomic Conditions in South Africa

South Africa's socioeconomic landscape bears the imprint of its tumultuous history, marked by the institutionalized racism of apartheid. The system, which endured from 1948 to 1994, entrenched structural inequalities, thereby limiting access to resources and opportunities based on race. Post-apartheid, the nation faces the arduous task of dismantling these disparities.

Persistent socioeconomic challenges manifest prominently in income inequality, with South Africa reportedly having the highest income inequality worldwide as measured by its Gini co-efficient. The Gini index represents the extent to which a resource is equitably distributed amongst a population on a scale from 0 to 1, where higher values indicate higher inequality (Gastwirth, 1972). A recent World Bank report estimated South Africa’s Gini co-efficient to be .67 as of 2022, which underscores the vast wealth gap (Sulla et al., 2022). While the end of apartheid saw the Black majority gain political power, economic transformation has been slower, as historical disadvantages endure (Levy et al., 2021). The New York Times recently reported that unemployment, notably affecting the Black population, remains around 33%, and 35% for high school leavers, exacerbating poverty and social unrest (Chutel, 2023).

Education disparities echo historical injustices, with underfunded schools predominantly serving black communities (Amnesty International, 2020). Consequently, unequal access to quality education perpetuates the cycle of poverty, hindering social mobility. Similarly, health disparities reflect inequalities, with marginalized communities double burdened by both chronic and infectious diseases. These disparities are closely linked to the challenges faced by individuals with low SES, including barriers to

healthcare access and limited resources, which exacerbate existing health issues. It's important to note that the relationship between SES and health in South Africa is complex, as conditions like obesity, hypertension, and diabetes are more common among higher SES individuals. Thus, simply summing the number of adverse health conditions reported by an individual may not accurately reflect the relationship between socioeconomic conditions and associated health outcomes.

Considering South Africa's complicated history marked by institutionalized racism and apartheid, a more nuanced conceptualization of SES is imperative for a thorough examination of the relationship between socioeconomic conditions and various outcomes of interest. Not only might such an approach allow for a more accurate understanding of the disparities faced by the South African population, but it may also aid in developing more targeted interventions tailored to the specific challenges rooted in the country's unique historical context. For this research, socioeconomic conditions are categorized under one of four kinds of capital: economic, human, cultural, and social (Bartee & Brown, 2007).

Economic Capital

Economic capital is commonly regarded as a type of financial currency, where the value is determined by an individual's possessions, encompassing both material and non-material assets, influencing the extent of exchange (Bartee & Brown, 2007). Economic capital is embodied in physical and monetary assets, or the means that influence one's ability to get ahead by influencing the availability of resources (Butler et al., 2008). For example, economic capital includes the income at the disposal of families that may shape educational trajectories by providing additional opportunities that support academic

development, including specialized educational programs, supplementary after-school activities, and individual, personalized tutoring etc. (Coleman, 1988). Notably, wealth distinguishes itself from income by providing a safety net during more immediate economic hardships, making a substantial purchase (e.g., private education), or starting a new business venture (Butler et al., 2008). Income, on the other hand, reflects more immediate earnings and providing resources for day-to-day expenses.

Human Capital

Human capital represents the skills, knowledge, and capabilities of an individual, and is key to their realizing their potential as productive members of society (World Bank, 2019). Education lays the foundation for intellectual growth and critical thinking, empowering individuals to adapt to evolving challenges in the workforce. Concurrently, prioritizing and receiving necessary healthcare not only enhance the well-being of the population but also contribute to increased productivity and economic participation. It is therefore important to consider how investments in education, health, and skills development might shape one's socioeconomic trajectory.

Educational Attainment. Examining both the educational attainment of the individual and that of their parent/caregiver/s is imperative, as education serves as a key indicator of human capital. In 2006, Hertz found that 30% of the variation in individuals' incomes could be attributed to both their own educational attainment and that of their parents. This is likely due to the relationship between education and earnings, as higher levels of education increase the financial resources available to parents and determine the expenditure thereof. Children from families with low educational attainment may also lack knowledge and skills needed to navigate educational systems and leverage available

resources, while children from families with greater historical educational attainment may have an advantage in this regard (De Graaf et al., 2000). This cyclical pattern reinforces the relationship between parental education levels and the educational trajectory of the child, contributing to the perpetuation of lower educational attainment across generations.

This is pertinent in South Africa, where racial division existed under colonial rule throughout the 19th century. At that time, the education system was designed to serve the needs of the colonial power and maintain the existing social hierarchy. Following the implementation of the apartheid system of racial segregation in 1948—which was legislated after the National Party took control of the country—racial separation within the education system proliferated. Shortly after coming to power, the apartheid government passed the Bantu Education Act of 1953 which legislated second-rate education for Black youth for the purpose of preparation for the unskilled labor market, thereby impeding their advancement (Christi & Collins, 2006). These discriminatory policies resulted in unequal access to primary and high schooling, leaving many Black individuals without basic education.

The 1995/1996 South Africa survey revealed that 3.8 million people lacked any formal education, 93% of whom were Black (Khuluvhe & Ganyaupfu, 2022). Black students who did receive an education attended schools that were without basic infrastructure, quality teachers, and sufficient learning materials, while those serving White students benefited from reliable infrastructure, more qualified teachers, and a variety of learning resources. This created a substantial disparity between the quality of

education for White and Black students, the legacy of which has pervaded through the present day.

These inequalities are compounded by the large returns on tertiary education in South Africa as it aligns with the dynamic demands of the labor market and provides individuals with the knowledge necessary for highly sought professions, thereby maintaining inequality (Francis & Webster, 2019). The Department of Higher Education and Training (DHET) reported that, as of 1994, only 1.7 million people in South Africa—approximately 4% of the population at the time—reported tertiary studies as their highest level of educational attainment, more than half of whom were white (Khuluvhe & Ganyaupfu, 2022). Racial disparities in access, success, and completion of tertiary education persist, with white completion rates averaging 50% higher than those of Black individuals (Smith, 2013).

Health. The World Bank (2019) suggests that the health and safety of the home environment, the provision of nutritious food, and access to health care—among others—increase one's productivity in the workforce and, indeed, their socioeconomic trajectories. Poor health can determine one's life course well before birth, and development is influenced by inadequate fetal growth, early birth, low birthweight, stunting, exposure to disease, and constrained access to health care; all of which are common amongst individuals living in poverty in South Africa (Richter et al., 2022). These are consequences of institutional racism, and despite post-apartheid institutional reforms aimed at addressing health care in South Africa, the public health care remains overburdened and without sufficient resources including staffing, the availability of appropriate medications, and infrastructure limitations (Maphumulo & Bhengu, 2019).

The existing conditions significantly impede the delivery of sufficient healthcare to economically disadvantaged individuals, particularly those living in rural areas characterized by predominantly low-income and Black populations (Naidoo, 2012). Those who possess health insurance, and thereby can utilize South Africa's private health care system, are predominantly White. Approximately 73.5% of White individuals are covered, in stark contrast to the mere 11.3% of Black individuals (Institute of Race Relations [IRR], 2016). Consequently, access to health care supports socioeconomic mobility for some, and constrains it for others, thereby reproducing patterns of inequality.

Cultural Capital

Cultural capital, as defined by Bourdieu (1986), refers to the process through which culture and education contribute to social reproduction. It involves the accumulation of specific knowledge, skills, and behaviors that individuals draw upon to demonstrate their cultural competence (Bourdieu, 1986). Cultural capital also plays a crucial role in maintaining social stratification due to its unequal distribution among individuals and groups which, in turn, reinforces existing social hierarchies (Bourdieu, 1977). Those with higher levels of cultural capital can more navigate educational and professional environments more effectively, accessing better resources and opportunities, often to the detriment of others. This creates a cycle through which their children inherit these advantages, allowing them to secure opportunities of their own.

Scholars suggest that cultural capital encompasses both embodied and objectified forms (Broer et al., 2019). Embodied cultural capital is evident in physical attributes, behaviors, and accents associated with different social classes. For example, individuals from higher social classes may exhibit polished and refined physical appearances, body

language, and accents, often tied to elite cultural practices. In contrast, those from lower social classes might display physical attributes and behaviors more reflective of their working-class backgrounds. This embodied cultural capital often influences how individuals are perceived and received in various social and educational settings. Recent research indicates a clearer link between embodied cultural capital and human capital, suggesting that the mechanisms through which embodied cultural capital operates involve enhancing human capital (Yamamoto & Brinton, 2010). In this context, human capital acquisition is dependent parental cultural capital, shaping the abilities and aspirations that are instrumental in determining an individual's success (De Graaf et al., 2000). Contrastingly, objectified cultural capital is tied to access to cultural resources: The availability of books, technology, and learning materials contributes not only to educational success but also plays a role in shaping the broader cultural competencies (i.e., embodied cultural capital) that can support socioeconomic mobility.

Notably, indicators of cultural capital, encompassing embodied and objectified forms, are not readily available in large datasets. Unlike social, human, and economic capital, the indicators of which are more easily quantified, cultural capital is nuanced and often implied by other types of capital. For instance, physical attributes and access to cultural resources provide clues to cultural capital but are not always explicitly measured. Thus, while it is indeed an important facet to consider in conceptualizing SES, it is not explicitly measured in this research.

Social Capital

Social capital, community influence, and class relations are interconnected concepts extensively studied in various disciplines such as sociology, political science,

and economics. Social capital, as described by Putnam (2000), encompasses the combined value of all social networks and the inclinations emerging from these networks to engage in reciprocal actions for the benefit of one another. Indeed, individuals' relationships—such as family, neighborhood, and other social connections—are key determinants in shaping one's economic trajectory. Thus, indicators of social capital encompass elements from both family and community contexts which appear not only to interact with, but also strengthen, other factors influencing mobility.

Family Structure. Research suggests that individuals who grow up in single-parent families are more likely to experience poverty (Musick & Mare, 2006; Sarsour et al., 2010). In South Africa, approximately 48% of children live in single-parent family structures (StatsSA, 2018). South Africa also ranks amongst the lowest in marriage rates (Richter, 2022). This is unsurprising, as the apartheid regime systematically disempowered non-White South Africans, notably through the deliberate dismantling of family structures. Migrant laborers, predominantly men, were compelled to reside miles away from their families as they sought employment in urban areas. Concurrently, women were mandated to remain in designated rural zones known as *homelands*. This policy disrupted family units and, in turn, perpetuated social and economic disparities which have persisted since the advent of the country's democracy in 1994. One study suggests that the benefits associated with two-parent households—including greater income to support investment in children, general economic stability, and subsequent school achievement—will be passed on to only about 30% of South African children (Richter, 2006).

Community Influence. Community is another important social structure. Community support encompasses the relationships and shared values that foster cooperation and collaboration within a community (Christoforou, 2013). Families with increased cultural capital are often better positioned to leverage community support. Robust social ties within a community lay the groundwork for mutual assistance and resource-sharing. For example, within families, active participation in community initiatives and building connections with neighbors contribute to this process. Engagement in mentorship programs, participation in local events, and involvement with support organizations also increases social capital. These relationships and networks may contribute to overall societal and economic progress.

Trust. Social networks characterized by trust facilitate cooperation and coordination among individuals for mutual benefit (Putnam, 2000). In his research on the role of social capital on civic life in Italy, Putnam (1995) found that regions that lacked in cooperation and trust among community members failed to flourish economically. Prior research suggests that South Africans with lower standards of living are less trusting than those of higher standards of living (Mmotlane et al., 2010). Similarly, those with lower educational attainment reported being less trusting compared to those with higher educational attainment (Mmotlane et al., 2010). These social inequalities are further evidenced in South Africans in formal urban areas being, on average, more trusting than those in informal urban or rural areas (Mmotlane et al., 2010). However, South Africans living in rural or tribal areas may exhibit a strong sense of community which arises from close-knit social structures, shared cultural values, and reliance on mutual support

systems that are integral to their daily lives, thereby fostering trust despite economic or educational disparities.

While the literature on social capital is diverse, there is overarching agreement on the importance of the possession of two key components of social capital: trust and networks (Bartee & Brown, 2007; Baron et al., 2000). Moreover, social capital is key in linking economics, society, and politics, because these fields share the belief that social relationships affect, and are affected by, economic outcomes (Grootaert, 2001). Indeed, social capital focuses on the social relationships and dynamics of economic agents and how the formal or informal organization thereof can improve economic outcomes (Bartee & Brown, 2007).

The relationship between social capital and economic outcomes is particularly pertinent in South Africa due to its historical legacy of apartheid and the persisting socio-economic disparities. In a society where historical divisions based on race and class persist, social capital becomes a mechanism through which individuals can access opportunities, resources, and support networks. The unequal distribution of social capital can contribute to the perpetuation of economic disparities, as those with limited social networks may face challenges in accessing information, job opportunities, and financial resources. Conversely, fostering social capital in communities can lead to increased collaboration, shared resources, and collective empowerment, potentially improving economic outcomes for marginalized populations.

Offering an Alternate Approach to the Measurement of Socioeconomic Status

A novel conceptualization of SES necessitates a novel approach, particularly given the concerns with various measurement approaches detailed previously. Network thinking provides a framework through which one might hope to understand the socioeconomic conditions that support socioeconomic mobility. The emergence of network thinking can be traced back to the broader foundation of systems theory which originated in the mid-20th century and focuses on understanding the interactions and interdependencies within complex systems. It provides a framework for studying the relationships between components, emphasizing that the whole system is greater than the sum of its parts.

What sets network analysis apart from prior attempts to incorporate complex systems theory is its foundation in a data-driven methodology (Deserno et al., 2022). With its robust empirical foundation, network science has empowered researchers to formulate theoretical insights about complex systems and their interconnections as well as about individual variables and their relationships with one another taking the entire system into account (Deserno et al., 2022).

Network thinking has seen an increase in the use of network approaches in several subfields across psychology, most frequently in clinical psychology and in psychiatry (Borsboom et al., 2022). This is motivated by a theoretical underpinning that renders the conceptualization of a network plausible (Borsboom et al., 2022). The network approach to psychopathology proposes, for example, that symptoms of disorders are causally related, such that activating one symptom renders another more likely to occur (Borsboom et al., 2022). This differs from the traditional view of psychiatric conditions

which posits that disorders arise because of some unknown dysfunction in one's biology (Bathelt et al., 2022). Here, symptoms would be conceptualized as a manifestation of some latent condition (Bathelt et al., 2022).

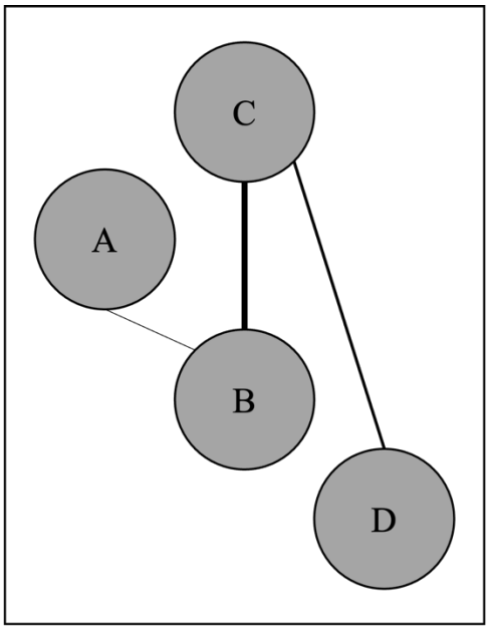
Indeed, network models are inherently exploratory, allowing for "open questions worthy of discussion and research" (Borsboom et al., 2022, p. 12). This means that researchers do not necessarily make a choice concerning specific components that might be at play, nor do they theorize how they work together; instead, network theory offers a perspective through which an empirical field might be observed and can be applied in several ways to various systems.

A key advantage of network models is that individual components are not obscured by the whole, because no such whole is modelled (Christensen et al., 2020). This addresses the unresolved argument over the use of formative and reflective approaches to modeling SES which explain the cooccurrence of SES indicators (i.e., income, education, and occupation) by invoking an underlying unobservable latent variable to explain the shared variance (Epskamp, 2017; van Bork et al., 2019). Instead, network psychometrics defines these interrelationships between the dimensions of interest using nodes to represent variables. These nodes are linked to show statistical relationships within a pairwise Markov random field (PRMF; Lauritzen, 1996; Murphy, 2012). A PMRF is a class of model that represents network without specifying directionality. These linked pathways, called edges, indicate the effect of one node on another after controlling for the other variables in the network (Borsboom et al., 2022, p. 12).

Research questions for which network analysis is employed might pertain to the role of specific nodes in the estimated network (Deserno et al., 2023). Earlier measures of these are like centrality measures in social network analysis, including degree, closeness, and betweenness (Deserno et al., 2023). The degree of the node measures the number of connections it has in the network (Deserno et al., 2023). Thus, the most central node might be connected to five others, while the least connected node is connected to just one. Closeness measures the distance to other nodes in the network. A low closeness centrality score indicates that the node is more central in the network and, consequently, does not have to travel as far as others to reach other nodes in the network (Deserno et al., 2023). Finally, betweenness measures how often a node lies on the shortest path that connects two other nodes, such that a node with higher betweenness is likely to connect groups (or clusters) of nodes together (Deserno et al., 2023). But the emergence of network psychometrics has resulted in the quantification of other metrics, including predictability of nodes (Haslbeck et al., 2021), expected influence (Robinaugh et al., 2016), and stabilizing/communicating nodes (Blanken et al., 2018). It is recommended that a combination of relevant metrics should be selected to support the study's hypothesis.

Figure 1

Pairwise Markov Random Field (PMRF)



Note. The circle A is a node. The line connecting node A and node B is an edge. Thus, nodes A and node B are conditionally dependent. The absence of an edge between nodes A and C suggests conditional independence. The weight of the edges indicates that the relationship between nodes B and C is relatively stronger than the relationship between nodes A and B.

The undirected nature of these PRMF network models stands out as a significant advantage as it aligns with the inherent ambiguity in understanding the nature of relationships between SES and outcomes of interest. For example, studies frequently report SES as a fundamental "cause" of health outcomes (e.g., Link & Phelan, 1995; Phelan et al., 2010). But it is also possible that health affects SES: chronic illness or disability, for example, may limit working capacity, thereby affecting income potential and hindering socioeconomic mobility. Similarly, many studies suggest that higher levels of education lead to better job opportunities and increased income, but it may be that the

reverse is also plausible, as financial constraints limit educational opportunities (Butler et al., 2008). Bidirectional influences simply cannot be excluded.

The Present Study

This research employs three different analytical approaches to analyze the dynamics of socioeconomic conditions and their influence on well-being outcomes using data from the nationally representative longitudinal South African National Income Dynamics Survey (NIDS). While economic, human, cultural, and social capital are essential components in understanding SES, it is noteworthy that the examination of cultural capital is limited due to the absence of specific variables in the dataset pertaining thereto. Consequently, I focus on economic, human, and social factors, thus inherently recognizing the importance of cultural capital in societal dynamics.

Thus, the objective of this study is to provide insights into the interplay of economic, human, and social capital on well-being outcomes. The adoption of a network perspective has the potential to yield a nuanced understanding of interactions within South Africa's distinctive socioeconomic landscape, presenting a novel approach to modeling SES dynamics.

CHAPTER III. METHOD

This study adopted a quantitative research design, employing secondary analysis of Wave 1 data from the National Income Dynamic Study (NIDS), conducted by the South Africa Labour and Development Research Unit (SALDRU, 2008).

Data

The dataset utilized in this study originated from Wave 1 of NIDS, a panel data study funded by the Department of Planning, Monitoring and Evaluation and executed by SALDRU at the University of Cape Town (UCT). NIDS surveyed individuals in private households and residents in work hostels, monasteries, and convents across the country, tracking the lives of approximately 28,000 participants since 2008.

The initial NIDS sample comprised 7,305 households across 409 Primary Sampling Units (PSUs), with data collection commencing in February 2008. Fieldworkers, numbering 300, were deployed to collect data from identified individuals across all nine provinces of South Africa. This effort resulted in a total of 28,255 respondents, and subsequent adjustments to design weights were made to align age-sex-race totals with the country's population estimates at that time. Themes covered in the study included experiences of poverty, household composition and structure, participation in the labor market, economic activity, health, well-being, education, and vulnerability (SALDRU, 2008).

In this study, the sample consists of individuals aged 15 and up who completed the original adult questionnaire, totaling 15,631 participants (n = 15,631). While 16,855 participants were initially identified, 1,224 of these individuals declined to participate and

are therefore excluded from the analysis. After listwise deletion, detailed later, approximately 78% of the sample was retained (n = 11, 959).

Measures

Demographic Variables

Demographic variables detail the individual and household characteristics of participants. These include race, age, biological sex, marital status, and geotype.

Biological Sex. Biological sex is a binary variable capturing participants' assigned sex at birth (0 = *male*, 1 = *female*).

Race. The race variable uses the South African government's classification of race groups in South Africa for the sake of consistency in data collection, analysis, and reporting. Participants reported their race group as *Black*, *Colored, Indian/Asian*, or *White*. The term *Colored* is a legal designation referring to members of multiracial ethnic communities whose ancestors originate from more than one of the populations who inhabited South Africa (e.g., African, European, and Asian) and is not considered offensive (Encyclopedia Britannica, n.d.)

Age. NIDS cross-referenced responses on the household- and individual-level questionnaire to determine the most accurate date of birth (SALDRU, 2008). This was then used to determine participants' ages. The continuous age variable was collapsed into eight age categories: *15–24 years*, *25–34 years*, *35–44 years*, and so on, up to *85 years or older*.

Marital Status. Participants selected one of five options best describing their relationship status (*married*, *living with partner*, *widow/widower*, *divorced*, *never married*).

Geotype. Geotype is used to differentiate geographical areas based on certain characteristics. NIDS used census data to describe participants' geotypes (*rural*, *tribal*, *urban formal*, or *urban informa*l). While there is no universally accepted definition of *rural* in South Africa, these areas are characterized sparse settlements, specific land use and/or economic activity (e.g., farming or forestry), and greater distance from established towns and cities. *Tribal* areas are inhabited by indigenous or tribal communities who adopt a communal form of land tenure that implies different social structures and behavioral norms (Daniels et al., 2013). *Urban formal* describes developed urban zones with organized infrastructure, and *urban informal* is reserved for urban areas that are characterized by spontaneous or unplanned development, often lacking formal infrastructure (Kovacic et al., 2016).

Socioeconomic Conditions

In keeping with the earlier conceptualization of socioeconomic status as a set of structural features that determine decisions and behavior, socioeconomic conditions are defined as factors that make upward social mobility more likely (Antonoplis, 2023). These socioeconomic conditions are classified as economic, human, or social capital.

Economic Capital. Economic capital refers to the economic resources that individuals possess.

Income. Income data for participants are made available in the full individual derived data set presented by the SALDRU. These income data are taken from participants' responses or are a product of imputation. Higher rates of non-response are common in collecting income data. For this reason, statisticians adopted regression imputation to report participants' income (Argent, 2009). For income sources where non-response rates exceeded 40%, no imputation was made. Because this was the case with very few of the participants ($n < 100$), non-response bias is minimal (Argent, 2009).

For this research, income is split into four categories. These are labor market income, capital income, government support income, and remittance income. Labor market income is calculated by summing the following individual level variables: income from main and secondary job, casual wages, self-employment income, income from a 13th cheque, other bonus income, income from helping friends, and income received from a piece-rate payment. This delineates the everyday income from capital income because capital income—which is more unequally distributed than labor income—is often indicative of wealth and presents a different socioeconomic condition of interest. Capital income is thus calculated by summing the total income from inheritance, retrenchment, *lobola*/bride wealth payments, gift income, repayment of loans, sale of household goods, and other miscellaneous income. Government grant income considers pensions, disability grants, child support grants, foster care grants, and care dependency grants. Finally, remittance income refers to the money received by families from migrant relatives who continue to financially support those in their country of origin.

Human Capital. Human capital represents the knowledge, skills, education, and health that individuals possess that, in turn, contribute to their taking advantage of the economic opportunities available to them.

Educational Attainment. Participants provided information on their highest level of education attained, which was subsequently grouped into distinct categories: *No education*, *some primary education*, *some secondary education*, *completed secondary education*, and *tertiary education*. The original survey employed 27 different codes for classification (Appendix A). These codes were condensed into the specified categories to align with the educational classification system utilized by the South African Government (Khuluvhe and Ganyaupfu, 2022). This classification system is also endorsed by lead authors affiliated with SALDRU who have published using these data (e.g., Fourie and Leibbrandt, 2012).

Access to Healthcare. Use of private medical insurance in South Africa is a useful indicator of access to healthcare in South Africa. In 2016, the National Department of Health (DOH) reported that 84% of South Africans depended on public healthcare, while remaining 16% belong to *medical aid* schemes and are serviced almost exclusively by the private sector (Naidoo, 2012). Participants' access to health care is thus determined based on their belonging to a medical aid scheme (0 = *no* and 1 = *yes*).

Social Capital. Social capital refers to the networks, relationships, and social connections that individuals possess, which can be valuable for accessing resources, opportunities, and support.

Occupational Prestige. Occupational prestige contributes to one's social capital by shaping one's professional networks and the social circles in which one moves (Conger & Donnellan, 2007). High-prestige occupations are often associated with increased respect and admiration, otherwise known as social status (Magee & Galinsky, 2008). Participants selected their occupation category according to the following classification: 1 = *legislators, senior officials, and executives*; 2 = *professionals*; 3 = *technicians and associate professionals*; 4 = *clerks*; 5 = *service, store, or market workers*; 6 = *skilled agricultural and fishing worker*s; 7 = *craft and related trade workers*; 8 = *plant and machine operators*; 9 = *elementary workers*; and 10 = *armed forces*. These codes were initially condensed into four categories to align with the ISCO-88 occupational classification system (Appendix B), which ranks broad skill levels on four levels, where 4 = *highly skilled* and 0 = *least skilled*. However, given the high rate of unemployment in the analytical sample, 0 was used to indicate unemployment, thus 1 = *least skilled* and 5 = *highly skilled*.

Organizational Memberships. South Africa boasts a substantial history of civic engagement and involvement (Burns, 2009). Social capital can be measured by examining organizational memberships and participation in voluntary associations (e.g., Kawachi et al., 2007). Respondents were asked to indicate their affiliation with various groups, including *stokvel*, *burial society*, *community garden group*, *farmers association*, *sewing group*, *sports group*, *study group*, *singing or music group*, *youth group*, *informal trader's group*, *men's association*, *women's association*, *school committee*, *water committee*, *development committee*, *tribal authority*, *and other*. Individuals are assigned a value of 1 if they belong to one or more organizations and 0 if they do not have any

organizational affiliations. This approach recognizes that even a single organizational connection can contribute positively to household welfare in South Africa (Burns, 2009; Maluccio et al., 2000). It also accounted for the non-normal distribution of the variable.

Community Trust. In the South African context, trust is a key indicator of community influence and social cohesion (Burns, 2009). Trust is foundational to building and maintaining strong social ties, fostering cooperation, and facilitating collaboration within communities, all of which may support economic growth (Knack & Keefer, 1997). Participants were presented with a hypothetical scenario concerning a lost wallet or purse discovered by a resident in their neighborhood and were asked to assess the likelihood of its return with its contents—R200 (approximately $10)—intact. The response options were structured as a ranked 3-point scale, which were reversed so that higher scores corresponded with greater trust: 1 = *not at all likely*, 2 = *somewhat likely*, and 3 = *very likely*.

Assets Index. The asset index method is a common approach to measuring SES often employed in the absence of income and/or expenditure data or in cases where researchers are concerned with multidimensional indicators of poverty that are not captured by money-metric approaches (Booysen et al., 2008). Demographic and household surveys (DHS) are common in African countries, and do not tend to include data on income and expenditure, thus researchers use a household's assets as a proxy for SES. In these surveys, participants report on their possession of certain assets, including televisions, vehicles, etc. The NIDS dataset is unique in that it surveyed respondents both on their income and expenditure, as well as on their ownership of various household

assets, public services, and household characteristics. For the sake of comparison to other socioeconomic conditions, this study calculated an asset index as a proxy for SES.

Many asset indices are constructed using either factor analysis (e.g., Sahn & Stifel, 2000) or a principal components analysis (PCA; Jollifee, 2002) approach (e.g., Filmer & Pritchett, 2001; Sahn & Stifel, 2000). This study employs multiple correspondence analysis (MCA; Blassius & Greenacre, 2010) as suggested by Booysen and colleagues (2008). Unlike PCA, which assumes linear constraints on the data such that the distances between the categories are uniform and that they are inherently ordered, MCA is more appropriate given the categorical nature of the asset data as collected in NIDS (Booysen et al., 2008).

Participants were asked to report on their ownership of several household assets including radios, bicycles, televisions and refrigerators (1 = *no* and 2 = *yes*). Prior research suggests that the inclusion of assets in an index are warranted so long as more than 5% and less than 95% of participants report owning them. All four of these indicators met this criterion. They also reported on the materials of their roof, their access to water, and their type of toilet facility. Mimicking the coding scheme of other research utilizing asset indices in African households (e.g., Booysen et al., 2008; Iddi et al., 2022), these responses were collapsed into four discrete categories (Appendix C).

With the assistance of Professor Frikkie Booysen at the University of the Witwatersrand in Johannesburg, South Africa, MCA was employed to create the asset index in a three-stage process. First, an indicator matrix of zeros and ones was created corresponding to the asset ownership of each respondent such that every respondent indicated a *1* in exactly one of each of the asset categories (Booysen et al., 2008). Next,

the MCA was applied to the indicator matrix to create a set of category weights from the first dimension of the analysis results (Booysen et al., 2008). Finally, we applied the MCA category weights to the matrix. The asset index is thus calculated by summing each participants' weighted responses (Booysen et al., 2008). This calculation can be represented as followed:

$$\mathrm{MCA}_i = R_{i1}W_1 + R_{i2}W_2 + \cdots + R_{ij}W_j \quad (1)$$

where MCA_i is the individual's composite asset indicator score, R_{ij} is the response of individual *i* to category *j*, and W_j is the weight of the first dimension of the MCA applied to category *j*.

The asset index scores were estimated using MCA and then standardized. Wealth quintiles were created (*1* = poorest, *5* = richest) based on these standardized scores. It is important to note that these quintiles did not necessarily correspond to exactly 20% of participants as there is often overlap based on the exact values of the cutoff points. Principal inertias (or eigenvalues), which explain the amount of variance accounted for by each dimension of the asset index, were also calculated. These inertias provide insight into the relative importance of each component in explaining the variability in asset ownership.

Outcome Measures

Four outcomes are analyzed, all of which were selected for their bearing on well-being. Indeed, well-being is important for individuals and society at large. The relationship between paid employment—and, to some extent, income—and well-being is well established (McKee-Ryan et al., 2005).

While there is no single definition for well-being, experts agree that it encompasses the presence of positive emotions, the absence of negative emotions, and satisfaction with life (CDC, 2022). Physical well-being (e.g., feeling healthy) is also critical to overall well-being (CDC, 2022). Because well-being is largely subjective, it is usually measured using self-reports. NIDS administered several self-report items to adult participants.

Depression Screening. The first outcome variable assesses participants' mental health status. They were asked ten questions about their emotional well-being, with eight focusing on negative feelings (e.g., "I was bothered by things that usually don't bother me" or "I felt depressed") and two on positive emotions (e.g., "I felt hopeful about the future" or "I was happy"). Responses were on a 4-point scale (4 = *rarely or none of the time*, 3 = *some or little of the time*, 2 = *occasionally or a moderate amount of time*, and 1 = *all the time*). Negative questions were reverse-coded. Lower scores indicate higher susceptibility to depression, while higher scores indicate lower susceptibility.

These are derived from the Center for Epidemiological Studies Depression Scale (CES-D 10), differing only in the coding of responses. Prior research supports the validity of the CES-D 10 in South Africa when administered of the country's official languages (Baron et al., 2017). It is a reliable measure of mental health status in the South African context (Baron et al., 2017). In this study, after accounting for participant weights, its reliability (α = .65) is acceptable (Cronbach, 1951). However, rather than relying on a cutoff score as an indicator of depression, the scale will be utilized as a continuous measure given the inconsistencies in cutoff scores across language groups in South Africa (Baron et al., 2017).

Perceived Health Status. Given the evidence for the association between income inequality and self-reported health (e.g., Hildebrand & Van Kerm, 2009), data were collected to establish a general assessment of one's health status. Self-reported health need not be connected to any specific illness; rather, it captures the physical and functional health of any one individual (Idler et al., 1999). Perceived health status was judged on a 5-point scale (1 = *excellent* and 5 = *poor*). These were reverse scored so that higher scores indicated better perceived health.

Life satisfaction. Prior research on SES suggests that one's own satisfaction may vary based on one's economic position (Adedeji et al., 2021; Adedeji et al., 2023; Proctor et al., 2009). Life satisfaction is a present cognitive evaluation of participants' overall well-being. Adult respondents reported how satisfied they were with life on a ten-point scale (1 = *very dissatisfied* and 10 = *very satisfied*).

Relative Happiness. It is essential to recognize that happiness is a subjective construct. Measuring changes in happiness over time avoids adopting a narrow deficit-oriented on present economic hardships. Participants were also asked to report their present levels of happiness compared to ten years earlier. This judgment was made on a 3-point scale (1 = *happier*, 2 = *the same*, and 3 = *less happy*). These were reverse scored so that higher scores indicated higher happiness.

Analytic Approach

Three kinds of models are presented for the purpose of offering different conceptualization and measurement approaches to SES. The first model, using path analysis, uses the asset index score as a measure of socioeconomic status. The second set

of models, both latent variable models, were specified first using formative indicators and then reflective indicators. These models adopt a triumvirate approach to measuring SES by incorporating an individual's income, highest level of education, and occupational skill score. Finally, the network model offers a more exploratory approach to understanding relationships between socioeconomic conditions and outcomes of interest. Unless otherwise specified, all analyses were conducted using the R Statistical Software.

Model 1: Asset Index Model

Path Analysis. Path analysis (Wright, 1918) is an approach used to examine relationships between sets of variables that are represented statistically by several linear regression equations. Variables in a path analysis are either exogenous, where their variance is not dependent on that of other variables, or endogenous, meaning that the variance of other variables determines its own variance. It is possible that exogenous variables are correlated with one another. Path models test the extent to which hypothesized relationships between variables of interest are reflected in the data (Lleras, 2005). Importantly, path models do not support causation, but they do necessitate clear and logical theories underlying the processes that might be expected to influence outcomes (Lleras, 2005). Another distinct advantage is that relationships can be more explicitly laid out and tested compared to employing multiple regression analyses. In this study, path analysis was employed to investigate the direct relationship between SES, operationalized by the asset index, and each of the outcome variables: life satisfaction, relative happiness, self-reported health, and score on a depression measure.

Model Specification. In the path analysis model, the asset index (the exogenous variable) was specified as the predictor of the outcome variables (life satisfaction,

happiness, health, and depression) using the R package **lavaan** (Rosseel, 2012) with the robust weighted least squares (DLWS) estimator. Because SES is presumed to be the driver of the model, paths were directed from SES to each of the endogenous outcome variables. No covariates were included, nor were any indirect effects assessed. Finally, the proportion of variance in the outcomes explained by the asset index was also assessed.

Models 2A and 2B: Latent Variable Models with Triumvirate Indicators

Models 2A and 2B use NIDS data to compare reflective and formative specifications of the triumvirate socioeconomic indicators, namely the individual's income, education, and occupational status.

Structural Equation Modeling. In these models, SES is conceptualized as a latent variable, thus structural equation modeling was employed. Latent variables are those that cannot be directly observed but are hypothesized to be related to other, observable variables. SEM is a multivariate approach combining confirmatory factor analysis (CFA) and path analysis to observe the structural relationships between the latent variables and the measured variables available.

Model Specification. In the reflective model, SES indicators were modeled as effects of a latent SES factor. In the formative model, these indicators are modeled as causes of SES. The structural model subsequently assessed the relationship between the latent SES variable and the outcomes of interest: life satisfaction, happiness, depression, and perceived health. The **lavaan** package contains functions to estimate these models (Rosseel, 2012). Because these models contained both continuous and categorical

variables, the diagonal weighted least squares (DWLS) estimator was specified, which is appropriate for sample sizes larger than $n = 1000$ (Li, 2021).

Model fit describes how well the proposed model fits the available data. The Chi-square goodness of fit test is commonly employed to assess model fit, where the resultant test statistic is assumed to follow a chi-square (χ^2) distribution. If the Chi-square goodness of fit test is significant, it suggests that the model covariance matrix differs significantly from the sample covariance matrix. This test, however, is sensitive to sample size, as smaller differences are more easily detected in large samples (Kenny, 2020).

Thus, given the large sample size, alternate model fit indices were assessed. For instance, the comparative fit index (CFI) requires a value of ≥ 0.90 for acceptable fit (Bentler, 1990). Ideally, the standardized root mean square error of approximation (SRMR) should be less than .05 (Byrne, 1998), although values up to .08 are thought to indicate acceptable model fit (Hu & Bentler, 1999). Finally, the root mean square error of approximation (RMSEA) typically falls between .05 to .08 for acceptable fit (Steiger, 1990). The proportion of variance in the outcomes explained by the latent SES factors was also assessed.

Model 3: Network Model

Network Thinking. Network modeling allows for the capturing and analyzing of complex relationships among observed variables without assuming an underlying latent structure. This is particularly advantageous when studying phenomena with multifaceted interactions that may not conform to a predefined set of latent variables. As such, it offers

an alternative approach that can potentially circumvent the ambiguity associated with SES as it is presented in contemporary research (e.g. Antonoplis, 2023).

Network Modelling. While many kinds of multivariate approaches might support a network representation of a domain of interest, this analysis employs a network model known as a *pairwise Markov random field* (PRMF; Lauritzen, 1996; Murphy, 2012). PRMFs capture conditional associations among variables, with nodes representing variables and edges indicating the strength of these associations after accounting for other network variables (Epskamp et al., 2022). In this model, the presence of an edge connecting two nodes denotes conditional dependency, while the absence of one suggests conditional independence. These edges are weighted to indicate the magnitude of the association after conditioning on all other variables in the model (Epskamp et al., 2022).

The R-package **mgm** (Haslbeck & Waldorp, 2020) was used to construct a mixed graphical model (MGM, Haslbeck & Waldorp, 2020). Within this structure, variables are represented as nodes, and the associations between them are represented as edges. The estimation algorithm provided by **mgm** allows variables of different kinds (e.g., continuous, categorical) to be modeled. If an edge was present between any two variables, a *weight* was estimated. If this association was between two continuous variables, only one parameter was present, and its absolute value was taken. The color of the edge indicated its sign. Thus, edges between continuous variables were constrained between -1 and 1, as the strength of association is quantified using regression parameters from generalized linear models of standardized variables (Epskamp, 2022). However, for interactions involving categorical variables—i.e., continuous-categorical or categorical-categorical—the mean of the absolute value of all the parameters was taken as the weight

of the edge, and there was no constraint on the range of weights for these edges (Epskamp et al., 2022).

To begin analysis, the type of each variable of interest is specified next to the data (*g* for Gaussian, *p* for Poisson, and *c* for categorical) along with the number of levels of each variable (convention is 1 for continuous variables). While the **mgm** package allows for the estimation of k-order MGMs, this analysis is concerned only with fitting a pairwise MGM, thus $k = 2$. For network estimation, the LASSO (Tibshirani, 1996) regularization parameter which was selected using the Extended Bayesian Information Criterion (EBIC). The EBIC relies on a *hypertuniningparamter* γ, which determines the trade-off between sensitivity and precision for complex models (Blanken et al., 2021). While this hypertuning parameter is usually set between 0 and .25, prior research suggests that when $\gamma = .25$, it decreases the likelihood of generating false positive edges without increasing the likelihood of generating false negative edges (Foygel & Drton, 2015; Haslbeck, 2015). The *fit_ads()* function in the **mgm** package returns all the estimated parameters.

The mgm package was written to integrate with the **qgraph** package (Epskamp et al., 2012). The *qgraph()* function is thus used to visualize the weighted adjacency matrix produced in the previous step. In the **qgraph** package, the default layout is computed with the Fructerman Reingold algorithm which displays edges of about equal length and with as few crossing edges as possible. Groups of variables (i.e., demographic variables, socioeconomic conditions, and outcome measures) were classified by colors.

The function *centralityPlot()* in the **qgraph** package was used to investigate the position and the role of nodes in this network (Deserno et al., 2021). Indeed, the position

of a node in the visualization of a network does not necessarily mean that it is most important (Deserno et al., 2021). Instead, centrality measures (for both direct and indirect connectivity) are used to make this determination. Node strength, a measure of direct connectivity, sums the absolute value of the weights of the edges connected to a node in the network (Deserno et al., 2021). Node closeness, which quantifies how far-removed nodes in the network are from other nodes, is calculated by taking the inverse of the sum of all the distances from the node in question to all other nodes (Deserno et al., 2021). Finally, betweenness measures how often a node lies on the shortest path between two other nodes, such that a node with high betweenness tends to connect other nodes together (Deserno et al., 2021).

Relationships between continuous variables were interpreted using the model, with the width of the edge proportional to the absolute value of the parameter, and the edge color indicating its sign in terms of the relationship between the two variables (Haslbeck, 2015). For categorical variables, a different approach was employed, as the presence of an edge reveals only that there was a relationship: The *showInteraction()* function in the **mgm** package was used to investigate these. For categorical-continuous interactions, the coefficients were interpreted consistent with standard regression frameworks. It is important to note that the software automatically scaled all Gaussian nodes to $\mu = 0$ and $\sigma = 1$, and parameters were interpreted accordingly.

In the second phase of interpretation, which pertains to the regression on the categorical variable, probabilities were modeled for each category. In each equation, a term for the continuous variable was included. Positive parameters showed that an

increase in the continuous variable raises the probability of a specific category, while negative parameters showed the opposite effect.

For the interpretation of a categorical-categorical interaction, *showInteraction()* function reports parameters in a regression framework. The output structure included two components: Predict_Y and Predict_X. The overall interpretation involved combining information from both Predict_Y and Predict_X to derive a comprehensive understanding.

Following the analysis, parameter stability and accuracy were assessed post-hoc. Edge weights were estimated using 95% confidence intervals (CIs) by using non-parametric bootstrapping (Fried et al., 2022). The output object of the *mgm()* function, the fit_mgm, was the input for the function *resample()*, along with the data and the desired number of bootstrap samples (Haslbeck & Waldorp, 2020). Lower- and upper-quantiles were specified as .025 and .975, respectively. Finally, a random seed was included to make the output reproducible. The function *plotRes()* was used to produce a plot that displays the bootstrapped sampling distributions.

Finally, predictability measures were obtained using the *predict()* function in the **mgm** package. This necessitated calculating the mean of the conditional distribution of the node of interest given all its neighbors. For continuous variables, the measure of predictability was the proportion of explained (R^2), while the predictability of categorical variables was specified as correct classification ("CC") and normalized accuracy ("nCC"). The accuracy of the intercept model was requested ("CCmarg") to break down the total accuracy of the intercept model and other variables' contributions. The same weighted adjusted matrix produced earlier was provided in addition to the list requesting

the nodewise predictability measures to the *qgraph()* function in the **qgraph** package. This produces ‘rings’ around each node which visually represent the predictability.

Missing Data Management by NIDS

Little research exists on handling missing data for the abovementioned estimators (Fried et al., 2022), and MGMs cannot be computed with incomplete data. Thus, methods for handling missing data in regression models are appropriate for univariate network estimation. In the case of some variables in the NIDS individual derived dataset, values for missing data were imputed using regression approaches and based on demographic variables including gender, race, age, trade union membership, province, education, geotype, marital status, home attributes (e.g. number of rooms, type of dwelling etc.), and interview month (Argent, 2009).

CHAPTER IV. RESULTS

Preliminary Analyses

Several preliminary analyses were performed to gauge the nature of the variables in this study. Given the large sample size, visual inspection was employed to assess the normality of the continuous variables as well as those with > 5 categories that might otherwise be able to be treated as continuous (age; labor, government, capital, and remittance income; perceived health; life satisfaction; relative happiness; and depression score). Only depression and life satisfaction were relatively normally distributed, while the remaining variables did not follow a normal distribution. Thus, education, medical aid, occupational skill level, community trust, group membership, perceived health, and relative happiness are treated as ordinal. Demographic variables are treated as nominal.

Missing data analyses were performed using the **mice** (Multivariate Imputation by Chained Equation) package (Van Buuren & Groothuis-Oudshoorn, 2011). 77.92% of cases were complete across the study variables, and rates of missingness for variables ranged from 0.11% to 11.86% (Table 1). Given the lack of guidance for dealing with missing data in network psychometrics, it was decided that listwise deletion was appropriate, especially since doing so retained 77.92% (n = 11,959) of the sample.

Weighted means for the study's demographic variables and the socioeconomic conditions are available in Table 2 and Table 3, respectively. These weighted means are calculated using the post-stratification weights at the household level available in the NIDS data (w1_wgt) and were calculated using the **survey** package (Lumley, 2004). Notably, even after the exclusion of missing cases, the proportion of the NIDS sample,

when stratified by race, corresponded to the government's national estimates for population groups for the same year in which the first wave of NIDS data collection took place: Black = 79%, Colored = 9%, Indian/Asian = 3%, White = 10% (StatsSA, 2008). StatsSA (2008) also reported that as of mid-2008, 52% of the sample were female. In the NIDS weighted analytic sample, 55.87% were female. Means, standard deviations, and correlations for the study's outcome variables are available in Table 4.

Model 1: Asset Index

Descriptive Analysis of the Asset Index

Table 6 shows the variables included in the asset index and the weights obtained from the MCA. The presence or absence of these assets determined possible levels of the asset index for the single items, while the water source, toilet facilities, and roofing materials were ordered. The overall MCA results (Table 5) also show the proportion of principal inertia (eigenvalues) explained by the set of seven variables, as well as the first component, 85.69%.

Taking weights into account, the mean asset index score was $M = .17$ ($SD = .93$). When using the asset index to separate individuals into income quintiles, 2,143 participants were in quintile 1. 2,621 were in quintile 2. 2,350 were in quintile 3. 2,450 were in quintile 4. Finally, 2,395 were in quintile 5. Correlation analysis indicated that the asset index was positively correlated with life satisfaction ($r = .32$, $p < .01$), relative happiness ($r = .22$, $p < .01$), self-reported health ($r = .09$, $p < .01$), and depression score ($r = .19$, $p < .01$).

Path Model

The path model included one predictor variable—the asset index—and four outcome variables: life satisfaction, happiness, health, and depression. Given the simplicity of the model with no degrees of freedom, the fit indices suggested perfect fit to the data (CFI = 1.000, TLI = 1.000, RMSEA = 0.000, SRMR = 0.000). But achieving model fit is inevitable in such a simple model and these fit statistics do not provide meaningful information about the extent to which the model is appropriate and generalizable. In this case, only the R^2 values are worth assessing (Caughlin, 2024).

The estimated path coefficients revealed significant relationships between the independent variable and the dependent variables. Specifically, the path coefficient from the SES to life satisfaction was $\beta = .842$, SE = .035, $\beta^* = .315$, $p < .001$. Similarly, the path coefficient from SES to happiness was $\beta = .237$, SE = .017, $\beta^* = .216$, $p < .001$. The path from the SES variable to health was also significant, $\beta = .115$, SE = .015, $\beta^* = .106$, $p < .001$. Finally, SES significantly predicted depression, $\beta = .907$, SE =.059, $\beta^* = .197$, $p < .001$. The path model accounted for 10% of the variance in life satisfaction ($R^2 = .10$), 5% of the variance in happiness ($R^2 = .05$), 1% of the variance in health ($R^2 = .01$), and 4% of the variance in depression ($R^2 = .04$).

Latent Variable Models

In the second set of models, SES was modeled as a latent variable using income, education, and occupational skill as indicators. These indicators were modeled reflectively (Figure 2) and formatively (Figure 3). These analyses were conducted using lavaan 0.6.16 with the robust weighted least squares (DWLS) estimator.

For the model to converge, income had to be categorized. Rather than using cutoffs to create arbitrary categories of total income, the decision was made to separate the sample into wealth quintiles. Mimicking NIDS' strategy to create quintiles based on per capita household income (e.g., Ardington & Case, 2013), cut off points were estimated to separate the sample by calculating the household income divided by the number of residents in the household (M = 2,143.40, SD = 4,341). Because of survey weights, the quintiles did not necessarily contain the same number of people.

Model 2A

The reflective model theorized that the latent variable SES was defined by three ordinal indicators that were modeled reflectively. Standardized factor loadings for income (.682, SE = .016), education (.675, SE = .016), and occupation (.522, SE = .018) are available in Table 7. In the structural model, SES significantly predicted four outcome variables: satisfaction (β = 1.203, SE = .072, β^* = .358, $p < .001$), happiness (β = .429, SE = .030, β^* = .319, $p < .001$), health (β = .430, SE = .027, β^* = .320, $p < .001$), and depression (β = 1.871, SE = .112, β^* = .324, $p < .001$). Model fit indices were marginally below what would otherwise be considered adequately fit the data: $\chi^2(8)$ = 140.310, $p < .001$; CFI = .917; SRMR = .039; RMSEA = .057 (90% CI [.052, .062]).

The total amount of variance in life satisfaction accounted for by SES with reflective indicators was 13.0% (R^2 = .13). SES also accounted for 10.2% of the variance in happiness (R^2 = .10). The total amount of variance in health accounted for by SES was 10.0% (R^2 = .10). Finally, SES accounted for 11.0% of the variance in depression (R^2 = .11).

Model 2B

The alternate model theorized that the latent variable SES was defined by three ordinal indicators that were modeled formatively. Standardized factor loadings for income (.674, *SE* = .028), education (.450, *SE* = .036), and occupation (.094, *SE* = .042) are also available in Table 7. In the structural model, SES also significantly predicted four outcome variables: satisfaction (β = .684, *SE* = .030, β^* = 0.278, $p < .001$), happiness (β = .233, *SE* = .013, β^* = 0.227, $p < .001$), health (β = .340, *SE* = .014, β^* = 0.322, $p < .001$), and depression (β = 1.130, *SE* = .050, β^* = .264, $p < .001$). Model fit indices indicated a poorer fit to the data compared to the reflective model: $\chi^2(6) = 266.276$, $p < .001$; CFI = 0.821; TLI = 0.821; RMSEA = 0.060 (90% CI [0.054, 0.067]).

The SES variable, when modeled formatively, also accounted for less variance than the reflective model in life satisfaction (R^2 = .08), happiness (R^2 = .05), and depression (R^2 = .07). It accounted for approximately the same variance in health (R^2 = .10). Taken together, these results suggest that the reflective model of SES is a better representation of the data, and it accounts for more variance in well-being variables.

Network Model

Network Visualization

The network (Figure 4) demonstrated that nodes belonging to each group were, for the most part, associated with one another, close to each other, and reasonably well-separated from nodes from other groups. This suggests a delineation in the types of capital each socioeconomic condition represents. It also suggests that the well-being variables are closely related, which is not unexpected. Cross community connections

were found between human and social capital, human and the demographic variable marital status—which may itself be a form of human capital—and, finally, between human and some elements of economic capital.

Edges

The values of the edge weights are represented by the thickness of the edge line connecting two nodes. For pairs of continuous variables, the edge connecting them is either green or red, indicating a positive or negative relationship, respectively. Thicker, more saturated green lines indicate a strong positive relationship. Thicker, more saturated red lines represent a strong negative relationship. An edge connecting two variables is gray if at least one of them is categorical. The absolute values of the edge weights are available in Table 8, with the caveat that edge weights between a pair of continuous variables are constrained between -1 and 1, while this is not necessarily true for edges connecting a pair of variables where at least one of them is categorical.

Centrality

Node centrality refers to the influence that each individual variable has on the rest of the variables in the network. These measures are plotted in Figure 5. A summary is available in Table 9. Concerning human capital variables, level of education (node 6) scored highest on strength (3.82), closeness (.021), and betweenness (34), and thus was the most central node in the network. This means the level of education is relatively close to other nodes in the network (closeness), on the shortest path between two nodes approximately 34 times (betweenness) and is highly influential (strength).

Access to private healthcare (node 7) also scored highly on strength and on closeness but was not as high on betweenness. Concerning economic capital, labor income (node 5) was the strongest of the income types, though not as strong as variables from other kinds of capital. It also was low on betweenness, as were all kinds of income, meaning they were further removed from the network. Remittance income (node 5) was not at all connected in the network. For social capital, occupational skill (node 8) was strongest, and scored highly on closeness, however it was not as high on betweenness. Both community trust (node 9) and group membership (node 10) were comparatively weaker. They, too, scored low on closeness and on betweenness.

An assessment of the outcome variables shows that both self-reported health (node 11) and life satisfaction (node 12) were strong, meaning they were better predicted by the network than were the other aspects of well-being. Health also scored highly on closeness and betweenness, while life satisfaction was scored comparatively lower on closeness and even lower on betweenness. Depression was the weakest of the outcome variables, and lowest on betweenness. Relative happiness was only marginally stronger, approximately equal on closeness, and low on betweenness. Reasons therefore are discussed the next chapter.

Stability

Case-drop bootstrapping assesses whether the centrality of indices from the analytical sample correlate with centrality indices from a subset of that sample. Results of this iterative procedure are displayed in Figure 6. It is worthwhile noting that in cross-sectional data, strength centrality is weaker, thus only those with coefficients greater than .25 are interpreted (Epskamp et al., 2018).

Predictability

Figure 7 shows the predictability of each node in the network. The blue rings indicate the percentage of explained variance for the continuous variables, while the orange rings indicate the accuracy of the intercept model. The orange and red together indicate the full accuracy, and the normalized accuracy is represented by the ratio of red to red and white. A visual inspection reveals that, as expected, nodes with greater edges (both in number and in strength) can be predicted better, while those with lesser edges (again, in number and in strength) cannot be predicted as well. Comparing the R^2 statistics (Table 10) shows that the network model accounted for more of the variance in perceived health, life satisfaction, relative happiness, and depression than the other three models. The predictability results for the all the remaining variables in the network, including the categorial ones, are available in Table 10.

Intracommunity Interactions

Intracommunity interactions are reported for socioeconomic indicators classified under the same types of capital (or *community*) to support their being grouped together. Intercommunity interactions are reported in the discussions section in the context of larger network findings.

Human Capital. Human capital conditions were closely related with one another. Participants with no education and some primary education were less likely to report having medical aid. Participants with some secondary education were no more likely to report having medical aid. Participants who had completed secondary—as well as those who had tertiary education—were more likely than not to report having medical aid. Participants with some primary education were no more likely than those with no

education to be without medical aid. Every increase in education level thereafter decreased the likelihood of not having medical aid. Correspondingly, participants with some primary education were no more likely than those with no education to report having medical aid. But, with every increase in education thereafter, participants were increasingly more likely to report having medical aid compared to those who had no education, respectively.

With every increase in level of education, the likelihood of participants reporting *very poor health* decreases. The same is true of participants' reporting *poor health*. There is no difference in the likelihood of reporting *average health* across education levels. With every increasing level of education, the probability of participants' reporting being in *good health* increases. The same is true of participants' reporting *very good health*.

In considering the interaction between education (categorical) and life satisfaction (continuous), regression parameters suggest that there is no change in life satisfaction if an individual has some primary education compared to no education. However, having some secondary education, completed secondary education, and tertiary education increases life satisfaction by .02, .05, and .06, respectively, compared to having no education. The increases in life satisfaction are incremental, with tertiary education leading to the most substantial improvement in life satisfaction.

With every increase in level of education, the likelihood of participants reporting *being happier* increases. With every increase in the level of education, participants are less likely to report *no change in happiness*. There is no difference in the probability of reporting *being unhappier* across education levels.

The interaction between education and depression suggests that there is no significant difference in depression when one has some primary education compared to no education. However, depression improves by .12, .15, and .11 when individuals have some secondary education, completed secondary education, and tertiary education, respectively, compared to having no education.

Medical aid was the other important kind of human capital. Surprisingly, no edge was present between medical aid and self-reported health. The interaction between medical aid and life satisfaction suggests that having medical aid is associated with a .28 increase in life satisfaction compared to not having it. There is no difference in the probability of reporting *being unhappier* for those who have medical aid compared to those who do not. The same is true of reporting *no change in happiness*. Having medical aid, however, is associated with an increase in the likelihood of reporting *being happier* than before. Finally, having medical aid is associated with a .15 improvement in depression.

Social Capital. Occupational skill was the most influential kind of social capital in the network, but it was not strongly associated with community trust, and the interactions between these nodes are inconsequential and therefore not necessary to interpret. The association between occupational skill and group membership is also weak, but the only significant interaction term is worthwhile highlighting, as the only significant difference between the likelihood of reporting being in no community groups and one or more community groups was for those with a level-5 skilled occupation. This reiterates the extent to which social capital operates better in well-governed, richer communities compared to those that are poorer (Putnam, 1993).

CHAPTER V. DISCUSSION

The study investigated conceptualizations of socioeconomic status (SES), the measurement methods, and modeling approaches to examine its associations with life satisfaction, health, depression, and perceived health. In the first model, a single asset index score was constructed through MCA as an SES proxy. The second model employed SEM to represent SES using three indicators: income, education, and occupation, examined both reflectively (Model 2A) and formatively (Model 2B). The third model utilized network modeling to reveal the associations between economic, human, and social capital indicators of SES.

Model 1: Asset Index Model

The first model used an MCA-derived assets index to investigate the relationship between SES and life satisfaction, happiness, health, and depression. Given the well-established relationship between SES and well-being, it was expected that SES—when measured using an asset index—would be positively associated with perceived health, relative happiness, life satisfaction and depression.

In the African context, the use of an assets index as a measure of SES is fairly common practice (Booysen et al., 2008; Dossa et al., 2011; Somi et al., 2008; Wittenburg & Leibbrant, 2015). The results from the MCA used to estimate the asset index score suggest that the asset index is indeed a valid measure, with the proportion of principal inertia exceeding the 80% threshold (Booysen et al., 2008). The weights for each component of the asset index show that the types of assets that one would associate with improved standards of living are positive contributors to the index, while the ones associated with lower standards of living contribute negatively. This reiterates that these

assets, for the most part, exhibit similar behavior towards the axis (Ezzari & Verme, 2012). The percentage inertias for the individual asset variables are highest for 'surface water,' 'no fridge,' and 'no TV,' respectively. This suggests that not having these assets is particularly discriminant in distinguishing those of lower SES from those of higher SES.

Thus, according to these results, higher household SES is characterized by the presence of a radio, television, house, and fridge, a flush toilet, piped water, and a roof made of high-quality material, as these have positive coefficients. Findings from the StatsSA (2021) General Household Survey (GHS) support this: approximately 95% of household in income quintile five (the highest) used a flush toilet compared to just 43.3% of households in quintile one. The report also revealed a proportional increase in the number of households with access to piped water increase with higher income quintiles, while the number of households reliant on public sources of water decreases (StatsSA, 2021).

Constructing an asset index as measure of SES is a common practice in well-being research (Filmer & Pritchett, 2001; Filmer & Scott, 2011). Not only does an asset index provide information about poverty dynamics, but it also estimates the vulnerability of households to certain economic stressors. For instance, Carter and Barrett (2006) argue that a household suffering a temporary loss of income might not see a decline in its asset base, potentially enabling a swifter return to its pre-shock level of well-being. Thus, using an asset index to identify persistently poor households is an important step in devising interventions targeting South Africa's lowest quintile.

It is noteworthy that asset indices are not necessarily a perfect approximation of income and expenditure, specifically. This is because assets are slow-moving, whereas changes in income and expenditure are measurable almost immediately (Booysen et al., 2018). It is probable that an asset index is more likely to reflect increases in income—rather than decreases—since assets are not necessarily immediately disposed of following a decline in income. However, Filmer et al. (1999) maintain that these metrics are more highly correlated in developing countries. An asset index might pose alternate challenges in these same countries, though, since assets are less discriminatory at lower levels of poverty, particularly when there are fewer unique values (i.e., less variability) for the asset index (Booysen et al., 2018). Therefore, when examining extreme poverty, an asset index might be strengthened by the inclusion of other correlates of SES, including income and occupation (Booysen et al., 2008).

Furthermore, drawing on this study's operationalization of SES, it is evident that asset indices may be susceptible to bias. If socioeconomic conditions are "normatively valued," then using an asset index in any heterogenous setting—like South Africa—may not appropriate, given that assets that are valued by one household might not necessarily be valued by the next. Additionally, certain assets might be more prevalent in everyday households, particularly as media and communications technology become more accessible and affordable. For instance, the presence of a television in 2008 might not reflect the SES of a household the same way it did a decade earlier as they become more common in lower income households. Finally, it is important to note that the provision of some assets in this index, such as piped water and sanitation facilities, are a result of governmental interventions. While these are indeed salient in considering well-being,

they may not always reflect levels of poverty and inequality in South Africa since households benefitting from the governments' improving infrastructure are likely among the poorest in the country.

Models 2A and 2B: Latent Variable Models using Triumvirate Indicators

The second models included SES as a latent variable with three indicators: income, education, and occupational skill level. In both the formative and reflective models, the SES variable was significantly associated with perceived health, relative happiness, life satisfaction and depression.

There were notable differences in the factor loadings between the reflective and formative specifications of the latent SES variable. Education had the highest factor loading in both the reflective and formative models (.68 and .67, respectively). But the factor loadings of the income and occupation variables revealed greater discrepancies. For the reflective model, the factor loading for total income was .75, compared to .45 in the formative model. This could suggest that in the reflective specification, income is more representative of the underlying latent SES variable than it is in the formative model. In the formative model, the low loadings for occupation and income indicate that most of their contribution to SES is already captured through the education variable, and they do not provide additional explanatory power. Conversely, the reflective model yielded a higher factor loading for the occupation indicator (.52 and .09, respectively), indicating that the three variables (education, occupation, and income) share substantial common variance.

Not only did the reflective model reveal higher factor loadings, but it was also a better fitting model and explained more of the variance in perceived health, relative happiness, life satisfaction and depression. This corroborates that a latent SES variable with reflective indicators might be more appropriate than a formative one. However, one must interrogate the extent to which this specification aligns with one's theoretical understanding of SES. To some, a reflective model might suggest that a one-unit increase in SES should result in some meaningful change in all its indicators (NCES, 2022). But this might not be true in practice: a change in SES does not necessarily result in a change in all three of its indicators. A change in SES that is reflected in a loss of income would not mean that one's education level decreases, too. Furthermore, reflective models assume that latent variable indicators are not interchangeable, which does not seem appropriate for the alternate conceptualization of SES offered here.

However, the formative model is also flawed. Not only are its factor loadings lower, but the model also demonstrates poorer overall fit. This is not surprising, since Bainter and Bollen (2014) showed that formatively measured variables result in a well-fitting structural model when all the outcomes associated with the formative variable can be attributed only to that variable. Therefore, SES would only fit these data well if perceived health, relative happiness, life satisfaction, and depression result solely from SES, which is unlikely. Furthermore, these indicators are not exchangeable in formative models (Bainter & Bollen, 2014). For instance, removing the occupational skill indicator would not yield a model equivalent in meaning because each indicator uniquely contributes to the explained variance in the outcome. Consequently, it may indeed be

more appropriate to analyze each indicator separately and refer only to ‘the effects of income’ or ‘the effects of education’ on some outcome of interest.

Model 3: Network Model

The network model uncovers the associations between all 14 variables included therein. First, I explore the relationship between the socioeconomic conditions in the model and their association with each of the four outcome variables: perceived health, relative happiness, life satisfaction, and depression.

Different socioeconomic conditions were relatively more or less important for different aspects of well-being. The results of the network model also demonstrated that education emerged as the socioeconomic factor most strongly associated with perceived health. This is unsurprising, especially given the robust association between education, life expectancy, and morbidity. Research suggests that by aged 25, a college graduate is expected to outlive an individual who did not complete high school by at least a decade (Case et al., 2023). This association is consistent across gender, too. A study involving about 6,000 males found that those who completed graduate school had a 42% risk of developing heart disease compared to 59% of men who reported completing only primary school (Kubota et al, 2017). Among the 7,000 females, those with a graduate degree had a 28% risk of developing heart disease, while those with primary school only had a 50% risk (Kubota et al, 2017).

The interaction terms between education and health supported this, showing that the likelihood of reporting being in very good health increased exponentially with every higher level of education. But there was no difference in the likelihood of reporting being

in average health across education levels. Notably, tertiary education decreased the likelihood of reporting being in very poor health, albeit not to the extent observed with completion of secondary education. This observation suggests that achieving a high school diploma might offer sufficient health literacy and access to resources to buffer against the most severe health conditions.

Education is also an important factor in individuals' health through its influence on other socioeconomic determinants. Indeed, this network analysis revealed that education was most influential in the network on the two-step expected influence metric (3.98). This reveals that education has the highest indirect effect on other communities in the network through at least one other node. Because education plays an important role in determining employment opportunities and income levels, for example, those with lower educational attainment are less likely to possess the kind of social and economic capital necessary to support occupational, residential, and recreational activities that are associated with better health and well-being outcomes (CDC, 2023). This is echoed by the WHO Health Commission (2008), who advocates for taking action to improve the social determinants of health in pursuit of health equity. Collectively, these findings support that education is likely the most critical point for interventions designed to improve well-being amongst South Africans.

Perceived health was also ranked second highest on 'betweenness' after education, demonstrating the extent to which health channels the activity or influence between any other two other nodes in the network (Epskamp, 2022). This underscores the multidimensional nature of health and its associations with several facets of one's life, as

well as mediating the relationship between various socioeconomic conditions and other elements of well-being.

Occupational skill was the next strongest node in the network (3.31). This, too, is unsurprising, especially given the high rate of participants without work in the current sample, estimated at about 70% (n = 8,890). Among these individuals, 1,080 were above the age of 65 and therefore would not be classified as unemployed. Still, the highest rate of unemployment was observed for people between the ages for those under the age of 25. Notably, these data were collected during the 2008 financial crisis, which may help explain the exceptionally high unemployment rate in this sample.

Indeed, data from across the world suggests that there were increased rates in anxiety, depression, and suicide following this economic recession (Chang et al., 2013). There is evidence for a significant inverse relationship between financial resilience and mental health amongst South Africans specifically (Essey Gaisel et al., 2023). In their extensive meta-analysis, Paul and Moser (2009) found that, across 237 cross-sectional and 87 longitudinal studies, the effect size of unemployment on mental health was d = .51. The same study found that there were significant differences between the employed and the unemployed on symptoms of depression, and that these effects were more severe in countries with weaker economic development (Paul & Moser, 2009). Another meta-analysis concluded that job insecurity had a significant impact on both physical and mental health outcomes, but that the effect on mental health outcomes was more substantial (Sverke et al., 2022).

Because employment is an important source of financial security, social support, purpose, and meaning in life, it makes sense that the network analysis revealed

employment was the node that had the highest 1-step expected influence (3.13), meaning that it was most strongly connected to the nodes outside its own community. While the strong association between education and occupation skill in this network likely accounts, in part, for this finding, it may also suggest that occupational skill (or indeed, simply securing a job) is another important intermediate link when intervening to improve well-being outcomes (i.e., a different community in the network).

Marriage was the socioeconomic condition most associated with relative happiness. Diener and colleagues (1999) assessed several large-scale surveys and found that married people were happier than those who have never been married or are widowed, divorced, or separated. Additionally, among the unmarried, cohabitation was associated with greater happiness than any of the other conditions (Diener et al., 1999). The interaction terms between these two variables in the network further support this, showing no difference in the probability of reporting being happier between those who were married and those who were living together. Although classified in this network as a demographic variable, marital status remains an important socioeconomic condition. Married or co-habiting partners can combine their economic resources and may be more likely to share responsibilities, such the division of labor. It also facilitates greater social capital by enabling families to pool their social networks and support systems.

Access to private health care emerged as the socioeconomic condition most strongly associated with both life satisfaction and depression. This is particularly noteworthy given that it was the most unequally distributed socioeconomic condition in the network, with only 17.36% of people (n = 1,410) reporting belonging to a medical aid scheme. In the United States, having health insurance does not appear to be significant in

determining socioeconomic mobility (Butler et al., 2008), though this may not be the case in South Africa. Indeed, access to private health means that participants are less likely to be in poor health that is associated with declining life satisfaction. Even though some studies suggest that subjective health is the best predictor of life satisfaction (Ferna et al., 2016), this was not the case in this network. It is perhaps more likely that health insurance serves as a proxy for other socioeconomic advantages in this context. Individuals accessing private health care are likely to have higher incomes or better employment benefits to afford it, which could also contribute to their overall well-being. Indeed, having access to private healthcare (i.e., medical aid) was the third strongest node in the network, suggesting that it was strongly related to many other nodes in the network.

Another intriguing finding was the relatively weak connection between income and well-being outcomes, contrary to common expectations. Labor income was not associated with any of the four well-being outcomes. This is surprising, especially since material support is important for well-being, and one's earnings are key in securing such resources (Parcel & Dufur, 2006). However, given high rates of participants without work in the sample, the labor income variable was highly skewed, which may account for this finding.

Government income, or the receipt of social grants (including disability, child support, foster care, and care dependency) was more strongly associated with health than it was with any of the other outcomes. Assessing this interaction reveals that government income decreased exponentially with reporting increasing levels of health (compared to reporting being in very poor health, respectively).

Capital income was associated with health, happiness, and depression only, though these associations were much weaker than other socioeconomic conditions. This underscores the importance distinguishing between income and wealth, as wealth inequality is typically higher than income inequality in South Africa (Valodia, 2023). Indeed, the top .01% of people, just 3,500 individuals, own 10% of South Africa's wealth, while the top .1% account for a quarter of it (Valodia, 2023). The repercussions of this profound wealth disparity are discussed below.

The Case for Network Models

Synthesizing findings across these models reveals the need for a more nuanced understanding of SES and its implications for individual well-being. These findings align with existing research indicating variations in rich-poor differences based on the selected economic status measure (Filmer & Scott, 2011). The discrepancies in the assignment of individuals to quintiles based on an asset index (Model 1) and the quintiles derived from the household income (Model 2) are indicated in Table 11. Indeed, there are inconsistences in these assignments which, in turns, highlights the complexity and the subjectivity inherent in selecting an 'SES' measure when it is not clearly operationalized.

The network model is useful in understanding the nuanced nature of the relationship between income and well-being. By discerning the association between different income sources and the indicators of well-being measure here, it becomes clear that they are not necessarily associated with well-being in the same manner. For example, the receipt of social grants decreases as health increases, but no such trend is observed for capital income. Thus, by grouping these difference income sources into a single

category—as was done in the second set of models—threatens the kinds of inferences one might make about the nature of the relationships between these variables.

It is also prudent to evaluate the proportion of variance in well-being outcomes explained by the different models to gauge their effectiveness. However, this comparison should be approached with caution, as the variance explained by each node in the network model is not directly comparable to the r^2 values reported for the first and second sets of models. Nevertheless, when considering life satisfaction, the asset index model only accounted for 10% of the variance in life satisfaction, whereas the better-fitting—though theoretically-contradictory—reflective model explained 12.8% of the variance. Consequently, if researchers were to analyze these same data, their results might vary depending on how they conceptualize and measure the so-called 'SES' variable. Indeed, the network model broadens one's perspective and reveals that 23% of the variance in life satisfaction is explained by the model. While it is important to consider the repercussions of the inclusion of so many variables in the model (i.e., the multicollinearity of the data), edges existed between life satisfaction and only three of the ten possible socioeconomic conditions in the network model. This highlights the selective influence of socioeconomic conditions, as opposed to just 'SES,' on well-being outcomes.

This bears significant implications for policy and practice, particularly in designing and delivering interventions aimed at improving aspects of well-being among individuals categorized as 'low SES.' Targeting the poorest quintile based on traditional SES metrics could yield different results depending on the chosen metric. However, leveraging a network model would enable the identification of the most central socioeconomic condition that is most closely related to a certain outcome, thereby

facilitating a more targeted and impactful intervention. Moreover, this approach would allow for the identification of aspects of well-being that may permeate multiple facets of the individuals' lives. The repercussions seem especially important if said intervention sought to improve perceived health, for example, as the network model revealed its associations with elements of economic, human, and social capital.

It is also important to reiterate that network models are inherently exploratory and, as a result, should be view as "hypothesis generating" (Epskamp et al., 2021, p. 16). Despite this, they are inherently useful in navigating complex models efficiently and in a way that is understandable (Epskamp et al., 2021). Thus, in my view, the purpose of employing a network model is not to establish and report causal relationships. Rather, a network model should be used to understand the nature of the relationship between socioeconomic conditions and outcomes of interest, such that the resultant associations—which cannot be explained away by other variables in the data—guide researchers in conceptualizing and measuring socioeconomic conditions of interest.

Conclusion

When a network model is used to inform the operationalization of—and approach to—modeling socioeconomic conditions, the validity of the measure is strengthened. Adopting this approach would allow researchers to make a substantial argument for the inclusion of socioeconomic conditions, as opposed to including the broader SES construct without due consideration for the socio-historical context in which research is taking place. Thus, when SES is operationalized by a set of conditions that are relevant to a population, there is greater alignment that supports the study's theoretical objectives which ultimately strengthens the argument to interpret its findings. The network model in

this study revealed that failure to do so renders measures susceptible to overlooking nuanced socioeconomic factors and their relationship with an outcome of interest.

Researchers collecting their own data are encouraged to assess the relevant socioeconomic conditions pertinent to their study population critically and ensure they select appropriate instruments to measure these conditions. Those using secondary data should carefully choose variables that capture as many contextually relevant socioeconomic conditions as possible, with the understanding that this approach may not provide a comprehensive assessment of the entire socioeconomic landscape and its association with outcomes of interest. This research also suggests that scholars use a network model as an exploratory tool to confirm first that the selected socioeconomic conditions are relevant and that they function in a manner consistent with their conceptualization.

With a deliberate shift in focus, the theoretical claims and interpretations of a study are purposefully limited to the chosen socioeconomic conditions (Antonoplis, 2023). From a policy perspective, this approach also increases the ease of addressing specific mechanisms through which social mobility can be promoted, and encourages targeted interventions based thereon.

Limitations

This study is not without limitations. First, the use of a secondary dataset constrained the selection of variables. For example, specific socioeconomic conditions indicative of cultural capital were not included, as there were no variables in the data to capture these. Furthermore, there were inconsistences in the reporting of the parental

education variable which could not be reconciled even after consulting with the NIDS research team. Additionally, the construction of the asset index was limited by those available in the data, and the collapsing of these assets into ranked categories is prone to researcher bias, as the response options were nominal rather than ordinal.

Additionally, network models aim to capture the relationships and interactions between multiple variables. For these models to be effective, they need to include a broad array of relevant conditions or factors. In the context of SES, this means incorporating diverse indicators that capture socioeconomic conditions of interest. If the model only includes a narrow set of SES indicators, in this case constrained by availability of secondary data, it may miss important interactions and relationships that might explain variability outcomes of interest.

In addition, use of the Macarthur SSS or some other subjective measure of SES might have strengthened the argument for the use of socioeconomic conditions by offering an alternative SES metric to model the association associated with well-being, but such a scale was not administered. Finally, the case for considering socioeconomic conditions might be strengthened by examining their association with other kinds of outcomes available in later waves. Constructing a similar network model from similar surveys administered more recently would also make these findings more applicable, as these data were collected approximately 16 years ago. In that time, South Africa has faced the remainder of the global recession and navigated the global COVID-19 pandemic. Wealth inequality continues to increase, as does unemployment, thus these may be even more influential in understanding socioeconomic conditions in South Africa.

It is essential to recognize the limitations associated with cross-sectional data, restricting the ability to make causal statements about the relationships observed (though the network model was not employed for this purpose). Longitudinal network models with $k > 2$ would strengthen these findings by estimating all pairwise and three-way interactions, although these are significantly more complex to model and interpret. Moreover, the novelty of network psychometrics as an emerging field proved challenging as there are far fewer examples from which to draw, especially with MGMs. Consulting with prolific scholars in this domain would likely increase the interpretability of these findings.

Table 1

Missing Data

	n	%
Demographic variables		
Biological sex	0	0
Race	0	0
Age	18	.11
Marital status	60	.38
Geotype	0	0
Socioeconomic conditions		
Labor income	0	0*
Capital income	0	0*
Government income	0	0*
Remittance income	0	0*
Education	0	0*
Medical aid	106	.68
Occupational skill	51	.33
Trust	1,066	6.82
Group membership	316	2.02
Assets		
Radio	34	.22
Fridge	26	.17
Television	19	.12
Bicycle	36	.23
Toilet facility	61	.39
Water source	108	.69
Roof material	136	.87
Outcome variables		
Perceived health	95	.61
Life satisfaction	1,853	11.86
Relative happiness	500	3.20
Depression	279	1.72
Total	**3,671**	**76.51**

Note. $N = 15{,}630$. * Previously imputed.

Table 2

Demographic Information

		n	Weighted Sample (%)
Sex			
	Female	7,099	55.88
	Male	4,860	44.22
Race			
	Black	9,220	76.50
	Colored	1,756	8.55
	Indian/Asian	192	2.88
	White	791	12.07
Age			
	15–24	3,694	29.64
	25–34	2,310	23.12
	35–44	2,009	18.23
	45–54	1,672	13.31
	55–64	1,172	8.99
	65–74	734	4.85
	75–84	313	1.64
	85+	55	0.22
Marital status			
	Married	6,177	49.32
	Living with partner	336	3.36
	Widow/widower	984	6.56
	Divorced	1,135	9.37
	Never married	3,327	31.39
Geotype			
	Rural	1,284	7.41
	Tribal	4,664	28.84
	Urban formal	5,298	55.13
	Urban informal	713	8.62

Note. $N = 11{,}959$

Table 3

Socioeconomic Conditions

	n	Weighted Sample (%)
Education		
No education	1,465	7.43
Some primary school	2,906	19.52
Some secondary school	4,820	42.44
Completed secondary school	1,720	17.38
Tertiary qualification	1,048	13.23
Medical aid		
No	10,539	82.64
Yes	1,420	17.36
Occupational skill		
Not working	8,890	69.84
Skill level 1	1,040	7.50
Skill level 2	1,358	15.03
Skill level 3	148	1.82
Skill level 4	523	5.81
Community trust		
Not likely	8,967	71.61
Somewhat likely	1,741	15.18
Very likely	1,251	13.21
Group membership		
None	7,638	63.17
One or more	4,321	36.83

Note. $N = 11,959$

Table 4

Outcome Means, Standard Deviations, and Correlations

	M (*SD*)	1	2	3
1. Perceived health	3.54 (1.24)			
2. Life satisfaction	5.47 (2.44)	.13**		
		[.12, .15]		
3. Relative happiness	2.19 (.81)	.18**	.44**	
		[.16, .20]	[.43, .45]	
4. Depression	28.59 (4.35)	.28**	.22**	.24**
		[.26, .29]	[.20, .24]	[. 23, .26]

Note. Perceived health and relative happiness treated as continuous for these calculation

Table 5

MCA Results for Asset Categories

	n	Weighted mean (%)	MCA Weights	Inertia (%)
Radio				
Does not have a radio	3,806	29.60	-.497	.011
Has a radio	8,153	70.40	.232	.005
Television				
Does not have a television	4,007	28.45	-1.721	.142
Has a television	7,952	71.55	.867	.071
Bicycle				
Does not have a bicycle	10,970	90.71	-.162	.003
Has a bicycle	989	9.29	1.799	.038
Fridge				
Does not have a fridge	4,989	38.97	-1.449	.125
Has a fridge	6,970	61.03	1.037	.090
Water source				
Surface	1,064	5.56	-2.859	.104
Well or borehole	331	1.68	-1.817	.013
Public	289	2.12	-1.670	.010
Piped	10,275	90.64	.402	.020
Toilet				
None	971	5.76	-2.535	.075
Other	578	4.61	-.730	.004
Pit	4,586	32.29	-.884	.043
Flush	5,824	57.34	1.191	.099
Roof material				
Natural	788	4.60	-2.645	.066
Rudimentary	101	.89	.621	.000
Low quality	7,938	62.94	-.298	.008
High quality	3,132	31.57	1.400	.073

Note. $N = 11{,}959$. Results have been standard-normalized.

Table 6

MCA Adjusted Inertias

Dimension	Principal inertia	Percent (%)	Cumulative percent (%)
Dimension 1	.062	85.69	85.69
Dimension 2	.001	1.78	87.47
Dimension 3	< .001	.70	88.17
Dimension 4	< .001	.02	88.19
Dimension 5	< .001	.00	88.19

Table 7

Latent Variable Model Results

	Indicator	Reflective model	Formative model
SES	Income	.682	.674
	Education	.675	.450
	Occupational skill	.522	.094
		β* (*SE*)	
Health		.320 (.027)***	.322 (.014)***
Happiness		.319 (.030)***	.227 (.013)***
Life satisfaction		.358 (.072)***	.278 (.030)***
Depression		.324 (.112)***	.264 (.050)***
		R^2	
Health		.102	.104
Happiness		.102	.051
Life satisfaction		.128	.077
Depression		.105	.070
CFI		.975	.821
SRMR		.039	.000
RMSEA		.037	.060

Note. N = 11,959. *** indicates $p < .001$

Table 8

Edge Weights Matrix

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Mar	-													
2. Lab	.21	-												
3. Cap	.16	.12	-											
4. Gov	.08	.00	.00	-										
5. Rem	.00	.00	.00	.00	-									
6. Edu	.64	.22	.29	.03	.00	-								
7. Med	.23	.34	.35	.09	.00	.86	-							
8. Occ	.32	.84	.43	.14	.00	.79	.29	-						
9. Tru	.06	.02	.06	.00	.00	.12	.13	.07	-					
10. Grp	.16	.00	.00	.00	.00	.00	.00	.10	.08	-				
11. Hea	.39	.00	.02	.26	.00	**.64**	.00	.22	.06	.00	-			
12. Sat	.02	.00	.00	.00	.00	.06	**.22**	.00	.08	.05	.02	-		
13. Hap	**.12**	.00	.03	.02	.00	.10	.04	.09	.06	.02	.23	.50	-	
14. Dep	.08	.00	.04	.05	.00	.08	**.11**	.01	.02	.00	.36	.09	.22	-

Table 9

Centrality Measures

Node	Betweenness	Closeness	Strength	Bridge expected influence (1 step)	Bridge expected influence (2 steps)
Marital status	10	.016	2.46	2.46	7.61
Labor income	0	.014	1.74	1.62	5.16
Capital income	0	.013	1.49	1.38	4.47
Government income	0	.010	.67	.67	1.93
Remittance income	0	n/a	.00	.00	.00
Education	34	.021	3.82	2.96	9.09
Medical aid	8	.018	2.66	1.80	6.48
Occupational skill	9	.017	3.31	3.13	8.56
Community trust	0	.007	.76	.61	1.99
Group membership	0	.008	.41	.22	.96
Perceived health	26	.018	2.18	1.58	5.22
Life satisfaction	1	.011	1.04	.42	1.51
Relative happiness	3	.011	1.43	.48	2.11
Depression	0	.012	1.06	.40	1.86

Note. $N = 11{,}959$.

Table 10

Predictability

Node	Predictability
Marital status	.16
Labor income	.36
Capital income	.10
Government income	.06
Remittance income	.00
Education	.14
Medical aid	.24
Occupational skill	.18
Community trust	.00
Group membership	.00
Perceived health	.11
Life satisfaction	.23
Relative happiness	.19
Depression	.16

Note. Predictability for a continuous variable is its computed R^2. Predictability for a categorical variable is its computed *nCC*.

Table 11

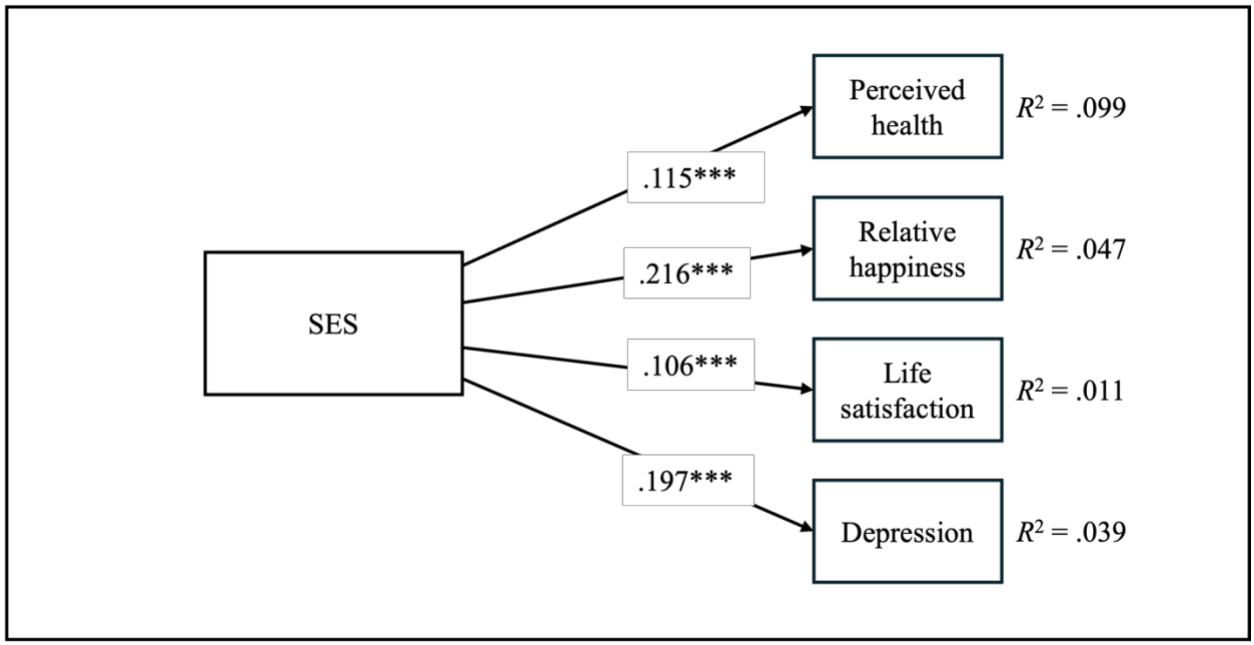
Frequency Table Across Education and Occupational Skill Levels

	Quintiles (Assets)				
Quintiles (Income)	1	2	3	4	5
1	510	591	578	594	552
2	524	622	545	603	566
3	482	584	509	563	576
4	387	495	412	420	428
5	240	329	306	270	273

Note. $N = 11{,}959$.

Figure 1

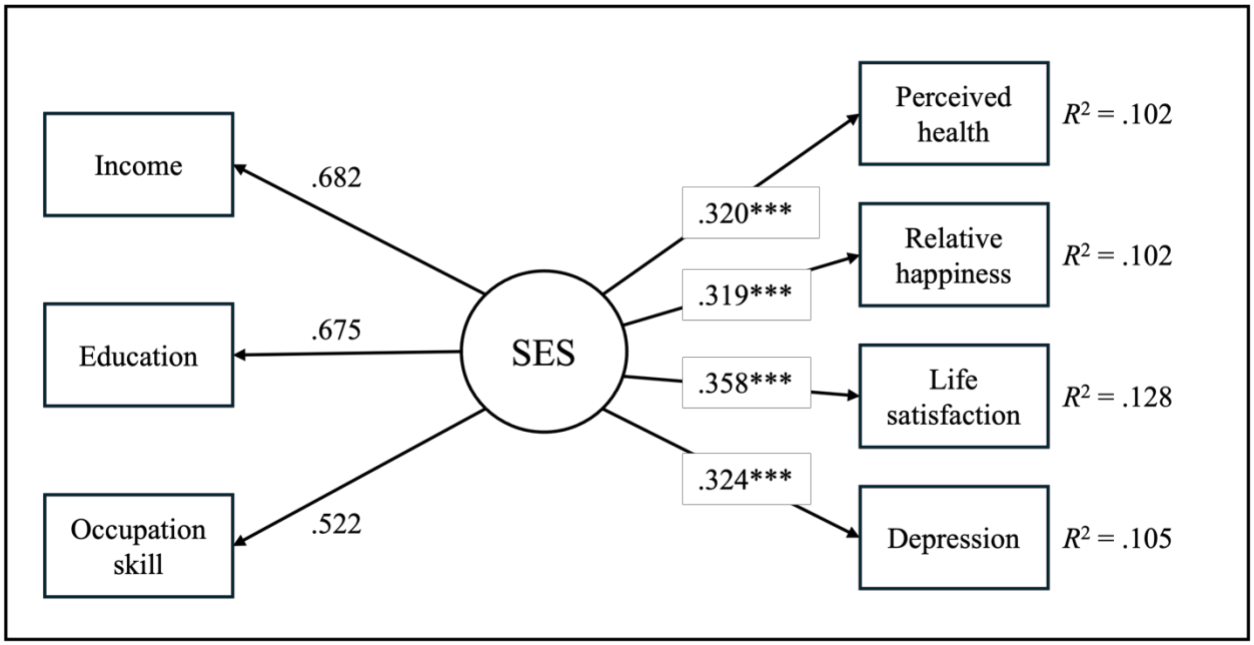
Path Model



Note. ***$p < .001$

Figure 2

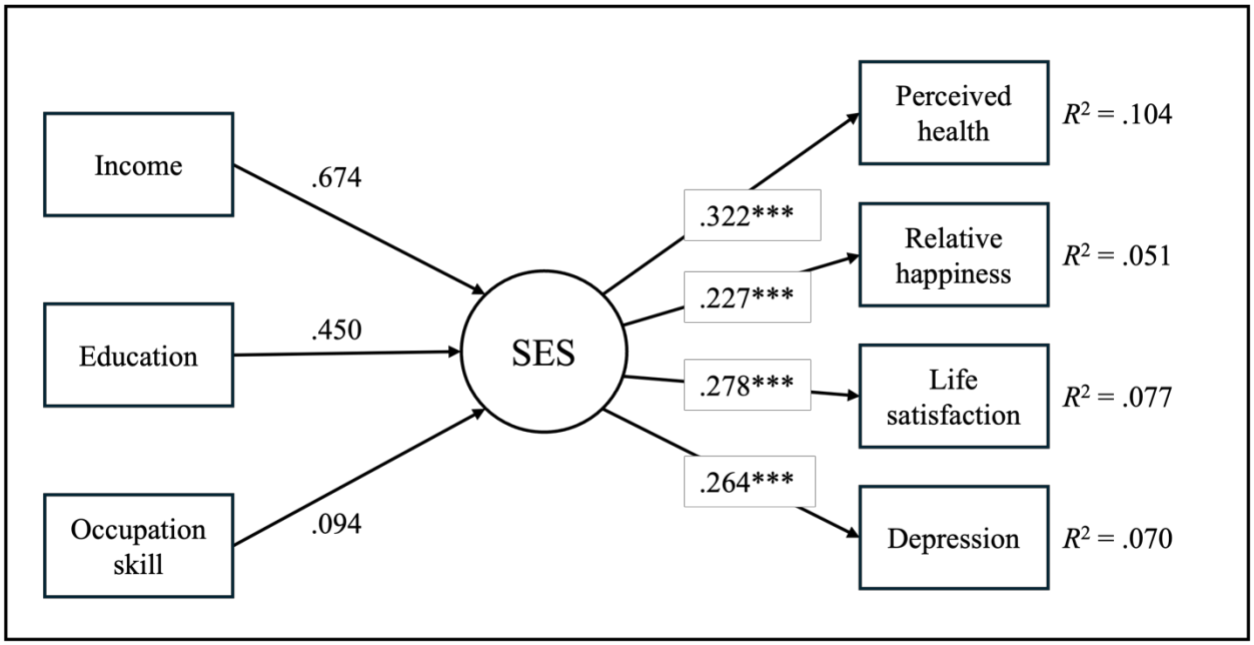
Reflective Model



Note. ***$p < .001$

Figure 3

Formative Model



Note. ***$p < .001$

Figure 4

Network Model

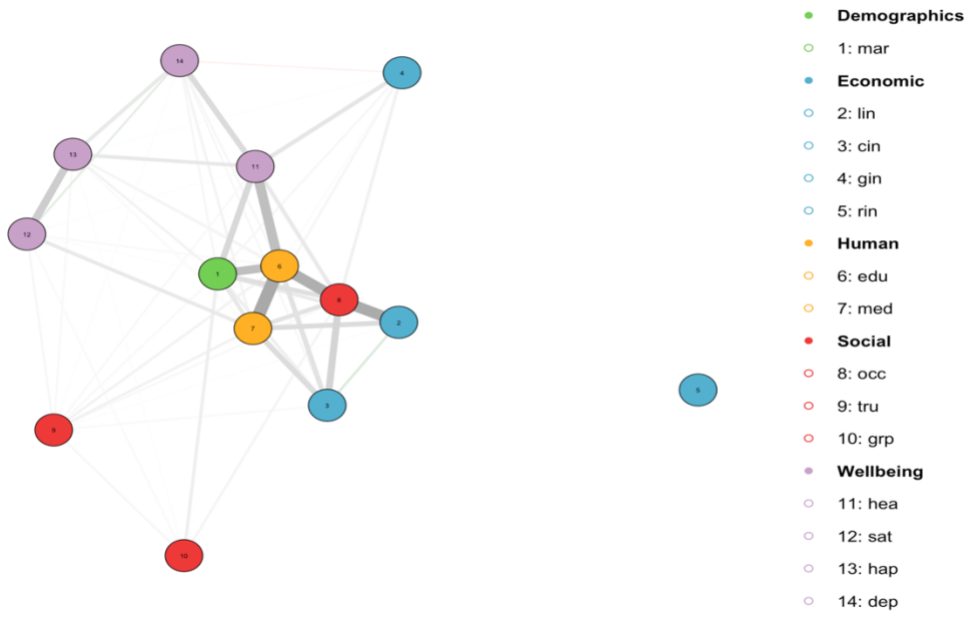


Figure 5

Model Centrality

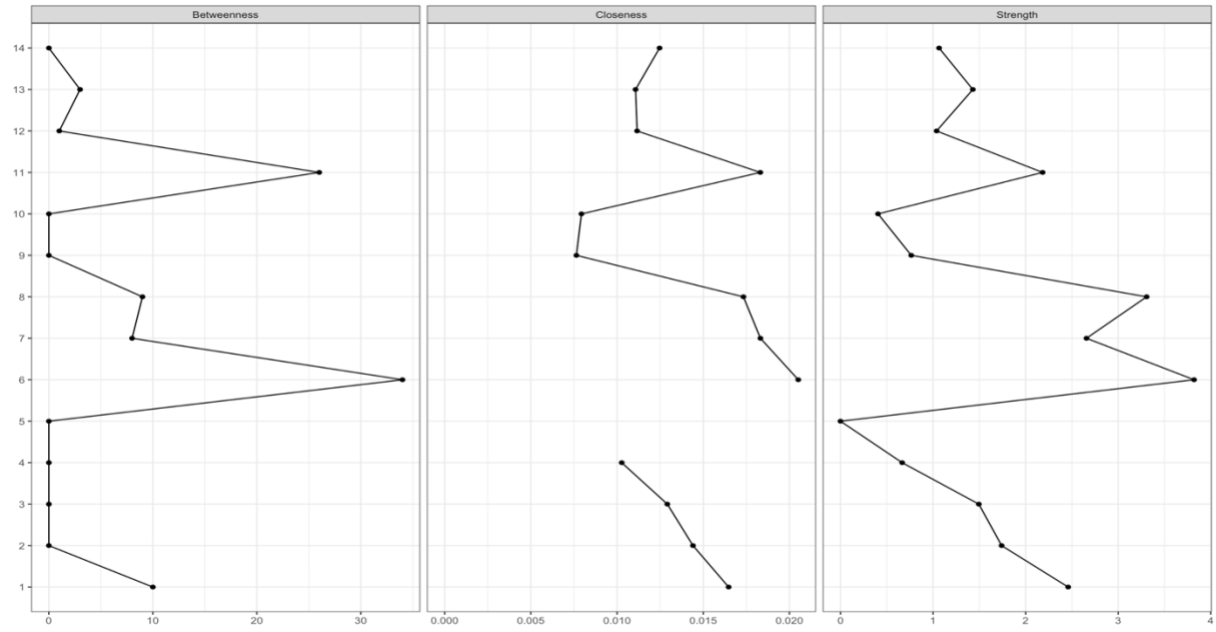


Figure 6

Network Stability

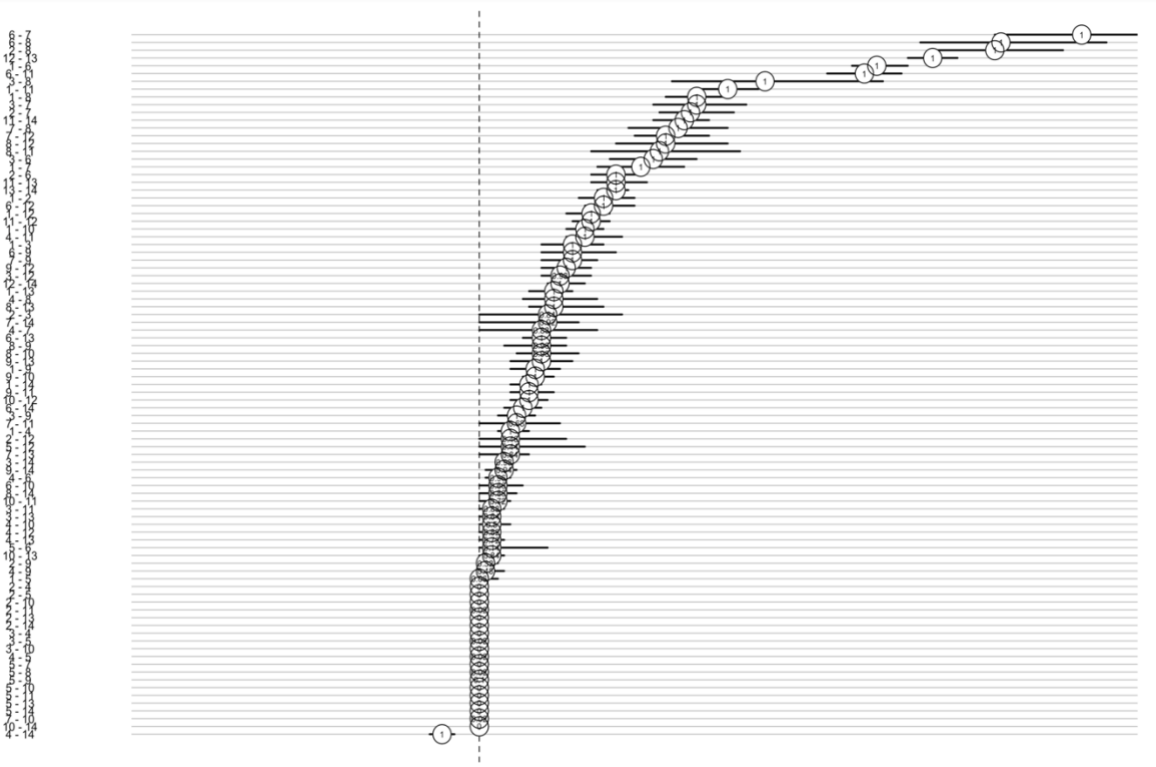
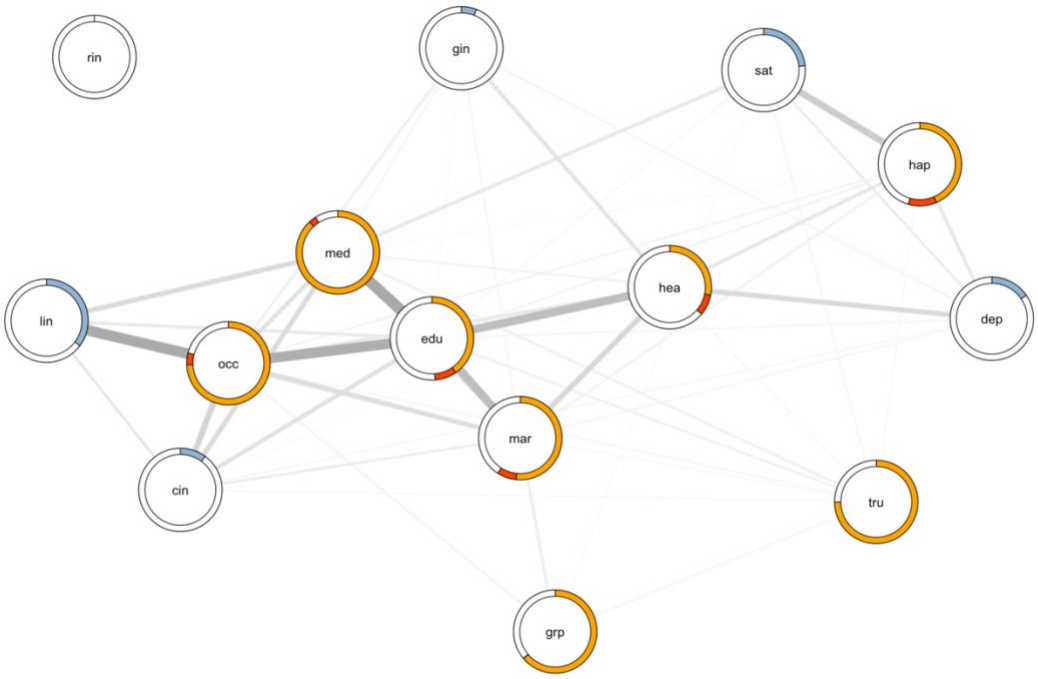


Figure 7

Network Predictability



Appendix A

Educational Classification Codes

Original code	Description	New code	Description
-3	Missing	n/a	n/a
-9	Don't know		
-8	Refused		
-5	Not applicable		
0	Grade 0	1	Some primary
1	Grade 1		
2	Grade 2		
3	Grade 3		
4	Grade 4		
5	Grade 5		
6	Grade 6		
7	Grade 7		
8	Grade 8	2	Some secondary
9	Grade 9		
10	Grade 10		
11	Grade 11		
12	Grade 12	3	Completed secondary
13	NTC 1	2	Some secondary
14	NTC 2		
15	NTC 3		
16	Certificate with less than Grade 12		
17	Diploma with less than Grade 12		
18	Certificate with Grade 12	5	Tertiary
19	Diploma with Grade 12		
20	Bachelor's degree		
21	Bachelor's degree with diploma		
22	Honors degree		
23	Higher degree (masters or doctorate)		
24	Other		
25	No schooling	0	No education
55	No higher education	*No entries*	

Appendix B

Occupational Classification Code

Original code	**Description**	**New code**	**Description**
-3	Missing	n/a	n/a
-9	Don't know		
1	Legislators, senior officials, and managers	4	Level 4
2	Professionals		
3	Technicians and associate professionals	3	Level 3
4	Clerks		
5	Service workers and shop and market sales workers	2	Level 2
6	Skilled agricultural and fishing workers		
7	Craft and related trade workers		
8	Plant and machinery operators and assemblers		
9	Elementary occupations	1	Level 1
-7	Never worked	0	Not working

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