Poverty Dynamics and Life Satisfaction Within the Context of South Africa: A Longitudinal Multi-Level Modelling Approach

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Abstract

This study examined the longitudinal relationship between life satisfaction and poverty, and the effects of intertemporal patterns of poverty. Data from all five waves of the National Income Dynamics Study (NIDS) were used. Longitudinal multi-level modelling results showed that an individuals' life satisfaction tended to differ considerably between measurement occasions with variation being explained by multidimensional poverty status. Additionally, statistically significant differences in initial life satisfaction were found between individuals depending on the intertemporal patterns of poverty; individuals who were non-poor across all occasions tended to report higher life satisfaction compared to individuals who were classified as transiently poor, whilst chronically poor individuals tended to report the lowest levels of life. Intertemporal poverty status was however not found to be a statistically significant predictor of rate of change in life satisfaction. Overall, these results support the need to include intemporal patterns of poverty as a key consideration both in future poverty research and in poverty intervention.

Keywords: poverty, multidimensional poverty, chronic poverty, transient poverty, life satisfaction, subjective wellbeing.

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Introduction

Context

Poverty is amongst the most widespread, and pervasive issues that South Africa faces (Bundy, 2020). The state of deprivation and inequality in South Africa has its roots in the country's historical context, characterized by apartheid, and political instability, however it remains to be a challenge today (Bundy, 2020). Whilst there have been considerable efforts to address poverty in South Africa - including the introduction of social assistance grants, in addition to investment in healthcare, education, infrastructure, and housing (Bundy, 2020) - the latest estimates from the World Bank (based on data from 2014/15) suggest that approximately 55% of the population were living below the upper bound of the national poverty line, with food poverty impacting 25% of the population (World Bank, 2023).

The pursuit of poverty eradication is a central priority of the United Nations, with sustainable development goal number 1 outlining a shared commitment to 'end poverty in all its forms everywhere' by 2030 (United Nations, 2015). It is estimated that the achievement of this objective is not possible at the current trajectory (Chigova, 2021). Because of the difficulty in lifting South Africans out of poverty, the pursuit towards the development of a greater understanding of the dynamics of poverty in South Africa is necessary.

Research Aims

This research aims to examine changes in life satisfaction over time in relation to poverty dynamics with the context of South Africa.

Review of the Literature

Introduction

This chapter presents an overview of the academic literature on poverty and life satisfaction. The following provides and overview of the conceptualisation of poverty and life satisfaction, as well as outlining the role of time as a key element of poverty. Furthermore, an overview and synthesis of relevant empirical findings relating to the relationship between poverty and life satisfaction is presented.

Poverty

The way in which poverty can be best conceptualised, and subsequently how poverty can be appropriately measured and alleviated represent issues that have occupied a point of contention within the poverty literature for decades. In analysing poverty, we need to be able to identify who is poor, and so the extent to which we are able to capture the characteristics of poverty is essential. Between different measures of poverty there can be significant variation in who is classified as poor (see e.g., Jansen et al., 2015), which may have implications for study outcomes and subsequently for poverty alleviation strategy. The choice of poverty conceptualisation and measurement can be located as a critical element of poverty research.

Perhaps one of the most influential, and historically dominant approaches to measuring poverty sees poverty in terms of monetary deprivation. The monetary conceptualisation follows the assumption that poverty can be best understood as a deprivation of income (or consumption expenditure); positing that poverty is due individual or household earnings being insufficient to purchase the goods and services required to meet one's basic needs

(Wijekoon et al., 2021; Wisor & Wisor, 2012). Accordingly, measures that utilise this conceptualisation for the identification of poverty focus on monetary thresholds that represent a level of income or expenditure. For instance, those who are living on an income that falls below the 'poverty line'- representing the minimum level of income deemed adequate to meet basic needs in a particular country- are classified as poor (Ravallion, 2010). Although use of the monetary approach to measure poverty is still prevalent within the poverty analysis (see e.g., Pryor et al., 2019; Fitzsimons et al., 2017), the importance of shifting away from unidimensional monetary measures of poverty has been widely recognised (Atkinson, 2019; Cooper et al., 2012). Monetary measures of poverty have been broadly applied, both within research and as official poverty measures used by most of the world's countries (Alkire & Santos, 2014). Whilst it is undoubtable that income plays a significant role in the lives of poor people, it has been widely argued that a non-monetary approach capturing the multiple dimensions of deprivation is better suited to the analysis of poverty (e.g., Alkire and Foster, 2011; Atkinson, 2019; Ravallion, 2011; Whelan et al., 2014).

Alkire & Santos (2014) posit that methods of poverty measurement can be categorised most fundamentally in one of two ways: poverty can be measured using the *direct* method or using the *indirect* approach. The indirect method or monetary approach determines whether a person is living in poverty based on an income or consumption level at which some basic needs can be satisfied. Direct methods on the other hand measure poverty in terms of observed deprivation, focusing on whether specified basic needs or acceptable living standards are satisfied (Alkire & Santos, 2014). The degree to which indirect, income or consumption-expenditure based measures can adequately represent a proxy for deprivation is limited. A conceptualisation of poverty only as a shortfall of income is unable to capture the complexity and multidimensionality of poverty. As posited by Narayan & Petesch (2007),

"lack of money is just one of many disadvantages of being poor and one of the many obstacles to escaping a life of impoverishment" (p. 2).

One of the limitations of the monetary approach is that it is not sensitive to differential patterns of consumption behaviours; the attainment of a level of income that meets or exceeds that specified by the poverty line does not guarantee that an individual will meet their basic needs (Sen, 1981). Additionally, the cost and/or difficulty of meeting the same basic needs may differ considerably depending on a variety of factors specific to one's circumstance (Sen, 1981). For instance, costs may differ my geographic location, climate, and conditions such as disability (Alkire & Santos, 2014). Furthermore, it is often the case that observable indicators of deprivation, such as access to access to clean water, education, or adequate sanitation are either subsidised or provided as free public services (Evans et al., 2020). For instance, Finn et al. (2013) found that between 1993 and 2010 multidimensional poverty reduced at a rate that outpaced the reduction in money-metric poverty, a difference attributed to significant increases in public expenditure relating to the provision of education, electricity, and sanitation within poor communities. A similar finding was observed in a more recent study by Fransman & Yu (2018), who found that both the incidence and intensity of non-monetary, multi-dimensional poverty declined more rapidly compared to money-metric poverty between 2001 and 2016. Because it is often the case that not all of one's basic needs are not accessed via the market, income or consumption is not necessarily going to be reflective of the range or extent of experienced deprivation.

The recognition of these limitations has prompted the utilisation of direct and multi-dimensional approaches to the measurement of poverty; identifying whether individuals actually fail to meet the accepted minimum standards in non-monetary indicators related to

basic needs and core functioning's (Alkire & Santos, 2014). There have been a number of studies in South Africa that have used the multidimensional approach to poverty measurement. Klasen (2000), used a composite index of deprivation based on a total of 14 components, comparing this deprivation index to an expenditure-based poverty measure. Another study considered the multi-dimensional nature of poverty, investigating how poverty differs by geographical location in terms of non-monetary deprivation (Burger et al., 2004). The index used by Burger et al. (2004) included 10 poverty dimensions; the results estimated that the dwelling dimension was the most important contributor to overall deprivation whilst income was estimated to be the least important. More recently, Bhorat & Van der Westhuizen (2013) utilised factor analysis to construct a non-income welfare index as a measure of non-monetary dimensions of poverty. This index included two categories of variables, household characteristics (e.g., material construction and source of energy) and household assets (e.g., ownership of vehicle or TV), and was used to examine changes in poverty rates over time. Perhaps most prevalent within multidimensional poverty research in South Africa, particularly in recent years, is the application of the Multidimensional Poverty Index (MPI) approach. The MPI is an internationally comparable index that identifies the poor based on experienced deprivation across a combination of education, health, and living standards. A number of studies have utilised the MPI to investigate poverty in terms of non-monetary variables (see Finn et al., 2013; Fransman & Yu., 2019; Katumba et al., 2019; Megbowon, 2018; Rogan, 2016).

Another notable consideration when it comes to poverty measurement concerns the decision of whether to use the household or the individual as the primary unit of measurement. Many metrics that use the household as the unit of measurement (e.g., household income or consumption-expenditure), do not consider potential differences in the allocation of resources

within the household (Vijaya et al., 2014). Vijaya et al. (2014) argue that it is problematic to equate the household with the individual given the evidence on intra-household inequalities, positing that an 'individual level analysis enables the identification of individuals who may be experiencing deprivation even within "non-poor" households. For instance, such measures do not take into account potential intra-household differences in resource allocation. Indirect measures that aim to estimate an individual's level of deprivation based on household income hold the assumption that this captures the experience of all household members, however this is not always the case. A study conducted by Onah & Horton (2018) highlights gendered differences in access to household financial resources, with female household members being less likely to utilise formal healthcare relative to male household members as a result of differences in decision-making power over the allocation of financial resources. As we can see here (highlighted by observed differences in access to healthcare), the limitations associated with using the household as the unit of measurement also apply when considering non-monetary dimensions of poverty. It could thus be argued that it is favourable to use the individual as the primary unit of measurement when it comes to capturing experienced deprivations.

Utilising household-level data, however, offers the advantage of accounting for economies of scale within the household (Browning et al., 2013). For example, regarding goods or assets, whilst an individual may not personally own a tv, a fridge, or a vehicle, another household member may own tv, a fridge, and a vehicle. In this case, an individual that may be identified as poor based on individual-level data may actually experience living conditions of a standard that could be considered to be outside of poverty. Whilst the same limitations previously discussed may apply, in terms of differences in resource allocation within the household, household ownership could be considered to be reflective of individual deprivation to the

extent that access can be considered to be shared (Browning et al., 2013). In summary, whether there is a focus on household-level or individual-level data, each comes with a risk of incorrectly identifying someone in regard to their deprivation status.

Regarding the multidimensional poverty index, the limitations and advantages of household-level measures are a necessary consideration given that it is fundamentally a household-level poverty measure. The MPI identifies whether an individual is deprived based on indicators that are located at the level of the household in which one is living (see table 4). However, in the MPI's measurement of living standards focuses on conditions and resources that can reasonably be considered to be shared. Because of this, we can consider household living conditions to be appropriately reflective of individual deprivation.

Intertemporal Poverty

Many studies contributing to the literature are insensitive to time as an element of poverty, rather, limiting attention to single-period considerations (Bossert et al., 2019).

Even with the use of longitudinal data, a measure of poverty that considers the level of experienced deprivation at a given point in time, treating each time point as distinct, may be blind to potential effects of previous conditions - not everyone below the poverty line is the same. Whilst some individuals may drift into and out of poverty, perhaps due to a vulnerability to negative financial shocks, others may have always lived below the poverty line. Let's take two individuals that are poor to the same degree at present, although one individual was also poor during the preceding period and the other was not. Perhaps it would not be a reasonable assumption that the consecutive experience of poverty would not influence the negative effects of being in poverty. Differences in temporal incidence are

relevant when it comes to one's experience of poverty. For instance, Dutta et al. (2013) suggests that periods living out of poverty may provide individuals with the opportunity to replenish their resources, enabling them to be better equipped to deal with temporary states of poverty.

Similarly, not all individuals who can be categorised as non-poor at a given time point are alike. Of the people that currently experience a non-poor standard of living, many have never been poor, and do not foresee a drop in living standards below an adequate level at any time horizon. However, some may face a non-negligible risk of falling into poverty. At another given point in time, these individuals may have experienced a level of deprivation that would locate them as multi-dimensionally poor. Bossert et al. (2019) posits that "The relative degree of overall poverty when comparing the two individuals over time depends on the role and evaluation of *persistence* in a state of poverty" (pp. 63), arguing that the negative effects associated with poverty are cumulative. An analysis that treats poverty only as a static state is blind to differences in the temporal dynamics of poverty (Schotte et al., 2018). Accordingly, this study considers the role of intertemporal poverty, expanding its attention beyond single-period considerations.

The literature commonly makes a distinction between two forms of poverty, namely acute or transitory poverty and chronic or persistent poverty (Foster & Santos, 2013). Poverty is a time-dependant state, and thus is dynamic in nature; including time as an additional dimension of poverty is important for the investigation of poverty dynamics. Poverty can be temporary (acute or transitory poverty) or it can persist over extended periods of time (chronic or persistent poverty) (Arif & Bilquees, 2007). The transiently poor typically live above the poverty line, albeit marginally, and are pushed below the poverty line as a result of

temporary adverse shocks, although are able to rebound relatively quickly. In the case of transient poverty, a temporary reduction or loss of income, perhaps attributed to a loss of employment, results in a relatively short-term experience of poverty, although the transient poor have access to sufficient resources to enable them to recover, generally without explicit external assistance (Barrett & Swallow, 2006). Chronic poverty on the other hand, refers to a state of deprivation that persists over long periods of time, frequently spanning inter-generationally (Israeli, & Weber, 2014; Shepherd et al., 2019). Those below the poverty line will often become trapped, subject to self-reinforcing mechanisms giving rise to conditions which can thwart social mobility, such that "living in poverty for long periods is not only a symptom of past deprivation, but also the cause of future destitution" (Arif & Bilquees, 2007). This phenomenon can be categorised by circular and cumulative causal processes driving a cycle of poverty, thus sustaining the impoverishment of individuals, households, and communities (Maru et al., 2012).

Chronic poverty and transient poverty are distinguishable from one another not only in their duration, but they are also distinct in their associated causal mechanisms, and thus require unique approaches in terms of poverty alleviation. Transient poverty may be caused by sudden shocks. Such a shock may be individual or household specific (for instance in the form of illness or loss of employment), region specific (e.g., natural disaster or conflict), or may be on a macro-economic scale (e.g., inflation) (Bayudan-Dacuycuy & Lim, 2014). On the other hand, the chronic component of poverty can typically be linked to structural factors that create self-reinforcing conditions of relative deprivation within social-ecological systems, keeping such systems in persistent poverty (Maru et al., 2012). Such structural mechanisms can be located at macro-, meso-, and micro-scales of analysis (Barrett et al., 2016). For instance, at the macro-level a self-perpetuating state of poverty can be produced

by institutional failings that can trap regions or even entire countries into poverty (Barrett et al., 2016). At the meso-level, a lack of access to education can hinder the acquisition of skills and knowledge, limiting employment prospects and trapping individuals in low-paying jobs; a lack of access to credit can exclude individuals or households from access to productive assets and limiting financial growth prospects (Banerjee et al., 2019).

The durational element of poverty has been demonstrated to play a mediatory role in the relationship between poverty and subjective well-being. A study conducted by Clark et al. (2015) investigates the link between poverty and subjective well-being using longitudinal panel data from Germany, focusing on the role of time in this relationship. The results indicate a significant negative association between both poverty intensity and incidence, and life satisfaction. The results also demonstrate that the effects of poverty on well-being extend beyond the time-point at which poverty was experienced, revealing that past poverty can scar current well-being. Including the role of chronic and persistent poverty in their analysis, Clark et al. (2015) considers an individual's cumulated experience of poverty (past number of years spent in poverty), as well as whether experienced years of poverty were consecutive. A succession of shorter exposures to poverty was found to have a less-negative effect on wellbeing compared to consecutive years of poverty/one longer exposure to poverty. This indicates that an experience of chronic poverty may have a greater negative effect on wellbeing compared to an experience of transient poverty.

The literature reveals temporal poverty and chronic poverty to be conceptually distinct, as well as differing in their relationship with well-being and in their required approach to alleviation. Because these two forms of poverty are distinct, they must be treated as such. Incorporating this dynamic perspective of poverty into this study, specifically inclusion of a

temporal dimension to our measurement of poverty is important for an understanding the relationship between multidimensional poverty and well-being. It allows us to consider possible differences in the hypothesized relationship between multi-dimensional poverty and life satisfaction depending on the temporal nature of poverty. With the availability of panel data, it is desirable to incorporate a dynamic perspective in the analysis multi-dimensional poverty, with emphasis on different poverty duration experiences (Alkire et al., 2017).

Subjective Wellbeing and Life Satisfaction

Subjective well-being can be defined as "the experience of joy, contentment, or positive well-being, combined with a sense that one's life is good, meaningful, and worthwhile" (Lyubomirsky, 2013, p. 32). The well-being literature makes a distinction between the '*objective* conditions of one's life, and one's *subjective* evaluations of and feelings about one's life' (Maddux, 2017). The objective conditions of someone's life can be captured by assessing tangible indicators of the standard of living, reflecting the extent to which one's needs are met. The psychological construct of subjective well-being captures one's perception of their life, representing the degree to which an individual favourably assesses their overall quality of life (Voukelatou et al., 2021).

Prominent theoretical perspectives posit that subjective well-being consists of two main components: a cognitive component (reflected in a judgement of global life satisfaction) and an affective component (Diener, 1984; Henriques et al., 2014; Kahneman & Deaton, 2010). Some research, following Diener's (1984) tripartite model of subjective well-being, further separate this affective component into positive affect and negative affect, an operationalization that has been highly influential (Metler & Busseri, 2017). Other research has favoured a bi-factor model, treating the affective component as one of two dimensions

(life satisfaction being the other) (Kahneman & Deaton, 2010). Within the literature, this affective component, often referred to as happiness or as emotional well-being, is generally viewed as a hedonic concept, reflecting an in-the-moment emotional state that is ultimately fleeting in nature (Badri et al., 2022; Gilbert, 2009). On the other hand, previous research suggests that life satisfaction is a more temporally stable component of subjective well-being compared to happiness, capturing a more eudaemonic element of subjective well-being (Helliwell et al., 2017). Compared to life satisfaction, the affective dimension of subjective well-being is a more dynamic construct, fluctuating considerably over time. Previous research suggests that test-retest of self-reported measures of global life satisfaction are approximately r = 0.60 over 2 year intervals (Anusic & Schimmack, 2016; Schimmack & Oishi, 2005), compared to an estimated stability of approximately r = 0.35 for experiential or affective measures of well-being over the same 2 year intervals (Hudson et al., 2017; Hudson et al., 2020; Krueger & Schkade, 2008). A relatively low stability of the affective component indicates that how an individual is feeling at one time point has little to do with how they are feeling at the next, which may present challenges given the context of the current study. Given that the data collection intervals of the current study are approximately 2 years a focus on life satisfaction would be optimal.

Relevant Empirical Findings

This section explores and summarises relevant past and present literature relating to the research topic. This review limits inclusion to studies published within the past 10 years (2013 - current) and emphasises studies conducted within the context of South Africa using longitudinal data, particularly those conducted using the NIDS data. Key words used in literature search: poverty, multidimensional poverty, transient poverty, chronic poverty, South Africa, life satisfaction, psychological well-being.

Whilst there is a breadth of research focusing on poverty and psychological wellbeing, there has been relatively little attention afforded to multidimensional poverty, with most research focusing on income poverty. There exists an extensive body of literature investigating the relationship between income and life satisfaction.

Meyer (2017) conducted a cross-sectional study investigating the relationship between poverty and life satisfaction, analysing the impact of poverty on the life satisfaction of individuals living within a low-income community. This study focused on the Sileco township, a poor community within South Africa, located in southern Gouteng (Meyer, 2017). This community's population consisted of approximately 4000 housing units, 15,200 people at the time of the study (Meyer, 2017). This study was conducted using primary data, collected using a questionnaire that was administered by trained field workers during a random socioeconomic household survey. A total of 374 questionnaires were returned and captured, out of the intended sample of 400 households (which would have represented 10% of the total population). Poverty was measured based on monthly household income and participants were categorised in terms of poverty status according to a poverty line of R660 per month (based on US $2 per day). Life satisfaction was measured using the SWLS, a single-item measure asking, "how satisfied are you with life in general". Responses were based on a scale ranging from 1 (very dissatisfied) to 5 (very satisfied). The results of this study indicate that households below the poverty line tended to report being less satisfied/more dissatisfied with life compared to households above the poverty line; 71% of participants below the poverty line reported being either dissatisfied or very dissatisfied with their life compared to 51% of those above the poverty line reporting that they were either dissatisfied or very dissatisfied with their life. The results of the Chi-square test indicates that

this difference in perceptions regarding life satisfaction between households below and above the poverty line are statistically significant (Chi-square value of 23.68 and a p-value of < 0.001).

A number of other studies have investigated this relationship using longitudinal data. Stoop et al. (2019) conducted a study investigating the relationship between psychological wellbeing and poverty dynamics in South Africa. Based on waves 1-5 of the NIDS, Stoop et al. (2019) performed a descriptive analysis including per capita household expenditure, life satisfaction, and depression. This study reports a strong negative correlation between psychological well-being and per capita household expenditure, with individuals in lower expenditure deciles displaying lower levels of life satisfaction in addition to significantly higher risks of depression. More recently, Alloush & Wu (2023) conducted a study within a South African context using the NIDS data, finding that a 20% increase in monthly household income per capita was associated with a 0.2-point increase in life satisfaction on a 10-point scale, demonstrating a causal relationship between income and life satisfaction. Whilst Alloush & Wu (2023) used the receipt of the Older Persons Grant as the source of this increase in income, this grant increased several household metrics of economic wellbeing, and Alloush & Wu (2023) found that the demonstrated effect extended to all household members. Another study conducted by Gaya (2021) utilized waves 1-4 of the NIDS data to investigate the relationship between individual income and life satisfaction in South Africa. However, Gaya (2021) found that the variance in life satisfaction decreased at higher income levels, indicating that severe life dissatisfaction disappears at a higher income, although higher income was not found to lead to increased life satisfaction.

Other studies, such as that conducted by Posel (2014), considered the effects of relative poverty on life satisfaction in South Africa. Posel (2014) used 'perceived economic rank' as a measure of deprivation in addition to reported income, including individual perceptions of current (relative economic status) and future (expectations of upward economic mobility) economic rank. Posel (2014) investigated the effects of relative poverty and economic mobility on individual life satisfaction using data from the first two waves of the National Income Dynamics Study. To estimate the correlates of life satisfaction, Posel (2014) utilised pooled and fixed effects regression analysis, finding both that an increase in perceived economic rank and positive expectations regarding future economic rank predicted were associated a higher degree of reported life satisfaction.

Whilst studies have investigated the effects of poverty on life satisfaction within the context of South Africa, such studies tend to focus on econometric-based poverty indicators. There is a notable lack of attention within the South African context on the effects of *multidimensional* poverty on life satisfaction. Recent evidence from Hong Kong, from a study conducted by Zhu & Chou (2023), suggests that multidimensional poverty significantly reduces life satisfaction. This study was conducted with a sample of 563 older adults (60 years and older), with data collected over 3 measurement occasions spanning 5 years (Zhu & Chou, 2023). The analysis considered four indicators of poverty (income, expenditure, assets, and material deprivation) and life satisfaction was measured using a Chinese adaptation of the Life Satisfaction Index-A (LSI-A) (Zhu & Chou, 2023). Analysis was performed using a lag regression model linking life satisfaction to the four poverty indicators (Zhu & Chou, 2023). Results indicated that material hardship and asset-based poverty negatively predict life satisfaction when confounding variables are controlled, however expenditure-based and income-based indicators were not found to be statistically significant predictors of life

satisfaction (Zhu & Chou, 2023). Whilst the inferences made on the basis of the results of this study are limited due to the focus on older adults, a similar relationship between multidimensional poverty and life satisfaction can be observed elsewhere in the poverty literature. Another study, conducted by Delugas & Brau (2021) in the context of Italy, adopts a multidimensional perspective in their investigation on the role of poverty in impacting life satisfaction. This study used data from a national-level survey, the EU-SILC, including a final sample comprising 23,193 individuals (aged 16 and above). Whilst this study has a primary focus on energy poverty, Delugas & Brau (2021) also consider the role of additional socio-economic factors such as education, employment status, self-assessed health, material deprivation, and dwelling quality, that capture additional dimensions of participant experience of poverty. The study findings indicate that the level of energy poverty is positively associated with unemployment, material deprivation, and dwelling quality (Delugas & Brau, 2021). These results highlight a statistically significant relationship between non-monetary poverty dimensions and life satisfaction.

Moreover, previous studies have emphasised the importance of the role of time in the relationship between poverty and life satisfaction. Clark et al. (2015) conducted a study using panel data from Germany, investigating the link between income poverty and subjective well-being, focusing on the mediating role of time. This study included data from approximately 49,000 individuals, and results were estimated using fixed-effect regression analysis controlling for a range of individual characteristics (i.e., age, employment status, marital status, education, and number of children) (Clark et al., 2015). The results indicate a significant negative association between both poverty intensity and incidence, and life satisfaction. Additionally, Clark et al. (2015) demonstrates how of time effects this relationship. The results suggest that the effects on life satisfaction extend beyond the

duration of poverty, suggesting that past poverty scars current well-being (Clark et al., 2015). Also found was that a succession of shorter exposures to poverty had a less-negative effect on life satisfaction compared to consecutive years of poverty/one longer exposure to poverty (Clark et al., 2015). This indicates that an experience of chronic poverty has a greater negative effect on life satisfaction compared to a transient experience of poverty.

Based on this collection of research it is evident that there is an opportunity to gain a better understanding of the relationship between poverty and life satisfaction within the context of South Africa. The aforementioned studies that have been conducted within the context of South Africa identify a gap in the research. Meyer (2017): cross sectional study using income to measure poverty. Whilst the findings from Meyer's (2017) study are valuable - demonstrating a statistically significant relationship between poverty and life satisfaction within the study context – these findings do not tell us about how this relationship may change over time, or whether the findings extend beyond the context of the Sileco township. Stoop (2019) and Gaya (2021) investigated this relationship using longitudinal, nationally representative data, providing some valuable insight into how life satisfaction changed over time relative to poverty. However, the conceptualisation of poverty in these studies was limited to monetary measures, with Stoop (2019) using per capita household expenditure and Gaya (2021) using income. Based on the literature discussed previously, the inclusion of a multidimensional conceptualisation of poverty, as well as the inclusion of an intertemporal facet of poverty, may enhance our understanding of the relationship between poverty and life satisfaction within the context of South Africa.

Study Purpose and Research Questions

This study makes a novel contribution to the literature by analysing the relationship between multidimensional poverty and life satisfaction in South Africa using longitudinal data, considering the role of poverty duration/persistence by incorporating intertemporal poverty as a predictor. This study utilises multi-level modelling to capture how individual life satisfaction change over time as a function of multidimensional poverty; additionally investigating how this relationship varies depending on whether an individual can be categorised as chronically poor, transiently poor, or non-poor.

Singer & Willett (2009) distinguishes between two types of questions that form the basis of any study investigating change: (1) 'questions addressing *within-individual change* and (2) *inter-individual differences in change'*. Questions about within-individual change over time are descriptive in nature, concerning the 'characterisation of each person's *individual growth trajectory* – each person's unique pattern of change over time' (Singer & Willett, 2009). Questions about inter-individual differences in change are relational in nature and relate to the association between predictors and the patterns of change (Singer & Willett, 2009).

In this study, four main research questions were addressed:

1. *How does each individual's level of life satisfaction change from wave 1 to wave 5?*
2. *Do individual change trajectories change as a function of multidimensional poverty?*
3. *Can we identify differences in individual change trajectories in life satisfaction based on differences in the intertemporal nature of poverty experience?*
4. *Does the interaction between multidimensional poverty and life satisfaction change based on differences in the intertemporal nature of poverty experience?*

Data and Methodology

Data and Participants

This study utilized secondary data obtained from the National Income Dynamics Study (NIDS). The National Income Dynamics Study (NIDS) is a longitudinal household panel study in South Africa. It consists of 5 waves of data and spanning a period of 9 years from 2008 to 2017. The NIDS sample is comprised of 28,226 individuals from 7296 households, and in all nine provinces in South Africa. The NIDS is an initiative of the Department of Planning, Monitoring and Evaluation (DPME), and is implemented Southern Africa Labour and Development Research Unit (SALDRU) with an aim to track and understand changes in poverty over time. It includes data which covers various dimensions of the lives of participants, including information pertaining to education, labour market participation, income, and well-being among other variables.

Wave 1 of the study was undertaken in 2008, and the four subsequent waves were undertaken in 2010, 2012, 2014, and 2017. The current study considers all five time points. The attrition rate between wave 1 and 2 was 21.93%, 15.94% between wave 2 and 3, 14.01% between wave 3 and 4, and 14.76% between wave 4 and 5. Data across all 5 waves was included in the analysis of this study.

The NIDS data was collected using four different questionnaires: a ‘Household’, an ‘Adult’, a ‘Child’, and also a ‘Proxy’ questionnaire. The current study limits the analysis to adult participants (those who were at least 15 years old at the time of the first wave of the study). In terms of participant demographics, the sample is limited further by population group. Only respondents who identified as ‘African’ or ‘Coloured’ were included in the analysis. The

reason for the exclusion of participants who identified as ‘Asian/Indian’ or ‘White’ is due to the high attrition rate for both of these groups. Respondents who identified as ‘White’ or ‘Asian/Indian’ had much lower probabilities of being reinterviewed in each subsequent wave compared to ‘African’ or ‘Coloured’ respondents (Branson & Wittenberg, 2019). Participant attrition between waves based on population group is depicted in table 1. The values presented in table 1 below are based on data published in the National Income Dynamics Study Panel User Manual (Brophy et al., 2018).

Table 1

Participant wave on wave attrition rates by population group.

Population Group	Wave 2	Wave 3	Wave 4	Wave 5
African	18.57	13.37%	11.17%	11.84%
Coloured	26.95%	18.3%	16.75%	18.68%
Asian/Indian	40.56%	36.44%	43.74%	44.82%
White	53.87%	50.07%	54.41%	62.69%
Total	21.93%	15.94%	14.01%	14.76%

Note. The values presented are based on data published in the National Income Dynamics Study Panel User Manual (Brophy et al., 2018)

Furthermore, only respondents who participated in all 5 data collection waves were included in the analysis. The final unweighted sample comprises a total of 10,335 participants. The unweighted sample characteristics are displayed in table 2 below.

Table 2

Demographic Characteristics of the Unweighted Sample by Sex and Population Group

Population Group	Male		Female		Total	
	Number	% of total sample	Number	% of total sample	Number	% of total sample
African	3302	31.9%	5322	51.5%	8624	83.4%
Coloured	649	6.3%	1062	10.3%	1711	16.6%
Total	3951	38.2%	6384	61.8%	10335	100%

Panel weights were used to make individual-level response adjustments, correcting for unequal probabilities of selection and adjust for bias due to non-random attrition (Branson & Wittenberg, 2019). This enables us to yield accurate population estimates from the data, enabling us to make inferences about the population from the sample. For waves 1-5 of the NIDS data, longitudinal and cross-sectional weights were provided (Branson & Wittenberg, 2019). This study used the panel weights (waves 1-5) presented in variable 'w5_pweight' available in the 'indderived' data file.

The panel weights reflect: (1) the calibration weights for wave 1 (represented by 'w1_wgt'), reflecting the probability of appearing in the wave 1 sample, and (2) the conditional probability of being successfully reinterviewed in each subsequent wave (Branson & Wittenberg, 2019). The calibration weights make adjustments so that individual characteristics (age, sex, and race) correspond with 2008 population estimates produced by StatsSA (Wittenberg, 2009; Branson & Wittenberg, 2019). This adjustment is necessary for

the purpose of producing a nationally representative sample because the wave 1 sample differs systematically from the national population. For instance, older Africans are overrepresented within the sample and younger Africans are underrepresented within the sample (Branson & Wittenberg, 2019). The weights are scaled so that the weighted total sample is equal to the estimated total population of 48,687,000 (Branson & Wittenberg, 2019). An adjustment based on the conditional probability of being unsuccessfully reinterviewed (based on a range of individual characteristics) corrects for systematic differences in attrition. For instance, the attrition rate was lowest among older individuals (> 50 years of age), and the attrition rate was higher amongst those who were employed, as well as amongst those who lived in urban areas (Ingle et al., 2021). After weights were applied, we were left with a final weighted population of 23,022,762 participants (see table 3).

Table 3

Demographic Characteristics of the Weighted Sample by Sex and Population Group

	Male		Female		Total	
Population Group	Number	% of total sample	Number	% of total sample	Number	% of total sample
African	8794995	38.2%	11976950	52.0%	20771944	90.2%
Coloured	922077	4.0%	1328741	5.8%	2250818	9.8%
Total	9717072	42.2%	133056690	57.8%	23022762	100%

Variables

Multidimensional Poverty

This study followed the methodology proposed by Alkire-Foster (2011) for the measurement of deprivation and the identification of multidimensional poverty, utilising the UNDP's Multidimensional Poverty Index (MPI). The MPI represents the first nationally comparable implementation of the direct method to poverty measurement, using indicators of deprivation across health, education, and standard of living dimensions to identify and capture the intensity of poverty. Specifically, this study follows the 2023 revised global MPI which captures deprivations in 10 indicators at a household level that span across 3 dimensions: health, education, and living standards (Table 4).

Table 4

2023 Revised Global Multidimensional Poverty Index

Dimensions of Poverty	Indicator	Deprived if Living in the Household where …	Weight
Health	Nutrition	At least 1 adult (18 years or older) has a BMI of less than 18.5.	1/6
	Child Mortality	Any child under the age of 18 in the household has died within the 24-month period preceding the survey.	1/6
Education	Years of Schooling	No household member aged 'school entrance age + six years or older has completed at least six years of schooling.	1/6

	School Attendance	Any school-aged child is not attending school up to the age at which he/she would complete class eight.	1/6
Standard of Living	Cooking Fuel	The household does not use electricity, gas, or paraffin for cooking.	1/18
	Sanitation	The household uses a no flush toilet or pit latrine, or the household shares with another.	1/18
	Drinking Water	No piped water in dwelling or on stand.	1/18
	Electricity	The household has no electricity.	1/18
	Housing	At least one of the three housing materials for roof, walls and floor are inadequate: the floor is of natural materials and/or the roof and/or walls are of natural or rudimentary materials.	1/18
	Assets	Household does not own more than one of radio, TV, telephone, refrigerator, bicycle, and does not own a car or truck.	1/18

Note: Obtained from *2023 Global Multidimensional Poverty Index (MPI)* by the UNDP (United Nations Development Programme) (Modified slightly from source).

This study follows the 2023 revised global MPI as closely as possible, although some modifications were made given the available data. For instance, regarding the 'child mortality' dimension, the 2023 revised global MPI specifies that an individual can be identified as deprived in this dimension if 'any child under the age of 18 years has died in the

family in the five-year period preceding the survey'. Regarding household mortality, the NIDS dataset includes data on reported household deaths that occurred within 24 months prior to each survey. For the identification of deprivation in 'housing', there is not available data on participant floor material at wave 1 of data collection. Because of this, only the material of house walls and roof can be considered. Based on the available data, materials for walls or roof are deemed inadequate if they are made of plastic, cardboard, mixture of mud and cement, wattle and daub, mud bricks, or thatching. Regarding the identification of deprivation in the 'assets' dimension, the 2023 revised global MPI also considered ownership of an animal cart which was not included here due to data availability. Regarding the ownership of a car or truck, the current study also only considers ownership of motor vehicles *in running condition*, a distinction that is not specified in the 2023 revised global MPI.

Slight modification was made to the nutrition indicator due constraints regarding data availability. The 2023 global MPI specifies that an individual is deprived in relation to nutrition if living in a household where 'At least 1 adult (18 years or older) has a BMI of less than 18.5' (See table 4). However, BMI data was only available for the respondent, and thus it was not possible to determine whether other household members fall below the specified threshold. Given this limitation, only the respondent themselves could be determined to be undernourished. An individual was identified as being deprived in this area if they had a BMI of less than 18.5. To identify deprivation in nutrition, firstly BMI was calculated based on the available data on the height and weight of respondents, using the following formula: BMI = weight (kg)/ height^2 (m). Because participant height is depicted in centimetres on the NIDS questionnaire, these values were converted to meters prior to calculating BMI.

The global MPI utilises a dual cut-off approach to poverty identification, identifying poverty within a multidimensional context based on two distinct sets of thresholds (Alkire & Foster, 2011). The first cut-off identifies whether someone is deprived within each dimension, identifying whether an individual meets the specified deprivation criteria for each indicator (Alkire & Foster, 2011). For each indicator, an individual is categorised as either deprived (assigned a score of 1) or not deprived (assigned a score of 0). The second cut-off identifies the multidimensionally poor based on a 'count' of the number of deprivations that someone experiences, weighted to adjust for the relative contribution of each dimension (Alkire & Foster, 2011).

The education and health dimensions are each represented by 2 indicators: years of schooling and child enrolment, and child mortality and nutrition respectively. The living standards dimension is represented by 6 indicators: electricity, drinking water, sanitation, cooking fuel, assets, and housing (see table 4). Each dimension contributes equally to the total deprivation score, with each of the 3 dimensions attributed a weight of 0.33. Accordingly, each indicator score is weighted according to the number of deprivation indicators that are included within each respective dimension. Within each dimension all indicators are weighted equally. Values for the 2 indicators within each of the education and health dimensions receive a weighting of 0.17 each, and values for the 6 living standards indicators are weighted at 0.056 each. An individuals' final deprivation score is based on the sum of all weighted indicator values, resulting in a score ranging from 0 to 1, with higher values indicating a higher level of deprivation (Alkire & Santos, 2014).

MPI values are an indication of the aggregate presence of non-monetary deprivations, capturing the experience of poverty in terms of the number of deprivations that an individual

experiences. Accordingly, MPI values increase when people experience a greater number of deprivations and decline when people experience fewer deprivations. The global MPI poverty cut-off, or the minimum deprivation score that is required for a person to be identified as poor, is 0.33. Accordingly, an individual was identified in this study to be multi-dimensionally poor or non-poor at each given observation based on this cut-off. If the deprivation score is equal to or exceeds 0.33 then an individual was categorised as multidimensionally poor.

Table 5

Multidimensionally Poor as a Percentage of Total (Weighted) for Waves 1-5.

Poverty Classification	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Poor	3.4%	2.7%	2.3%	6.3%	2.0%
Non-Poor	96.6%	97.3%	97.7%	93.7%	98.0%

Table 5 above presents the percentage of the total population that were categorised as multidimensionally poor according to the MPI. We can see that the proportion of the population that can be identified as poor remains relatively consistent, with the exception of a notable increase at wave 4, the data from which was collected in 2014. Table 6 below presents the demographic characteristics of this multidimensionally poor group at each of the 5 measurement occasions. The demographic makeup of the multidimensionally poor group remains reasonably consistent over the course of all 5 waves. There are 2 broad themes that remain relatively stable across the 5 waves: (1) individuals who identified as ‘African’ make up the vast majority of the multidimensionally poor group, do a degree that is disproportionate to their representation within the total population (see table 3); and (2) female participants (both African and Coloured) tended to occupy a greater proportion of the

multidimensionally poor group compared to their male counterparts. This is with the exception of 'Coloured' individuals at wave 1 and both 'African' and 'Coloured' individuals at wave 5, where males made up a greater proportion of the multidimensionally poor group compared to females.

Table 6

Demographic Characteristics of the Multidimensionally Poor Group by Sex and Population Group as % of Total for Waves 1-5.

Sex and Population Group	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
African					
Male	41%	38%	40%	36%	47.6%
Female	53.7%	57.7%	54%	55.4%	44.9%
Coloured					
Male	3%	1.8%	2.3%	2.4%	4.4%
Female	2.2%	2.6%	3.8%	6.3%	3.1%
Total	100%	100%	100%	100%	100%

Intertemporal Poverty

To identify individuals based on their intertemporal experience of poverty, participants were categorised as either non-poor, transiently poor, or chronically poor. This was done based on the temporal incidence of multidimensional poverty for each individual. Intertemporal poverty is thus measured based on the proportion of the number of time periods under consideration, or the total number of occasions out of the 5 waves at which they were identified as being multidimensionally poor (i.e., Alkire et al., 2017).

Intertemporally non-poor individuals can be identified as those who were categorised as non-poor at all 5 data collection waves. Transiently poor individuals are participants who are occasionally poor although spend a considerable proportion of time out of poverty (Barrett & Swallow, 2006; Leal Filho et al., 2022). Transiently poor individuals were identified as those who experienced multidimensional poverty on at least 1 but no more than 3 of the 5 waves. Chronically poor individuals are participants who experience poverty as a state that is persistent over an extended period of time, having spent a large proportion of the time under consideration living in multidimensional poverty (Hulme & Shepard, 2003; Shepherd et al., 2019). Chronic individuals were identified as those who were multidimensionally poor on at least 4 occasions over the 5 waves.

Table 7

Non-Poor, Transiently Poor and Chronically Poor Groups as a Percentage of the Total (Weighted) Sample by Sex and Population Group.

Population Group	Non-Poor			Transiently Poor			Chronically Poor		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
African	34.6%	46.6%	81.2%	3%	4.6%	7.6%	0.7%	0.7%	1.4%
Coloured	3.8%	5.3%	9.1%	0.2%	0.4%	0.6%	0.05%	0.03%	0.08%
Total	38.4%	51.9%	90.3%	3.2%	5%	8.2%	0.7%	0.7%	1.5%

Life Satisfaction

Life satisfaction was measured using the single item measure included in the NIDS questionnaire. This measure read, “how do you feel about your life as a whole right now”, and responses are measured using a 10-point Likert-type scale ranging from 1 (*very dissatisfied*) to 10 (*very satisfied*). Higher scores indicate higher levels of life satisfaction. Previous research has demonstrated satisfactory reliability and validity of single-item life satisfaction measures.

Fonberg & Smith (2019) observed a highly significant and positive correlation between a single-item life satisfaction measure and a psychometrically well-established multi-item life satisfaction measure (Satisfaction with Life Scale) ($r = 0.85$, $p < 0.001$). Similarly, Cheung & Lucas (2014) found that single-item life satisfaction measures demonstrated a reasonable degree of criterion validity with the Satisfaction with Life Scale (SWLS) ($r = 0.62 - 0.64$), a result that remained consistent across three samples. Furthermore, Cheung & Lucas (2014) found that the single-item measure and the SWLS demonstrated very little difference in the magnitude of correlation with theoretically relevant variables (average difference = 0.001 – 0.005). This indicates that neither measure produces systematically different correlations compared with the other (Cheung & Lucas, 2014). Lucas & Donnellan (2012) produced an average estimated reliability of single-item life satisfaction measures of 0.72, representing an acceptable level of reliability.

Procedure

Data Processing

Prior to analysis of the data, it was necessary to address the organisation of the data-set given the nature of longitudinal data. Longitudinal data can be organised in two different formats: the person-level (or wide) format, or the person-period (or long) format.

- A *person-level data set*, in which each person has one record and multiple variables contain the data from each measurement occasion.
- A *person-period data set*, in which each person has multiple records—one for each measurement occasion (Singer & Willett, 2009).

The NIDS data is initially stored as a person-level data set. This format introduces a number of challenges for this longitudinal analysis. Firstly, the person-level format is not suited to analyses that intend to make inferences regarding how participant's change over time. Because observations from each distinct time point are depicted in different columns within the same row, longitudinal analyses are limited to wave-to-wave correlations and plots, from which we cannot make inferences regarding how each individual changes over time (Singer & Willett, 2009). Additionally, the person-level data format does not have an explicit 'time' variable that corresponds with each measurement occasion. Because of this, it is not possible to address questions concerning the relationship between the outcome variable and 'time' (Singer & Willett, 2009), a key focus of this study. Person-level formatted data also presents difficulties handling predictor variables that can vary over time (Singer & Willett, 2009). This represents a challenge for the use of person-level formatted data when conducted analyses with this dataset due to the presence of a time-variant predictor variable. Intertemporal

poverty status is a time-invariant predictor, remaining constant across all 5 time points and thus only requiring a single variable. However, the multidimensional poverty status of each individual has the capacity to vary from wave to wave and so each individual requires a total of 5 columns, each corresponding to a different measurement occasion.

A person-period formatted data set contains multiple records for each individual, in this case the data for each individual is depicted in 5 rows (one for each measurement occasion). It includes a 'time' variable that acts as an identifier for each specific measurement occasion. For this dataset, this identifies the data collection wave (1-5). A person-period dataset also includes an 'id' variable that allows the records for each individual to be grouped into person-specific subsets. The capacity to group the data of each individual is crucial for this analysis, as it enables the examination of individual change trajectories.

For these reasons, Singer & Willett (2009) advise in favour of the use of person-period format for the purpose of fitting a multilevel model to longitudinal data. For the purpose of this analyses the structure of the data set was converted from person-level format to person-period format.

Data Analysis

The analysis of the data began with an exploratory descriptive analysis estimating OLS-Fitted Trajectories. The primary analyses consisted of fitting a series of multi-level models to investigate the relationship between life satisfaction, multilevel poverty status, and intertemporal poverty status whilst locating the data within nested structures of clustered data. All analyses were conducted in IBM SPSS Statistics version 29.0, and $p \leq 0.05$ was used as a pre-determined threshold for statistical significance.

For the following analysis, the variable *TIME* is coded as '*TIME* – 1' for the purpose of interpretation. Where the data collection waves were represented by the sequence 1, 2, 3, 4, 5 to depict waves 1-5, these values are now centred, redefining the starting point as 0 so that the value at the first measurement occasion corresponds with the y intercept. Waves 1-5 are therefore represented by the sequence 0, 1, 2, 3, 4 where '0' represents wave 1 and '4' represents wave 5. The following analyses were performed with weighted data.

Exploratory OLS-Fitted Trajectories

A preliminary descriptive analysis was conducted in order to ascertain descriptively the manner in which individual's outcome variables change over time, how individual change differs across people, and whether interindividual differences in change are associated with individual characteristics (Singer & Willett, 2009).

Here we adopt a linear individual change model, utilising the fitted intercept and the fitted slope as parameter estimates to summarise each individual's initial status and growth trajectories; describing fitted values at wave 1 of data collection and rates at which deprivation, depression and well-being change over time. Here I examine the population means of the estimated intercepts and slopes, sample variances of the estimated intercepts and slopes, and population correlation between the estimated intercepts and slopes, examining the observed *average* pattern of change.

Exploring the relationship between change and time-invariant predictors allows us to examine possible systematic patterns in the individual change trajectories (Singer & Willett, 2003). Within the context of this study, I examine differences corresponding to

interindividual variation in intertemporal poverty status. In doing so, the following questions were asked:

- *Do observed differences differ across groups?*
- *Do observed differences appear more in the intercepts or in the slopes?*
- *Are some groups' observed trajectories more heterogeneous than others'?*

Fitting the Multilevel Model

An individual's multidimensional poverty status can change across time. For any individual, the values of MPI can be either 0 or 1 at any given time point. Accordingly, this variable represents a person's potentially differing multidimensional poverty status at each associated time point. Because of this, multidimensional poverty status was treated as a time-variant predictor. As a time-variant predictor, multidimensional poverty was treated as a level-1, or within-person predictor.

Model A

The analysis began with the fitting of an unconditional means model, otherwise known as the 'multilevel null model'. Model A is an 'intercept only' model with no level-1 or level-2 predictors included, predicting life satisfaction from the overall mean. Model A was specified as:

$$Y_{ij} = \pi_{0i} + \varepsilon_{ij}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i}$$

The unconditional means model excludes predictors at every level; it stipulates that a flat individual change trajectory for person *i* at level-1. This model allows the intercepts (π_{0i}) to vary, whilst lacking a slope parameter, describing the change in each individual's life satisfaction over time with a slope of zero. Model A thus produces mean values of life satisfaction. The results of model A indicate (1) whether there is statistically significant between-person variation, and (2) whether there is sufficient variation at the within-person and between-person level to warrant further analysis. A non-zero variance component indicates that there is sufficient variation at that level to warrant further analysis (Singer & Willett, 2003).

A p-value of < 0.05, the results of this model can be interpreted as demonstrating statistically significant between-person variation, thus supporting the appropriateness of the use of a multilevel model. Another value of interest for model A is the intraclass correlation coefficient (ICC). The ICC is useful in estimating the portion of variance that can be attributed to within-person and between-person differences. The ICC is calculated based on the within-person and between-person variance values, producing a value ranging from 0 to 1. Whilst there are no rigid guidelines for the interpretation of the ICC within this context, a particularly high ICC value (approaching 1.0) would suggest that there is minimal variance in life satisfaction to be explained at the within-person level, in which case multilevel modelling may not be appropriate.

Model B

Model B is an unconditional growth model, introducing a level-1 'time' predictor to allow each individual's changes in life satisfaction to be modelled with a non-zero slope. This

model predicts life satisfaction from the intercept and time, both of which vary randomly across individuals. The unconditional growth model was specified as:

$$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \varepsilon_{ij}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{10} + \zeta_{1i}$$

Y_{ij} represents the value of *life satisfaction* for individual *i* at time *j*. With the introduction of a growth parameter, $\pi_{1i,}$ this model specifies that participant life satisfaction is able to change as a function of time at a non-zero rate. This model examine variance in life satisfaction across people and time, and partition it at each level. The fixed effects (population average intercept and slope, depicted by γ_{00} and γ_{10}) estimate the starting point and rate of change for the average individual within the population without controlling for additional predictors. The estimated random effects (variance components) allow us to determine the proportion of variation in life satisfaction that is systematically associated with 'time'.

Model C

Model C introduces the main effect of *MPI* as a fixed effect. Raudenbush & Bryk (2002) advise against a default estimation that all slopes vary randomly, and so *MPI* was included as a fixed effect prior to estimating the *MPI* slope as randomly varying. It is then possible to compare the fit of the two models. Model C was specified as:

$$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + e_{ij}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{10} + \zeta_{1i}$$

$\pi_{2i} = \gamma_{20}$

This equation models individual *i*'s life satisfaction at wave *j* as a function of time as well as their multidimensional poverty status at that given time point. Because multidimensional poverty status is time varying, this model estimates different population average change trajectories that correspond to various patterns of living in and out of poverty. Model C accounts for discontinuity in estimated change trajectories that is associated with changes in multidimensional poverty status. The model estimates two fitted growth trajectories, one for each dichotomous value of the predictor. However, because only the main effect of multidimensional poverty status is included, the two trajectories are constrained to be parallel – the trajectories are free to shift vertically independent of one another, whilst the rate of change is held constant. The degree to which multidimensional poverty status explains the observed changes in life satisfaction is assessed based primarily on the main effect of multidimensional poverty status. The main effect of multidimensional poverty status is assessed based on the gap between trajectories, or the population average difference, over time, between *MPI* = 0 and *MPI* = 1 (γ_{20}).

Model D

Model D introduces the effect of *MPI* as a random effect. Whilst model C estimates the *MPI* slope as fixed, this model allows the effect of *MPI* to vary randomly over time. This model therefore estimates the effect of MPI on both initial status and slope. Model D is specified as:

$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + \pi_{3i}\text{MPI x TIME} + e_{ij}$

$\pi_{0i} = \gamma_{00} + \zeta_{0i}$

$\pi_{1i} = \gamma_{10} + \zeta_{1i}$

$\pi_{2i} = \gamma_{20} + \zeta_{1i}$

$\pi_{3i} = \gamma_{30}$

Because model D allows the *MPI* slope to vary randomly, the parameter, γ_{20}, is interpreted differently compared to in model C. In this model, 'γ_{20}' is interpreted as the estimated average rate of change in life satisfaction scores based on an *MPI* value of 1 (among the multidimensionally poor).

Model E

This model predicts life satisfaction from intercept and time, in addition to asking whether the intercept and slope are effected by the individuals intertemporal poverty status. *POV* was coded as 0 = non-poor, 1 = transiently poor, and 2 = chronically poor.

Level-1/level-2 model:

$WELLBEING_{ij} = \pi_{0i} + \pi_{1i}TIME + \varepsilon_{ij}$

$\pi_{0i} = \gamma_{00} + \gamma_{01}POV + \zeta_{0i}$

$\pi_{1i} = \gamma_{10} + \gamma_{11}POV + \zeta_{1i}$

Model E includes 'intertemporal poverty status' as a time-invariant predictor at the level-2 or between-person level. The inclusion of this predictor allows for the examination of differences in individual growth trajectories based on differences in the intertemporal nature of poverty experience. Based on the estimated value for parameter γ_{01} we can examine the population average difference in life satisfaction intercept for a 1-unit difference in *POV*. Based on 'γ_{11}' we can assess the estimated effect of intertemporal poverty status on the rate of change in life satisfaction.

Model F

This model predicts life satisfaction from multidimensional poverty status and time. To examine between-person differences in life satisfaction, intertemporal poverty status was included as a time-invariant level-2 predictor. This model includes only transiently poor and chronically poor individuals, accordingly *POV* was coded here as 0 = transiently poor and 1 = chronically poor. The exclusion of multidimensionally non-poor individuals is due to challenges that this would introduce when it comes to the interpretation of 'γ_{20}' and 'γ_{30}'. Within this model, the coefficient 'γ_{20}' is an estimate of the average rate of change in life satisfaction based on occasions where individuals were multidimensionally poor, when *POV* = 0. Because individuals with a 'non-poor' intertemporal poverty status were not multidimensionally poor at any measurement occasion, this value would be meaningless. Similarly, the coefficient 'γ_{30}' is calculated as a function of multidimensional poverty status.

This allowed for an estimation of the degree to which the intercepts and slopes are affected by intertemporal poverty status. In other words, this enabled us to see whether there is a difference between the transiently poor and chronically poor in terms of the estimated growth trajectories.

A comparison of the model fit indicators between model C and model D - namely the -2 Log Likelihood, AIC, and BIC values – indicated that model C was a slightly better fit to the data. However, because model D is not able to account for differences in the duration of experiences of multidimensional poverty, it is possible that the fit of model D is poorer than model C because of this constraint. Given the numerous factors that can impact the experience of poverty, for example differences in the relative persistence of poverty (Bossert

et al., 2019), in the mechanisms associated with a state of poverty (Banerjee et al., 2019), or in preparedness to deal with states of poverty (Clark et al., 2015), it would not be reasonable to expect the effect of multidimensional poverty to be constant across the population. Because of this it was decided that it was more appropriate to treat the effect of multidimensional poverty as a random effect. Thus, model F includes MPI as a time-variant predictor assuming a random effect.

level-2 model:

$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + \pi_{3i}\text{MPI x TIME} + e_{ij}$

$\pi_{0i} = \gamma_{00} + \gamma_{01}POV + \zeta_{1i}$

$\pi_{1i} = \gamma_{10} + \gamma_{11}\text{POV} + \zeta_{1i}$

$\pi_{2i} = \gamma_{20} + \gamma_{11}\text{POV} + \zeta_{1i}$

$\pi_{3i} = \gamma_{30}$

Results

Exploratory OLS-Fitted Trajectories

For the purpose of this exploratory analysis, participant deprivation score will be used rather than participant multidimensional poverty status. This means that the values for MPI here are based on the sum of weighted indicator values, ranging from 0 to 1, rather than the dichotomous values (0 or 1) produced by the dual cut-off method. This is necessary due to the interpretive challenges associated with the inclusion of MPI as a dichotomous variable. Here, MPI values represent the degree to which an individual is deprived rather than an identifier of whether an individual is considered poor or non-poor at each given timepoint.

OLS-Fitted Trajectories of the Full (Weighted) Sample

In this section the OLS-Fitted Trajectories for the full sample are presented, including estimates for the individual growth parameters. Table 5 includes the parameter estimates from two models, one for life satisfaction and one for deprivation, modelling each as a function of 'time'.

Table 8

Descriptive statistics for the individual growth parameters obtained by fitting separate within-person OLS regression models for Life Satisfaction and Deprivation as a function of linear time.

	Initial Status (Intercept)	Rate of Change (Slope)
Life Satisfaction		
Mean	4.8076	0.0774
Standard Deviation	3.3238	0.9064
Bivariate Correlation		-0.906**
Deprivation		
Mean	0.0983	-0.0049
Standard Deviation	0.0975	0.0243
Bivariate Correlation		-0.706**

Life Satisfaction

Table 5 above shows an average estimated intercept of 4.81 and an average estimated slope of -0.08. This indicates that the average individual within this population had an initial observed

life satisfaction score of 4.41 at wave 1 and reported a subsequent increase in this score by an estimated value of 0.08 for each consecutive wave. A standard deviation of 4.57 for the mean estimated intercept and 0.024 for the mean estimated slope suggests that individual data points are scattered widely around the mean values. This indicates that individuals differ considerably in their initial life satisfaction scores, and individual growth trajectories. The correlation coefficient between the *a* and *b* value of -0.906 ($p < 0.001$) (shown in table 5) indicates a negative relationship between fitted initial status and fitted rate of change, suggesting that individuals with a higher initial life satisfaction score tend to become more satisfied, less rapidly over time.

Deprivation

Table 5 shows an average estimated intercept of 0.0983 and an average estimated slope of -0.0049. This indicates that the average individual within this population had an initial observed deprivation score of 0.0983 at wave 1, and this decreases by an estimated value of 0.0049 for each consecutive wave. A standard deviation of 0.0975 for the mean estimated intercept and a standard deviation of 0.0243 for the mean estimated slope suggests that individual data points are scattered widely around the mean values. This tells us that individuals differ considerably in their initial deprivation scores, and individual growth trajectories. The correlation coefficient between the *a* and *b* value of -0.706 ($p < 0.001$) (shown in table 5) indicates a negative relationship between fitted initial status and fitted rate of change, suggesting that individuals with a higher initial deprivation score tend to become less impoverished, less rapidly over time.

OLS-Fitted Trajectories by Intertemporal Poverty Status

This section presents the same models as above, although individuals are categorised in terms of their intertemporal poverty status. A total of 6 OLS regression models are fitted – table 6 includes the parameter estimates using the life satisfaction and deprivation data for participants who are categorised as non-poor, transiently poor, and chronically poor.

Table 9

Descriptive statistics for the individual growth parameters obtained by fitting separate within-person OLS regression models for Life Satisfaction and Deprivation as a function of linear time for non-poor, transiently poor, and chronically poor individuals.

Non-Poor	Initial Status (Intercept)	Rate of Change (Slope)
Life Satisfaction		
Mean	4.9345	0.0609
Standard Deviation	3.2545	0.8961
Bivariate Correlation		-0.904**
Deprivation		
Mean	0.0829	-0.0055
Standard Deviation	0.0775	0.0211
Bivariate Correlation		-0.802**
Transiently Poor		
Life Satisfaction		
Mean	4.1501	0.1419
Standard Deviation	3.2223	0.9084
Bivariate Correlation		-0.919**

Deprivation		
Mean	0.1836	-0.0005
Standard Deviation	0.1268	0.0396
Bivariate Correlation		-0.923**
Chronically Poor		
Life Satisfaction		
Mean	2.2518	0.5088
Standard Deviation	5.9105	1.3666
Bivariate Correlation		-0.962**
Deprivation		
Mean	0.3508	-0.0032
Standard Deviation	0.1415	0.0400
Bivariate Correlation		-0.905**

Life Satisfaction

The average estimated intercept for each group indicates that the average chronically poor individual reported a lower life satisfaction at wave 1 compared to the average transiently poor and average non-poor individual; furthermore, the average non-poor individual reported a higher satisfaction at wave 1 compared to the average chronically poor or transiently poor individual. The average estimated well-being score within the chronically poor group at wave 1 was 2.25 (SD = 5.91), whilst the average estimated well-being score within the transiently poor and non-poor group at wave 1 was 4.15 (SD = 3.22) and 4.93 (SD = 3.25) respectively.

Compared to the average individual within the total sample, the average non-poor individual had a higher reported satisfaction with life at wave 1 (4.93 compared with 4.81). Conversely, the average individual within each of the two multidimensionally poor groups reported a lower satisfaction with life compared to the average individual within the total sample. The average transiently poor individual had a life satisfaction value of 4.15 (SD = 3.22) at wave 1. The chronically poor group had an average initial status of 2.25 (SD = 5.91), considerably lower compared to the mean initial status within the total sample and even compared to the average transiently poor individual. We can observe a clear relative order of life satisfaction between the three groups (in terms of the mean intercepts), with non-poor individuals tending to report being most satisfied with life, and chronically poor individuals tending to report being the least satisfied with life.

Between the chronically poor, transiently poor, and non-poor group, similarity's regarding the direction of the average estimated slopes can be observed. Within each of the 3 groups, the average estimated slope is positive in direction, suggesting that the well-being score of the average individual tended to increase with each consecutive wave. Whilst the average individual within each group tended to increase in their well-being over time, they did so at different rates dependant on their intertemporal poverty classification. The data indicates that the well-being score of the average chronically depressed individual increased by an estimated value of 0.51 between each wave (SD = 1.37). This represents a steeper growth trajectory compared to the average transiently poor individual (b = 0.14, SD = 0.91) and the average non-poor individual (b = 0.06, SD = 0.90), who's well-being score increased at a much slower rate over the 5 waves. Life satisfaction appears to be most stable for the average non-poor individual, with only a minimal estimated increase over the course of the measurement period.

The standard deviations for both the intercept and slope estimates for non-poor, transiently poor, and chronically poor individuals indicate that the parameter values for each individual are scattered widely around these mean values. This suggests that there is considerable variation in individual change trajectories, both in terms of participant initial status and change over time, particularly with the chronically poor group.

Deprivation

The relative order of mean deprivation values at wave 1 between the three groups is consistent with expectations given that the categorisation of individuals in terms of their intertemporal poverty status is based on their multidimensional poverty status across the five measurement occasions. The mean estimated deprivation score within the non-poor group was 0.08 (SD = 0.08), indicating that the typical non-poor individual sat far below the multidimensional poverty threshold of 1/3. The mean estimated deprivation score within the transiently poor group was 0.18 (SD = 0.13), a value that is higher compared to the non-poor group although still falls short of the multidimensional poverty threshold. The mean estimated deprivation score within the chronically poor group was 0.35 (SD = 0.14), a deprivation score that is considerably higher compared to both the non-poor and transiently poor groups and exceeds the multidimensional poverty threshold.

There are also notable similarities differences between groups in terms of fitted rate of change for depression. The mean estimated slopes for all three groups are negative in direction, indicating that the average individual within each group tended to become less deprived over time. The non-poor group had a mean estimated slope value of -0.0055 (SD = 0.02), tending to become less deprived at the fasted rate compared to the other two groups.

The transiently poor group tended to become less deprived at the slowest rate compared to the other two groups, with a mean estimated slope value of -0.0005 (SD = 0.04) that approximates a flat curve. This makes sense when considering that the multidimensional poverty status of transiently poor individuals tends to fluctuate between multidimensionally poor and multidimensionally non-poor. The average chronically poor individual had an estimated rate of change of -0.0032 (SD = 0.04). The standard deviations for mean intercept and slope values across all three groups indicate that there is considerable variation in the individual change trajectories within non-poor, transiently poor, and chronically poor groups.

This exploratory analysis suggests that there are significant differences in individual change trajectories to be explained. These results highlight that the average parameters for each group (non-poor, transiently poor, and chronically poor) are distinct, indicating the presence of possible systematic patterns in individual change trajectories based on intertemporal poverty status. The inferences that can be made from the results of this analysis are limited by the assumption of linearity, however, these results are preliminary and used only to indicate the presence of possible systematic patterns in individual change trajectories. This assumption of linearity is relaxed later.

Assessing the Assumption of Linearity

Here I assessed the appropriateness of the use of a linear model to estimate individual change trajectories life satisfaction. A curve estimation analysis was performed, fitting the life satisfaction data to the following models: linear, logarithmic, quadratic, cubic, compound, S, and exponential. The estimates from all models were statistically significant ($p < 0.001$) so R Square values were used to compare model fit.

Curve estimation was performed for (1) the total sample, (2) the intertemporally non-poor group, (3) the transiently poor group, and (4) the chronically poor group. For all groups, the linear model was determined to be the poorest fit (R Square = 0.000). For all groups, a cubic model appeared to be the best fit for the data, with an R Square value of 0.017 for the total sample and the non-poor group, 0.02 for the transiently poor group, and 0.033 for the chronically poor group.

Although the associated R Square values observed here are small, this is consistent with expectations given that this is simply based on life satisfaction plotted against time. It would be reasonable to expect, given the research context, that time alone would explain a minimal amount of the variance in life satisfaction. Additionally, based on a visual inspection of individual change trajectories, there were a number of different patterns of life satisfaction change over time. Therefore there is no single model that would fit the data for every individual. The p-values are statistically significant ($p < 0.001$), which may indicate that the relationship between the variables may still be important despite only explaining a small amount of variation in the outcome. It is also critical to consider that the objective of this research is not to predict, but rather to understand the relationships between multidimensional poverty, life satisfaction, and intertemporal poverty.

Fitting Linear Change Trajectories Using Transformed Data

The following analysis fits a multilevel model to the life satisfaction data specifying linear change trajectories, using a transformed scale to account for non-linear patterns of individual change. Because a cubic model was statistically determined to be the best fit for the data, the outcome variable, *life satisfaction*, in the level-1 sub model was transformed accordingly.

This transformation was performed by 'cube rooting' the observed life satisfaction values. The outcome variable was transformed rather than *time* so that intuitive values that correspond to the 5 measurement occasions can be maintained. The original 10-point life satisfaction scale was arbitrary to a degree in terms of the magnitude of its values. Whether the scale values range from 0-10, 0-100, or 0-5 the interpretation remains the same (i.e., a life satisfaction score of 80 indicates a higher degree of life satisfaction compared with a score of 50). Thus, in transforming the observed life satisfaction values, an intuitive interpretation of the scale is maintained.

Although the relationship between life satisfaction and time is explicitly non-linear, fitting a linear growth model to the life satisfaction data is preferable due to its simple mathematical form (Singer & Willett, 2009). Fitting a linear model to transformed data offers clearly interpretable estimates, and still enables the tracking of individual life satisfaction over time and the identification of predictors associated with differential patterns of change (Singer & Willett, 2009).

Fitting the Multilevel Model with Transformed Life Satisfaction Data

Table 10

Parameter Estimates for the Six Growth Models.

		Parameter	Model A	Model B	Model C	Model D	Model E	Model F
Fixed Effects								
Initial Status,	Intercept	γ_{00}	1.678***	1.649***	1.649***	1.648***	1.655***	1.589***

π_{0i}								
			(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)
	POV	γ_{01}					-0.063***	-0.078**
							(0.008)	(0.027)
Rate of Change, π_{1i}	Intercept	γ_{10}		0.014***	0.014***	0.014***	0.013***	0.020***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
	POV	γ_{11}					0.005~	0.011~
							(0.003)	(0.010)
	MPI	γ_{20}			-0.002***	0.023***		0.024***
					(0.000)	(0.000)		(0.001)
	MPI by TIME	γ_{30}				-0.010***		-0.010***
						(0.000)		(0.000)
Variance Components								
Level 1	Within-person		0.065	0.045	0.045	0.045	0.045	0.049
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Level 2	In initial status		0.029	0.087	0.087	0.087	0.086	0.092
			(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)

	In rate of change	0.011	0.011	0.011	0.011	0.012
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	Covariance	-0.025	-0.025	-0.025	-0.025	-0.027
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goodness-of-fit						
	Deviance	102524 15.65	- 260153 23.30	- 2601540 3.72	- 260191 63.89	- 2417132 5.01	- 1674719. 10
	AIC	102524 21.65	- 260153 11.30	- 2601538 9.72	- 260191 47.89	- 2417130 9.01	- 1674699. 10
	BIC	102524 70.99	- 260152 12.63	- 2601527 4.60	- 260190 16.33	- 2417117 7.99	- 1674558. 17

*~ p < .10; * p < .05; ** p < .01; *** p < .001.*

Model A

Model A presents the results of fitting the unconditional means model to the wellbeing data.

$Y_{ij} = \pi_{0i} + \varepsilon_{ij}$

$\pi_{0i} = 1.68 + \zeta_{0i}$

Variance components:

Level 1 Within Person, $V(\varepsilon) = 0.065$; Level 2 Initial Status, $V(\zeta_0) = 0.029$

Its single fixed effect '$\hat{y}_{00}$' estimates the outcome's grand mean across all waves and individuals. The obtained value for this parameter of 1.68 ($p < 0.001$), when de-transformed (Cubed) is equal to 4.74, indicating that the average individual across all 5 waves reported/experienced a moderate level of life satisfaction/wellbeing.

Examining the random effects of model A, the estimated within-person variance is 0.065 (SE = 0.000), and the estimated between-person variance is 0.029 (SE = 0.000). Both of these variance components differ marginally from zero, indicating that there is some variation at both the within-person and between-person level that could potentially be explained by predictors. The relative magnitude of the within-person and between-person variance components indicates that the majority of the variance in our outcome is at the within-person level. The intraclass correlation coefficient (ICC) of 0.308 for model A suggests that 30.8% percent of the variance is at the between-person level, whilst 69.2% of the variance is at the within-person level.

Model B

Model B presents the results of fitting the unconditional growth model to the wellbeing data, introducing the predictor *TIME* into the level-1 sub-model.

$$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \varepsilon_{ij}$$

$$\pi_{0i} = 1.65 + \zeta_{0i}$$

$$\pi_{1i} = 0.014 + \zeta_{1i}$$

Variance Components:

Level 1 Within Person, $V(\varepsilon) = 0.045$; Level 2 Initial Status, $V(\zeta_0) = 0.087$; Rate of Change, $V(\zeta_1) = 0.011$; $Cov(\zeta_0, \zeta_1) = -0.025$

The fixed effects '$\hat{y}_{00}$', and '$\hat{y}_{10}$' estimate the starting point and slope of the population average change trajectory. The unconditional growth model estimated that the average true change trajectory for *life satisfaction* has a non-zero intercept of 1.649 ($p < 0.001$) and a non-zero linear slope of +0.014 ($p < 0.001$). The de-transformed value of '$\hat{y}_{00}$', 4.484, indicates that at wave 1 (time '0'), the average life satisfaction was 4.48. Allowing the intercept and slope to vary thus lead to the estimation of a slightly lower wellbeing value for the average individual at wave 1. This value that increased at an estimated rate (according to the transformed values of life satisfaction) of 0.014 per wave. When the values are de-transformed, as a function of $(\hat{y}_{10} \text{ x } (\text{time} - 1))^3$, we can assess the relative increase in life satisfaction relative to the initial status. Based on these de-transformed values, we can see that the rate of change accelerates, with the estimated change in life satisfaction increasing with each subsequent wave. At wave 2 the average estimated life satisfaction was $2.7e^{-6}$ higher compared to wave 1, whilst at wave 4 the value was $7.4e^{-5}$ higher compared to wave 1 and at wave 5 the value was $1.8e^{-4}$ higher compared to wave 1. This represents a statistically significant, although marginal increase in life satisfaction.

The level-1 residual variance depicts the average scatter of an individual's observed outcome values around his or her own true change trajectory (Singer & Willett, 2003). Comparing the level-1 residual variance in Model B to that of Model A, we observe a decline of 0.02 (from 0.065 to 0.045). This suggests that 30.8% of the within-person variation in *life satisfaction* is systematically associated with linear *time*. Because the level-1 variance in model B differs significantly from 0, this indicates that meaningful variation still remains at the within-person

level. The Level-2 variance components estimate the between-person variability in intercept and slope values. The level-2 variance in initial status, 0.087 (SE = 0.001), and level-2 variance in rate of change, 0.011 (SE = 0.000), suggests that there was variability in terms of individual's initial life satisfaction scores and in terms of their rate of change in life satisfaction over time. Based on the deviance, AIC, and BIC statistics, we can conclude that model B was a better fit to the data compared to model A.

Model C

Model C introduces multidimensional poverty status as a time-variant predictor, assuming a fixed effect. This model considers multidimensionally poor and non-poor occasions separately, allowing for the estimation of broken change trajectories.

$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + e_{ij}$

$\pi_{0i} = 1.65 + \zeta_{0i}$

$\pi_{1i} = 0.014 + \zeta_{1i}$

$\pi_{2i} = -0.002$

Variance Components:

Level 1 Within Person, $V(\varepsilon) = 0.045$; Level 2 Initial Status, $V(\zeta_0) = 0.087$; Rate of Change, $V(\zeta_1) = 0.011$; $\text{Cov}(\zeta_0, \zeta_1) = -0.025$

Model C estimated the average life satisfaction score to be 1.649 ($p < 0.001$) when both *time* and *MPI* are equal to zero. When de-transformed, This means that at wave 1 the average life satisfaction amongst individuals who were not multidimensionally poor was 4.484. Additionally, the conditional rate linear of change, given an *MPI* value of zero, was 0.014 (p

< 0.001). This indicates that for the average individual, the life satisfaction increased at a (transformed) rate of 0.014 during the period between measurement occasions, based on the occasions where the individual was not multidimensionally poor. These parameter values did not change with the introduction of multidimensional poverty as a time-varying predictor. This suggests that controlling for multidimensional poverty did not explain any of the observed increase in the observed initial status or increase in life satisfaction. The average effect of multidimensional poverty, however, was small but significant ($\gamma_{20} = -0.002$, $p < 0.001$). This indicates that the average life satisfaction was 0.002 lower among the multidimensionally poor.

The magnitude of the level-1 variance for model C was identical to that of model B, 0.045 (SE = 0.000), remaining stable. This suggests that introducing multidimensional poverty as a time varying predictor did not explain any additional variance at the within-person level compared to the unconditional growth model. Because the introduction of a time-variant predictor changes the meaning of the level-2 variance components, Singer & Willett (2009) posit that level-2 variance components cannot generally be interpreted in a meaningful way. The deviance, AIC, and BIC statistics indicate that model C was a better fit to the data compared to model B.

Model D

Model D introduces multidimensional poverty status as a time-variant predictor, assuming a random effect, specifying an interaction between multidimensional poverty and time. This model, similarly to model C, considers multidimensionally poor and non-poor occasions separately.

$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + \pi_{3i}\text{MPI x TIME} + e_{ij}$

$\pi_{0i} = 1.65 + \zeta_{0i}$

$\pi_{1i} = 0.014 + \zeta_{1i}$

$\pi_{2i} = 0.023 + \zeta_{1i}$

$\pi_{3i} = -0.010$

Variance Components:

Level 1 Within Person, $V(\varepsilon) = 0.045$; Level 2 Initial Status, $V(\zeta_0) = 0.087$; Rate of Change, $V(\zeta_1) = 0.011$; $\text{Cov}(\zeta_0, \zeta_1) = -0.025$

For model D, the average life satisfaction score at wave 1 was 1.648 ($p < 0.001$) given an *MPI* value of zero, 0.001 lower compared to the average estimated initial status in model C. When de-transformed, this produces a $\hat{y}_{00}$ value of 4.476, 0.008 lower compared to model C. Mean life satisfaction increased at a rate of 0.014 ($p < 0.001$) conditional on an *MPI* value of zero, an identical rate of increase compared to that estimated in model C (0.014, $p < 0.001$).

Model D estimates that the average rate of change in life satisfaction among the multidimensionally poor, γ_{20}, was 0.023 ($p < 0.001$), an increase that was small but statistically significant. This represents an average rate of change in life satisfaction higher than that among the multidimensionally non-poor ($\gamma_{10} = 0.014$, $p < 0.001$). Because these estimates are based on transformed values of life satisfaction, we can interpret that among the multidimensionally poor, increases in life satisfaction accelerate at a faster rate compared to the multidimensionally non-poor.

The interaction between multidimensional poverty and time was small but statistically significant ($\gamma_{30} = -0.010$, $p < 0.001$). Based on Singer & Willett's (2009) interpretive guidance, this indicates that (1) the effect of multidimensional poverty status on life satisfaction score varies over time, or (2) the rate of change in life satisfaction scores over the 5 waves differs by multidimensional poverty status.

Model E

Model E includes participant intertemporal poverty status as a predictor of life satisfaction initial status and rate of change, representing an unconditional growth model with uncontrolled effects of multidimensional poverty. *POV* was coded as 0 = non-poor, 1 = transiently poor, and 2 = chronically poor.

$$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \varepsilon_{ij}$$

$$\pi_{0i} = 1.66 - 0.063POV + \zeta_{0i}$$

$$\pi_{1i} = 0.013 + 0.005POV + \zeta_{1i}$$

Variance Components:

Level 1 Within Person, $V(\varepsilon) = 0.045$; Level 2 Initial Status, $V(\zeta_0) = 0.086$; Rate of Change, $V(\zeta_1) = 0.011$; $Cov(\zeta_0, \zeta_1) = -0.025$

Model E estimates that the population average of life satisfaction intercepts, $\hat{y}_{00}$, for individuals with a *POV* value of 0 was 1.655 ($p < 0.001$). De-transforming this estimate produces a value of 4.53. This represents the population average true initial status for individuals with a *POV* value of 0; indicating that the average individual who does not experience multidimensional poverty on any measurement occasion reported a (de-

transformed) life satisfaction score of 4.53 at wave 1. The average estimated initial status was thus higher compared to that estimated in model D. Model D produces this parameter estimate based on occasions where individuals were multidimensionally non-poor, including all individuals who had non-poor occasions (including those who experienced multidimensional poverty). Model E however, estimated parameter $\hat{y}_{00}$ (and $\hat{y}_{10}$) based on the life satisfaction data of individuals who were multidimensionally non-poor on every occasion. This indicates that individuals who were non-poor in terms of their intertemporal poverty status tended to have a higher satisfaction with life at wave 1 compared to individuals who had non-poor occasions although were multidimensionally poor at any measurement occasion.

Examining the estimated value for parameter Y_{01} we can see that the population average difference in life satisfaction intercept for a 1-unit difference in *POV* was -0.063 ($p < 0.001$). Based on this, at wave 1 we can see that on average, transiently poor individuals had a (transformed) life satisfaction score 0.063 lower compared to non-poor individuals, and chronically poor individuals had a life satisfaction score 0.13 lower compared to non-poor individuals.

The estimated value for parameter '$\hat{y}_{10}$' ($\hat{y}_{10} = 0.013$, $p < 0.001$) indicates that the population average linear rate of change for individuals with a *POV* value of 0 was 0.013. Whilst intertemporal poverty status was a statistically significant predictor of individual's initial life satisfaction, the estimated effect of intertemporal poverty status on the rate of change in life satisfaction did not differ significantly from zero ($\gamma_{11} = 0.005$, $p = 0.063$).

Model F

In model F, intertemporal poverty status was introduced as a time-invariant predictor of life satisfaction. Multidimensional poverty status was included as a time-variant predictor assuming a random effect.

$Y_{ij} = \pi_{0i} + \pi_{1i}TIME + \pi_{2i}\text{MPI} + \pi_{3i}\text{MPI x TIME} + e_{ij}$

$\pi_{0i} = 1.59 - 0.08POV + \zeta_{0i}$

$\pi_{1i} = 0.02 + 0.01\text{POV} + \zeta_{1i}$

$\pi_{2i} = 0.02 + \zeta_{2i}$

$\pi_{3i} = -0.01$

Variance Components:

Level 1 Within Person, $V(\varepsilon) = 0.049$; Level 2 Initial Status, $V(\zeta_0) = 0.092$; Rate of Change, $V(\zeta_1) = 0.012$; $\text{Cov}(\zeta_0, \zeta_1) = -0.027$

The intercept ($\hat{y}_{00} = 1.589$, $p < 0.001$) represents the estimated mean life satisfaction score for individuals who were categorised as multidimensionally transiently poor in terms of their intertemporal poverty status. When de-transformed, $\hat{y}_{00} = 4.01$, representing a population average true initial status for transiently poor individuals that is 11.5% lower compared to multidimensionally non-poor individuals ($\hat{y}_{00} = 4.53$, $p < 0.001$). The coefficient for the effect of intertemporal poverty status on the (transformed) intercept ($\hat{y}_{01} = -0.773$, $p < 0.001$) represents a statistically significant level-2 between main effect on the intercept. This coefficient represents the incremental difference in life satisfaction per unit difference in *POV* (Hoffman, 2019). This suggests that on average, chronically poor individuals had a life satisfaction score 0.773 lower at wave 1 compared to transiently poor individuals.

Model F estimates that the average life satisfaction score increased at a linear rate of 0.02 per wave ($\hat{y}_{10} = 0.02$, $p < 0.001$) for transiently poor individuals. However, the results from model F indicated that intertemporal poverty status was not a statistically significant predictor of rate of linear change in life satisfaction ($\hat{y}_{11} = 0.01$, $p = 0.249$). Additionally, model F estimates that the average rate of change in life satisfaction based on multidimensionally poor occasions, $\hat{y}_{20}$, was 0.024 ($p < 0.001$), an increase that was small but statistically significant. Similarly to the parameter values estimated in model D, this increase in life satisfaction among the multidimensionally poor was larger compared to the estimated increase among multidimensionally non-poor occasions ($\hat{y}_{10} = 0.02$, $p < 0.001$). Because these estimates are based on transformed values of life satisfaction, we can interpret that among the multidimensionally poor, increases in life satisfaction accelerate at a faster rate compared to the multidimensionally non-poor. The interaction between multidimensional poverty and time for transiently poor individuals was small but statistically significant ($\gamma_{30} = -0.01$, $p < 0.001$).

Discussion

In this discussion, I will consider the findings and their significance alongside related evidence within the field. I will also consider implications relating to poverty alleviation strategy, and make recommendations for future research.

Regardless of one's experience of poverty, these results suggest that people tend to become more satisfied with life over time, although there is considerable within-person and between-

person variability in reported life satisfaction. Each individuals' own reported life satisfaction differs between measurement occasions, and individuals differ from one another in terms of their life satisfaction change trajectories.

The results demonstrate a statistically significant main effect of multidimensional poverty status on one's own change trajectory. This suggests that the change trajectory for the average individual contained some discontinuity, with the average individual reporting a lower satisfaction over the occasions that they were multidimensionally poor compared to non-poor occasions. This is indicative of an association between multidimensional poverty and life satisfaction, reflecting findings from studies by Delugas & Brau (2021) and Zhu & Chou (2023). Delugas and Brau (2021) and Zhu and Chou (2023) who reported a statistically significant negative relationship between the severity of multidimensional poverty and life satisfaction. Whilst these studies differ in terms of study context, with Zhu & Chou (2023) focusing primarily on the older adult population in Hong Kong and Delugas and Brau's (2021) study being conducted in Italy within the context of an energy unaffordability crisis, findings show a similar association and are in concurrence.

Additionally, the results of this research suggest that an individuals' rate of change tended to be higher when estimated based on multidimensionally poor occasions compared to non-poor occasions. It thus appears that during multidimensionally poor occasions, the average individual reported a decreased level of life satisfaction, although increased in their life satisfaction at a faster rate during such occasions. This pattern of change could reflect differences in the variance of life satisfaction which was highlighted by Gaya (2021) whose findings indicate that variance in life satisfaction was greater at lower income levels compared to higher income levels. Whilst reported life satisfaction amongst lower income

individuals ranged from extremely dissatisfied to highly satisfied with life, severe life satisfaction was found to disappear with higher income levels (Gaya., 2021). We would therefore expect, amongst those in poverty, that a higher degree of change in life satisfaction would be possible compared to those higher income levels. This is a question for future research.

Intertemporal poverty status was a statistically significant predictor of differences in initial life satisfaction values between individuals. The average transiently poor individual reported a lower degree of life satisfaction compared to the average intertemporally non-poor individual at time one, and the average chronically poor had the lowest life satisfaction value at time one. The presence of these between group differences in life satisfaction values at the y-intercept, along with the relative ordering of these groups, is consistent with the relevant theoretical and empirical literature. Similar to findings from Clark et al, (2015) these results suggest that shorter exposures to poverty had a less negative effect on life satisfaction compared to longer/more persistent exposures to poverty that are characteristic of chronic poverty. It is notable, however, that intertemporal poverty status did not significantly predict differences in life satisfaction slope between individuals. Therefore, whilst significant differences were observable between groups in terms of relative degree of life satisfaction at the y-intercept, intertemporal poverty status was not associated with differences in how life satisfaction changed over time..

These results provide evidence regarding the role of deprivation in contributing towards ones' life satisfaction, highlighting the dynamic nature of this relationship over time. Additionally, the results highlight the importance of considering time in our understanding of poverty. Considering not only current poverty, but also previous experiences of poverty and the

durational patterns of poverty experience may allow for a better understanding of poverty. These findings demonstrate a meaningful distinction between transient and chronic poverty, and identify the chronically poor as being worse off in terms of their life satisfaction. Due to these demonstrable differences between the transient and chronically poor, future research into poverty would benefit from the use of longitudinal data, and a consideration of intertemporal patterns of poverty experience.

These findings also have practical implications when it comes to poverty reduction efforts, specifically in relation to guiding the targeting of poverty intervention. For instance, looking at table seven we can see that, as a proportion of the weighted sample, the transiently poor group represent 8.2% of the total sample, and the chronically poor group make up only 1.5% of the total sample. This highlights that approximately 84.5% of poor individuals spend a meaningful proportion of their time living above the poverty threshold within the measurement period. The implication is that most of the people who were classified as multidimensionally poor at any given point in time may have benefited from preventative measures during occasions where they were multidimensionally non-poor. This supports the value of utilising not only measures that target those in poverty, but also measures that target those who are not living in poverty but may be vulnerable to falling into poverty.

The results suggest that people living below the poverty line differ in terms of their intertemporal experience of poverty, and these differences are meaningfully associated with variances in life satisfaction. As such, these differences need to be considered in the way in which poverty alleviation strategies are targeted. Whilst transient poverty reflects vulnerability to external shocks, chronic poverty reflects a fundamental inability to achieve a sustained increase in ones' standard of living above that of a state of deprivation (Alkire et

al., 2017; Barrett & Swallow, 2006; Maru et al., 2012; Ward, 2016). Whilst transient poverty may be effectively addressed via the provision of temporary financial support for example, to effectively address chronic poverty, intervention may need to be directed at the systems and processes that drive a persistent cycle of poverty (Ssewanyana, 2010; Turner et al., 2014).

In the interpretation of the results and implications, we must consider limitations in relation to the generalisability of the findings, due to the exclusion of Asian/Indian and White participants. The cultural context in South Africa for Black and Coloured people could differ considerably from other countries, further limiting the transferability of the findings beyond South Africa. Another key limitation of this study is that it does not test for a bi-directional relationship between life satisfaction and deprivation. This could be a consideration that could be tested in future research. Additionally, further study could explore potential differences based on both population group and gender. A preliminary analysis that was conducted as a part of the current study consisting of fitting OLS regression models to identify possible systemic differences in life satisfaction and deprivation trajectories (see tables 8 and 9). This exploratory analysis revealed not only differences in change trajectories based on differences multidimensional poverty status, but also based on differences in population group and gender (see appendix A). An investigation into such differences was however beyond the scope of the current study. Furthermore, it would be of interest to investigate the relative effect of the individual dimensions and deprivation indicators included in the multidimensional poverty index. This would provide a greater insight into the complexities of poverty, and potentially provide a greater understanding of the factors that contribute to ones' satisfaction with life.

Future research could also consider how the relationships may change based on differences in poverty intensity. The current study only made a distinction at any given time point between poor and non-poor, although to consider additional thresholds based on poverty intensity may provide valuable insight. Similarly, future research should consider making further distinctions amongst individuals identified as poor. Whilst the non-poor group exhibit no change in multidimensional poverty status between waves, there a variety of different patterns that are possible based on the incidence and sequence of poor and non-poor occasions. For instance, within the transiently poor group there may an individual who was non-poor on the first 4 waves and poor on final wave, but also an individuals who was poor on waves 2, 3, and 5, but non-poor on waves 1 and 4. These two individuals both experienced changes between non-poor and poor status, although this change may have occurred under very different circumstances. As such, it would be desirable to make further distinctions between poor individuals, making it possible to capture more of the differences between poor individuals.

Conclusion

The purpose of this research was to examine changes in life satisfaction over time in relation to poverty dynamics with the context of South Africa, aiming to provide some insight into the complex, dynamic and multifaceted issue of poverty. This research indicates that multidimensional poverty plays a role in explaining variation and change in life satisfaction over time. Additionally, this research identifies some differences in life satisfaction based on differences in the intertemporal nature of poverty, supporting the role of ‘time’ as an important factor in the relationship between multidimensional poverty and life satisfaction. Whilst acknowledging that intertemporal poverty status was not found to be a to be a statistically significant predictor of rate of change in life satisfaction, statistically significant

differences in initial life satisfaction were found between individuals depending on the intertemporal patterns of poverty. This highlights the value of looking beyond the current experience of poverty; of considering one's current level of deprivation within the context of previous patterns of poverty experience. More research is needed so that we can better understand these relationships.

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Appendix A

Descriptive statistics for the individual growth parameters obtained by fitting separate within-person OLS regression models for Life Satisfaction as a function of linear time by sex and population group.

	Initial Status (Intercept)	Rate of Change (Slope)
Total Sample		
Mean	4.8076	0.0774
Standard Deviation	3.3238	0.9064
Bivariate Correlation		-0.906**
Male		
Mean	4.8989	0.0544
Standard Deviation	3.3665	0.9220
Bivariate Correlation		-0.902**
Female		
Mean	4.7409	0.0943
Standard Deviation	3.2906	0.8944
Bivariate Correlation		-0.909**
African		
Mean	4.6773	0.0915
Standard Deviation	3.3292	0.9145
Bivariate Correlation		-0.911**
Coloured		
Mean	6.0500	-0.0567
Standard Deviation	2.9996	0.8127

Bivariate Correlation		-0.876**