VALIDATION OF A NEW MEASURING INSTRUMENT OF QUALITY OF LIFE: A CONFIRMATORY FACTOR ANALYSIS APPROACH

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Abstract

Assessing quality of life is a challenge as the concept is multi-dimensional and there is no universal definition, therefore an integrative and well developed measure of quality of life can advance the measurement and analysis of this concept. In this research paper we validate an instrument of quality of life and determine the relationships between the different dimensions of the concept. The methodologies used are Explanatory Factor Analysis (EFA) and a form of Structural Equation Modelling (SEM) namely Confirmatory Factor Analysis (CFA), a sophisticated method of analysis. To the author's knowledge this is the first study of this kind in South Africa and one of the first studies internationally which validates a measuring instrument of quality of life and analyse the interrelationships between the different dimensions of the concept. A validated instrument of quality of life is essential to measure wellbeing and follow wellbeing trends. Furthermore the establishment of the interrelationships between the different dimensions of quality of life encourages an integrated policy approach which can realise collective achievements in various dimensions of quality of life. It was found that the model fitted the data well and the measurement of each sub-dimension, including 'housing and infrastructure', 'social relationships', 'socio-economic status', 'safety' and 'governance', were confirmed. Furthermore the relationships between the sub-dimensions of quality of life, except for the relationship between 'health' and 'housing and infrastructure' were found to be statistically significant and positive.

Key words: Quality of life, Composite indices, Gauteng City-Region, Subjective wellbeing, M

JEL classification codes: C31, C38, O15, O18, R11

1 INTRODUCTION

The almost universal development aim of nations is to increase the quality of life of people (CSLS 2011). South Africa shares this aim and states in its constitution (adopted in 1996) that the country's goal is to improve the quality of life of each person on South African soil (1996). But to determine if the quality of life has improved, it needs to be measured accurately. As Joseph Stiglitz stated, "what you measure affects what you do, if you don't measure the right thing, you don't do the right thing".[1]

The conventional approach to measuring quality of life is to use income measures such as GDP. This has however been challenged by academics and political leaders, as stated in the report on the Measurement of Economic Performance and Social Progress[2], "[t]he emphasis should be shifted from measuring economic production to measuring people's wellbeing" (Stiglitz, et al., 2009, p. 12). In order to measure wellbeing, validated instruments of quality of life are needed, and furthermore the relationships between the validated dimensions of quality of life should be explained.

Internationally, quality of life instruments have been validated, though these instruments are mostly applied in a health context. Examples of validated health related quality of life indices are to be found in the Directory of Instruments (Australian Centre on Quality of Life, 2013) and from the CVHL (Canadian Virtual Health Library) (2012). But very few studies on quality of life, as a measure of development, have up to now applied sophisticated methods of validating the scales that measure the different dimensions of quality of life.

Therefore, in this research, our first research objective was to address this shortcoming by validating an instrument of quality of life to measure the wellbeing of the people in the Gauteng City-Region (GCR). To validate an instrument, we needed to test if the scale (combination of questions), measures the latent variable it is purported to measure. This is essential for the development of measuring instruments for quality of life.

However, validation of the scales to measure quality of life is not sufficient to inform policy-makers on the measurement of quality of life. Vital to integrated, comprehensive policy, is

[1] Quoted in the New York Times, October 4, 2009.
[2] In the rest of the text referred to as the Stiglitz Report.

the knowledge of the linkages between the different dimensions of quality of life, for instance, what the effect is of government spending to improve health services on the level of education of a community. The Stiglitz Report (2009) shows a lack of research on the links between the dimensions of quality of life and emphasises the need for this type of analytical study. Hence, a second objective of the research was to determine the relationships between the different dimensions of quality of life in the GCR.

To the author's knowledge this is the first study of its kind in South Africa and one of the first studies done internationally to analyse the interrelationships between the different dimensions of quality of life. A validated instrument of quality of life is the basis for future measurement of the concept. For this purpose we employed the data set collected by the GCRO (2009) on the quality of life of the people in the GCR for the year 2009.

To achieve these research objectives we used Exploratory Factor Analysis (EFA) to determine the dimensionality of the scales and Confirmatory Factor Analysis (CFA) to evaluate the scales and establish the links between the different dimensions of quality of life.

The remainder of this paper is structured as follows. Firstly, a brief literature review on quality of life and the dimensions explaining quality of life as well as the relationships between these dimensions is given in Section 2. In Section 3 we discuss the GCRO and the data set. In Section.4 we discuss the methodology, including an explanation of the statistical techniques, the measures used in the analyses and the operational hypotheses analysed in the empirical section. In Section.5 we report and discuss the results of the empirical analysis. Lastly, in Section 6, we draw conclusions.

2. LITERATURE ON THE VALIDATION OF QUALITY OF LIFE AND THE ASSOCIATION BETWEEN QUALITY OF LIFE DIMENSIONS

In this section we briefly discuss the validation of measuring instruments and review current quality of life measures to determine the dimensions or scales of quality of life included in the indices and the measuring items used to measure these dimensions. Furthermore, the literature on previous empirical findings on the associations between the dimensions of quality of life is described.

2.1 A review of the validation of measuring instruments and current quality of life measures

To address the primary research aim, namely to validate a new instrument of quality of life, we needed to analyse the current trends in the development of quality of life instruments. From this analysis we could determine which dimensions were included in the current measures and which measuring items were used to measure the dimensions.

Literature on the validation of measuring instruments

As each dimension of quality of life is an abstract theoretical construct we often needed more than one measuring item to quantify the concept. We therefore needed a combination of survey questions to measure each dimension. The combination of questions included in the design of a questionnaire is referred to as a scale (DeCoster, 2000). To confirm that the measuring items included in a scale give a good representation of the underlying theoretical construct we needed to validate the construct (scale). With the validation of the scale we attempted to demonstrate whether the theoretical interpretation of the responses was represented by the measuring items included in the scale (DeCoster, 2000). Thus we needed to verify that the responses we received on the questions measuring a dimension of quality of life were good measures and representative of the dimension.

Although many quality of life measuring instruments have been developed and validated over the years, the majority of these instruments are health-related or are indices that measure subjective wellbeing. The health related quality of life instruments measure the quality of life of people afflicted with certain kinds of diseases or disabilities; for example, scales on the quality of life of patients having had a colostomy (Prieto, et al., 2005) or patients with Crohn's disease (Guassora, et al., 2000) . The Directory of Instruments (Australian Centre on Quality of Life, 2013) lists more than 800 health-related validated quality of life scales. An additional source of validated health related quality of life scales is available from CVHL (2012).

One of the best known quality of life scales that assesses the health of people is the Quality of Life – Bref (WHOQOL-BREF) (1991-2013)**,** developed by the World Health Organisation (WHO) to measure health related quality of life across cultures and countries. The instrument comprises 26 subjectively measured items, covering four dimensions of quality of life: physical health, psychological health, social relationships and environmental factors.

The subjective wellbeing indices measure the subjective opinions of respondents and often include only subjective measuring items and not objective measures, as was recommended by the Stiglitz Report (Stiglitz, et al., 2009). Examples of measuring instruments that have been validated and that measure subjective wellbeing or happiness are, among others, the Personal Wellbeing Index and the National Wellbeing Index developed by the International Wellbeing Group (2006)**,** and indices developed by Lyubomirsky and Lepper (1999), Howell et al. (2010)**,** Chen (2010) and Tomyn and Cummins (2011).

In this study the main concern was not the measurement of health related quality of life or the measurement of happiness, but rather the validation of a new instrument to measure quality of life from a developmental perspective. This new instrument should include both objective and subjective measuring items, as suggested by the Stiglitz Report (2009).

Current quality of life indices: dimensions and measuring indicators

In this section a few quality of life measures which include both objective and subjective measuring items as well as recommendations made in seminal reports on the construction of quality of life measures are reviewed. The measures and reports have been developed or published recently and include Your Better Life Index (OECD, 2011), Beyond GDP (European Commission, 2007), the Happiness Index of Bhutan (The Centre for Bhutan Studies, 2008), the Canadian Wellbeing Index (Canadian Index of Wellbeing, 2009), the recommendations of the Stiglitz Report (2009), the Happiness Index of the United Kingdom (UK) (Office for National Statistics of the United Kingdom, 2012) and the recommendations of the World Happiness Report (United Nations, 2012). The quality of life dimensions included in the measuring instruments and highlighted in the recommendations of the reports are shown in Table 1.

Table 1: The dimensions of quality of life measures

Dimensions of QoL* included in indices	Your better life index	Beyond GDP	Happiness Index of Bhutan	Canadian WB index	Stiglitz Report	Happiness Index of the UK	World Happiness Report
Housing	X			X			
Income/GDP	X	X	X	X	X	X	X
Jobs	X	X			X	X	X
Community	X		X	X	X	X	X
Education	X	X	X	X	X	X	X
Environment	X	X	X	X	X	X	X
Civic engagement/ good governance	X		X	X	X	X	X
Health	X	X	X	X	X	X	X
Life satisfaction	X	X	X		X	X	X
Safety	X				X	X	
Work Life Balance	X		X	X	X	X	
Culture			X	X			
Age, Gender							X

Source: Author's selection of indices
*QoL=Quality of life
**WB=Wellbeing

According to Table 1, the following dimensions of quality of life are included in the reviewed quality of life measures and are also recommended in the seminal reports on quality of life: housing, income, employment, community involvement, education, civic engagement, good governance, health, life satisfaction, safety, culture, work life balance, a dimension which includes a selection of demographic characteristics, and an environmental dimension. As can be seen from Table 1 the same dimension often recurs in the different measuring instruments.

Each of these dimensions is measured by either observable, objective measuring items or by measuring items which assess the subjective responses of respondents. Table.2 gives a number of examples of the measuring items used in the selected quality of life measures.

Table 2: The measuring items used in contemporary measures of quality of life

Dimension	Objective measuring items	Subjective measuring items
Housing	Type of housing Piped water in the house Electricity for lighting	Satisfaction with dwelling
Income/GDP per person	Income per month	Satisfaction with money available Income relative to neighbours Satisfaction with standard of living Perceived socio-economic status
Jobs/employment	Being employed in the previous seven days Type of employment	Satisfaction with working conditions
Community/ social connections	Membership of civic organisations	Satisfaction with time spent with family Satisfaction with time spent with friends Satisfaction with marriage
Education	Years of education Literacy rate School enrolment rate	
Environment	Emission indicators Access to clean water Deforestation	
Civic engagement/ good governance	Participation in elections	Opinion of political freedom Satisfaction with the performance of government
Health	Life expectancy Mortality rates HIV infection rates	Self-reported health
Life satisfaction		Perceived life satisfaction Perceived happiness
Safety	Crime rate	Self-reported safety
Work Life Balance	Hours spent at work Number of hours available for leisure	
Culture	Language Socio-cultural participation	
Age, Gender	Respondents age Respondents gender	

Source: Author’s selection of indices

Table 2 shows that the majority of the dimensions of quality of life can be measured by objective as well as subjective measuring items.

In this research, the selection of the measuring items to be included in an integrative model of quality of life was guided by the reviewed theoretical approaches and the reviewed current quality of life measures. The validated measuring items contributed to the construction of an integrative model of quality of life (see Section.3.2 for the measuring items included in the current analysis).

2.2 The relationships between the dimensions of quality of life

In addition to validating an integrative model of quality of life, the second research question investigated the links or interrelationships between the different dimensions. Previous research on the links between the dimensions of quality of life is limited. Although research was done on the bivariate relationship between certain of the dimensions, as far as could be ascertained, none had been done on the multiple relationships between the dimensions of quality of life.

The following section analyses the literature and the findings on the bivariate relationships between the dimensions of quality of life. In the literature we often do not find the precise dimensions as explained in quality of life literature, but rather referrals to quality of life indicators.

We organised this section by discussing a single dimension or indicator and its relationships to other dimensions of quality of life. The order of discussion was as follows: housing, income, health, governance, education, social relationships and the environment.

Housing

In research by DiPasquale and Claeser (1999), they study the relationship between home ownership and the dimensions of good citizenship, education and health. In their study, good citizenship is seen as membership in non-professional organisations and involvement in local politics. According to them there is a positive relationship between good citizenship and the time period a person stays in a specific house. The longer a person stays within a specific house in a given area, the more the person gets involved in organisations and in the politics of the community. Furthermore, home owners with longer periods of tenure, encourage income investment in local amenities and social capital, which often contributes to better health and education in the area.

In studies on the relationship between housing and health, the existence of a weak positive relationship was found. Breysse et al. (2004) researched the relationship between the concept 'healthy housing', which can be described as housing in a good environment, and the health of children, and found it to be weak and positive. Dalstra et al. (2006) also found a weak but positive relationship when studying the health of the elderly and the time period of housing tenure. Furthermore, in a study on the relationship between health and the type of housing, De Wet et al. (2011) found, by using data on urban communities in Johannesburg (South Africa), that the health of the head of the household in informal housing was significantly better than those living in formal housing (De Wet, et al., 2011) . According to the authors, a plausible explanation for this counterintuitive finding is that many of the respondents in the sample residing in informal dwellings were recent migrants and were younger than the respondents in formal dwellings.

Income

The relationship between housing and 'income and work status' of the head of the household was found to be positive (Arimah, 1992). Therefore, if the head of the household is employed and income earnings increase, there will be a higher demand for housing. This relationship follows the basic theory of consumption in economics which states that as income increases the consumption of normal goods increases (Fourie & Burger, 2010).

This positive relationship between income and consumption of goods is also demonstrated by the findings of Kennedy et al. (1996) and McDonough et al. (1997), which emphasise the positive relationship between income and health. Furthermore, Dalstra et al. (2006) established a positive relationship not only between income and health but also between 'income and education' and health. Although the relationship between income and health is positive, Cutler (2008) showed that the association varied across the life cycle of people, being stronger in the case of children (depending on the parents' income), and weakening in adulthood.

Income is related to governance though the direction of the relationship is uncertain. Todaro and Smith (2011) show that higher income earners have more lobbying power than lower income earners and have more power to influence the decisions taken by governments; thus if these decisions taken by government improve governance, there exists a positive relationship between income and governance, though if it makes governance less effective or corrupt, it decreases governance (a negative relationship).

Health

In their research on the association between health and social relationships, Caperchione et al. (2008) found that in a sample of Australian adults, physical health and social relationships were positively related. Gachter et al. (2010) and Wilkinson (1997) found similar results which showed that increased social relationships are highly correlated with increased health.

Governance

The concept of governance signifies a relationship where mutual interaction takes place between government and citizens so that the choices made by government reflect the wants of the people (Toksoz, 2008). If citizens are more involved in the process of governance they can voice their needs such as improved education, housing, health, safety and working conditions. The existence of good governance implies that these needs are addressed and the wellbeing of the people improved (Todaro & Smith, 2011).

Education

In the literature, a positive relationship was shown between education and most of the other dimensions of quality of life. For example, if the level of education increases the level of civil participation also increases (see Dee 2003 and Milligan et al. 2004). Samuel et al. (2012) established a positive relationship between education and 'work and income'. A similar result was found in a study using South African data in which Branson et al. (2009), found a strong positive relationship between education, employment attainment and earnings.

Furthermore, Todaro and Smith (2011) also established a strong positive relationship between education and health. In an analysis of the cost benefit ratio of investments in education on health, Furnee et al. (2008) found the ratio to be highly positive. Another study attempting to quantify the size effect of the relationship between education and health, using data on the Netherlands, found that the health benefits gained from investment in education are larger than the cost of one year's education (Groot & Maassen van den Brink, 2007). There have been studies on the causality between education and health, although it was found to be indeterminable (see Groot & Maassen van den Brink 2007 and Arendt 2005).

Social Relationships

In studies on social relationships the Stiglitz Report (2009) showed that citizens with good social relationships have a higher probability of finding employment. Furthermore, the Stiglitz Report also showed that the performance of democratic government may depend on the quality of social connections within a society.

Environment

The literature showed that a strong positive relationship exists between the environment and other quality of life dimensions. In the developing world more than half the economically active population directly depend in whole or in part on the environment through agriculture, fishing, hunting, forestry, foraging and animal husbandry (World Commission on Environment and Development, 1987). Therefore a healthy environment provides a means to earn a living and is positively related to food provision. The environment also has a direct effect on the health of people through air and water pollution and indirectly through climate change. In this research we unfortunately had to omit the environmental dimension due to a lack of data, though we realised that the environmental dimension is central to achieving a good quality of life.

To summarise, based on the literature reviewed we found a positive relationship between home ownership and good citizenship, and a positive but possibly weak relationship between housing and health. The literature showed the existence of a positive relationship between good social relationships and the dimensions of health, socio-economic status and good governance. Furthermore, the literature reviewed indicated positive relationships between the three dimensions of ‘income’, ‘education’ and ‘good governance’ and all the other dimensions of quality of life. Thus all the relationships between the dimensions of quality of life were found to be positive, although the strength of the relationships is uncertain.

3 THE GAUTENG CITY-REGION (GCR)

In this section, we briefly describe the region which is analysed in this thesis, namely the GCR. Furthermore, we discuss the data set used.

3.1 The GCR

South Africa is divided into a three-level structure model of governance, which includes national, provincial and local government. There are nine provinces and 283 local governments or municipalities in the country. For the purposes of this research we focused only on Gauteng Province and the cities (municipalities) in adjacent provinces that are economically and functionally linked to the province and are within a 175 km radius of central Johannesburg. This area is known as the GCR.

3.2 A description of the data used in Chapters 2 to 4

The data set analysed is the GCRO Quality of Life data set. It was collected by the GCRO in 2009 and released for analysis in May 2010. The data was collected in order to measure the quality of life and customer satisfaction of the people living in the GCR. Chapter 5 utilises a different data set on migrants in Johannesburg, which is discussed in that chapter.

The GCRO used a stratified sampling method to collect the data. The sampling frame was based on a population universe as at Census 2001. The sample was stratified by municipality to ensure significant coverage. A total of 6639 respondents in 602 wards in 17 different municipalities were interviewed (GCRO, 2011). In Table 3 the descriptive statistics on the demographic and socio-economic characteristics of the sample population are summarised.

Table 3: Descriptive statistics of the Quality of Life Survey

Geo Type	**Frequency (*N*)**	**% of Sample**
Urban formal (built up town or city area)	4156	62.6
Urban informal	1654	24.9
Peri-urban (mostly informal/smallholding)	609	9.2
Tribal Settlement	82	1.2
Farming	92	1.4
Income Groups		
R0-R1600	2157	33
R1601-R12 800	3065	46
R12 801- R102 400	720	11
R102 401- more	65	1
Race		
African	5452	82.2
Asian/Indian	79	1.2
Coloured	246	3.7
White	859	13.0
Gender		
Male	2708	40.8
Female	3928	59.2
Age		
18-20	460	7
21-30	1971	30
31-40	1604	24
41-50	1120	17
51-65	934	14
66-75	347	5
75+	133	2

Source: Author's calculations based on Quality of Life Survey (Gauteng City-Region Observatory (GCRO), 2009)

Table 3 shows that the majority of the respondents in the sample reside in urban formal or urban informal areas, which indicates the degree of urbanisation of the GCR, with only 2.6% of the respondents living in tribal or rural areas.[3]

The average income of the respondents was in the income bracket of R1 601 to R12 800 per month, with only 12% of the sample indicating an income in excess of R12 800 per month. The share of income of the lowest decile of the respondents was merely 2% of the total income earned by households in the sample, compared to 68% earned by the highest decile of income earners. This reflects the considerable skewness of the income distribution in the GCR (GCRO, 2011).

[3] The majority of the residence of Gauteng stay in urban formal and urban informal areas, thus very few respondents stay in tribal and rural areas. For the purposes of this analysis, only respondents in urban formal and urban informal geographical types are considered.

The sample represents the race distribution of South Africa with approximately 80% of the respondents being African and a much smaller percentage of the sample being from other race groups. More than half of the respondents were female and almost 93% of the respondents were of working age between 18 and 65 years.

4. METHODOLOGY

In this section we review the statistical procedures used to validate scales of quality of life and to determine the links between latent variables. We define the measurements used in the analyses and, lastly, we derive operational hypotheses, which are empirically tested.

4.1 Statistical analysis

Previous methods used to validate the scales of measuring instruments include item-response theory, Rasch Rating Scale Analysis, multi-dimensional scaling, correlation analysis, multiple regression estimation, Analysis of Variance (ANOVA) and EFA (DeCoster, 2000). These methods are adequate to evaluate the validity of observable indicators, although if the validity of latent variables (that are not directly observable) has to be evaluated these measures are not reliable. In recent years CFA has been developed to validate measuring instruments in which latent variables are used. CFA tests theoretical hypotheses on the structure of latent variables and analyses the relationships between latent variables. Therefore in this chapter, CFA is the ideal statistical method to address both the primary and the secondary research questions. In this study we also used EFA to analyse the structure of the dimensions of quality of life and to determine the uni-dimensionality[4] of the scales.

Factor analysis, EFA and CFA

Factor analysis is a statistical multivariate procedure of which the main purpose is to determine the number and nature of latent factors that account for the variation and co-variation among a set of observed variables (Brown, 2006). As mentioned previously, there are two main types of factor analyses, EFA and CFA. Although the main aim of the methods is similar, they differ in the a priori specifications and restrictions made on the factor model (Brown, 2006).

EFA is a data-driven method which explores the possible underlying factor structure of a set of observed variables without imposing a preconceived structure on the outcome. Thus by performing EFA, the underlying factor structure is identified and the number of factors that

[4] To test for uni-dimensionality all the indicator variables need to load on one factor.

exist in a set of variables and the degree to which the variables are related to the factors is determined (Kahn, 2006).

CFA is a confirmatory method which is used to verify the factor structure of a set of observed variables. In CFA a hypothesis is tested that a relationship between observed variables and their underlying constructs exists. Before a CFA is conducted a model needs to be specified based on theory and research literature. The model is specified by determining the number of factors to extract, stating the relationships between the factors, and specifying the interrelationships between the error terms and the latent variables. The hypothesised relationships between the variables are estimated through covariance algebra which can be used to infer the strength of the relationships between the variables by producing a population covariance matrix from the sample matrix.

To estimate and evaluate a model it needs to be identified (Diamantopoulos, 2000; Tabachnick & Fidell, 2007). Model identification is concerned with ensuring that it is possible to find unique values for the free parameters. If there are more data points than parameters to be estimated, the model is considered to be over-identified and to have positive degrees of freedom. If there are less data points than parameters to be estimated the model cannot be estimated and it is under-identified. A single-factor model with three indicators and no parameter constraints is called a just-identified or perfect-fitting model, and can be estimated (Kline, 2011).

CFA and EFA are often applied in the development of measurement instruments, for example satisfaction scales, or as in this study, the development and validation of scales to measure the different dimensions of quality of life (Browne & Cudeck, 1993).

In this paper EFA is used to analyse the factor structure of the responses received on the selected questions in the survey and CFA is used to test the hypothesis that a relationship between the items included to measure the scales of quality of life and their underlying latent constructs exists, and to determine the relationships between the scales.

In mathematical terms the common factor model which reflects both the EFA model and CFA model, can be stated as follows:

$$Y_j = \lambda_{j1}\eta_1 + \lambda_{j2}\eta_2 + \ldots\ldots\ldots\ldots\lambda_{jm}\eta_m + \varepsilon_j$$

with Y_j the *jth* of *p* indicators, λ_{jm} the factor loading, η_1 the factor and the ε_i the error term. The difference between the EFA model and the CFA model lies in the a priori restrictions imposed on the CFA model according to the model specification.

CFA utilises more than one statistical test to determine the significance of the analysis and to determine the adequacy of the model fit to the data[5] (Diamantopoulos, 2000), although in the early development of CFA only one test, the chi-square test, was used to measure model fit. The chi-square test used in CFA applies the reverse testing procedure (Blunch, 2008). In traditional statistical testing a null hypothesis (H_0) typically states the status quo and the alternative hypothesis (H_1) states an alternative outcome which the researcher wishes to test. If the data does not support H_0 the null hypothesis is rejected and H_1 is accepted as a better description of the data. In CFA it is the norm to reverse this logic (Blunch, 2008). In CFA the null hypothesis states the model that the researcher wishes to test and typically H_1 postulates the status quo. Therefore, in CFA, a chi-square value close to zero (significance $p > 0.05$) indicates good model fit and a large chi-square value (significant at $p < 0.05$) corresponds to 'not exact' fit and rejection of the null hypothesis. The chi-square test is a reasonable test for smaller samples, though in bigger samples the chi–square is almost always statistically significant, which leads to the rejection of the null hypothesis (Blunch, 2008). According to Blunch (2008), this is often the case if a two-sided test statistic such as chi-square is used in big samples. The indeterminacy of the chi-square test is one of the main reasons why additional measures of fit were developed.

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[5] This differs from traditional statistical methods in which only one statistical test is used.

The measures of fit broadly fall under three categories: absolute fit, fit adjusting for model parsimony and comparative or incremental fit.

Absolute fit indices assess model fit at an absolute level, thus testing a null hypothesis of perfect fit of the model to the data. The absolute tests include the chi-square (previously discussed) and the Standardised Root Mean Square Residual (SRMR) (See Table 4).

The SRMR can be understood as the average discrepancy between the correlations observed in the input matrix and the correlations predicted by the model. Thus it is derived from a residual correlation matrix (Brown, 2006). The SRMR can be calculated by summing the squared elements of the residual correlation matrix and dividing this sum by the number of elements in this matrix (on and below the diagonal) and computing the square root of this result. The SRMR can range between zero and one with 0.05 indicating a good fit; the smaller the value the better the fit (Bentler & Hu, 1999; Diamantopoulos, 2000; and Kahn, 2006).

The parsimony correction indices differ from absolute fit measures as they incorporate a penalty function for poor model parsimony. A widely used index from this category is the Root Mean Square Error of Approximation (RMSEA) which is related to the residual in the model (Brown, 2006). The RMSEA values range from zero to one with a smaller RMSEA value indicating better model fit. An acceptable model fit measured by RMSEA is a value of 0.05 or less (Bentler & Hu, 1999; Diamantopoulos, 2000; and Kahn, 2006). Between 0.05 and 0.08 is a reasonable fit, between 0.08 and 0.10 is a mediocre fit and more than 0.10 is a poor fit (Kahn, 2006). The RMSEA is computed as follows:

$$\text{RMSEA} = \sqrt{(d/df)}$$

where $d = X^2\text{-}df/(N\text{-}1)$and df the degrees of freedom (Brown, 2006).

Comparative fit indices evaluate the fit of a user-specified solution in relation to a more restricted, nested baseline model and are analogous to R-square in OLS regression analysis. Typically, the baseline model is a null or independence model, in which the covariances between all the input variables are set to zero. These indices include the Comparative Fit Index (CFI) and the Tucker Lewis Index (TLI).

The CFI is equal to the discrepancy function adjusted for sample size. The CFI ranges from zero to one, with a larger value indicating a better fit. Accepted model fit is indicated by a CFI value of 0.9 or more (Bentler & Hu, 1999). CFI is calculated as follows:

$$CFI = 1 - MAX[(\chi_T^2 - df_T), 0]/\max[(\chi_T^2 - df_T), (\chi_B^2 - df_B), 0]$$

Where *'MAX'* refers to the optimisation of the equation, χ_T^2, is the χ^2 value of the target model (i.e., the model under evaluation), , df_T, is the df of the target model, χ_B^2, is the χ^2 of the baseline model (i.e., the "null" model), f_B, is the df of the baseline model, '*max'* indicates the use of the largest value, for example, for the numerator use $(\chi_T^2 - df_T)$ or 0, whichever is larger (Brown, 2006).

The TLI is a non-normed fit index of which values of 0.9 or more are considered as a well-fitting model (Kahn, 2006). The TLI is computed as follows:

$$TLI = [(\chi_B^2/df_B) - (\chi_T^2 - df_T)]/\ (\chi_B^2/df_B) - 1]$$

Similar to the CFI, χ_T^2, is the χ^2 value of the target model (i.e., the model under evaluation), df_T, is the df of the target model, χ_B^2, is the χ^2 of the baseline model (i.e., the "null" model) and df_B, is the df of the baseline model (Brown, 2006)

In Table 4 a summary of the fit indices and the rules of thumb used to determine good model fit, as described in the previous discussion, is shown. According to Hu and Bentler (1999), the rules of thumb are not unambiguous cut-off criteria that objectively lead to the decisions to reject or retain a particular model, but serve only as guidelines, which should be considered in conjunction with the good judgement of the researcher.

Table 4: The rules of thumb for good model fit

Fit index	Rule of thumb
Absolute fit indices	
Satorra–Bentler chi-square	A non-significant result indicates model fit (Diamantopoulos 2000; and Kahn, 2006).
p-value for Satorra-Bentler chi-square (exact fit)	Significant p-value *(p*<0.05) indicates that the null hypothesis for exact model fit can be rejected
SRMR	Values below 0.06 indicate a good fit (Hair, et al. 1998)
Fit adjusting for model parsimony	
RMSEA	Values less than 0.05 indicate a good fit; Values between 0.05 and 0.08 are reasonable fit; Values between 0.08 and 0.10 are regarded as mediocre fit; Values greater than 0.10 indicate poor fit (Diamantopoulos 2000; and Kahn, 2006).
Incremental fit indices	
CFI	Values greater than 0.90 indicate good fit (Kahn, 2006)
TLI	Values greater than 0.90 indicate good fit (Kahn, 2006) Values greater than 0.80 are permissible (Hair, et al. 1998)

Source: Table adapted from Ribeira (2012)

According to Kline (2011), the tenability of a specified model should be decided on both the fit indices and estimated parameters. Therefore, after the model fit has been evaluated, the accuracy of the primary and secondary research hypotheses should be evaluated according to the model parameters, for example the factor loadings.

The factor loadings are the regression coefficients of each indicator on the common factor. If the variables have low factor loadings on all the factors it is an indication that the item can be a candidate for elimination (Kahn, 2006), since the item might not be closely related to the latent construct under consideration. According to Brown (2006), factor loadings of 0.3 or more are acceptable and factor loadings of less than 0.3 should be considered for deletion. The R-square estimate is derived from the factor loadings of each measuring item by squaring the factor loading, and is similar to the R-square used in regression analysis. R-square values are only appropriate for item analysis if the error terms are not correlated and the factor loadings of a measuring item only load on one factor (see Brown (2006). The R-square indicates the proportion of explained variance of an item as a result of the latent variable (Brown, 2006). In this study guided by Brown's recommendation of 0.3 or more as an acceptable factor loading, values of R-square of 0.09 (0.3^2) or more are indicative of salient indicators. Measuring indicators with an R-square value of less than 0.09 are considered for deletion.

CFA has certain advantages over other multivariate statistical methods. A fundamental strength of CFA approaches to construct validation is that the resulting estimates of convergent or discriminant validity are adjusted for measurement error. According to Brown (2006), each indicator in a set of observed measures is a linear function of one or more common factors and one unique factor. Factor analysis partitions the variance of each indicator into two parts: common variance (the variance accounted for by the latent factor) which is estimated on the basis of variance shared with other indicators in the analysis, and unique variance, which is a combination of reliable variance that is specific to the indicator and Ransom error variance (measurement error).[6] Thus CFA provides a stronger analytical framework than the traditional methods that do not account for measurement error, for example, Ordinary Least Squares (OLS). OLS approaches, including correlation or multiple regression, assume variables in the analysis to be free of measurement error (Brown, 2006), which is often not the case in the measurement of unobservable latent variables.

An additional advantage of CFA in relation to EFA is that factor scores do not need to be calculated. Using EFA the factor scores are computed and serve as proxies of the latent variables, though these factor scores suffer from factor score indeterminacy. Factor score indeterminacy results from the infinite number of sets of factor scores that can be computed from any given factor analysis, which are equally consistent with the same factor loadings (Brown, 2006)[7]. In CFA, indeterminacy of factor scores is not a concern as the latent factors themselves are used in the analysis (Brown, 2006).

To summarise, in this study the following procedures were utilised to conduct the statistical analysis to answer the primary and secondary research questions. Firstly, EFA was conducted on the scales of quality of life, in order to determine the uni-dimensionality of the scales. To test for uni-dimensionality we included all the items found to measure the specific scale and extracted the factors with an eigenvalue of more than one. If only one factor was extracted it implied uni-dimensionality. If a factor is uni-dimensional it indicates that the inter-correlations between the items that measure a specific scale of quality of life are due to a single dominant quality of life dimension. Once uni-dimensionality of the scales was confirmed, we proceeded to the second part of the analysis in which the uni-dimensional factors were subjected to CFA. CFA was used to evaluate the construct validity of the scales

[6] For a discussion of measurement error see Brown, 2006, p13.
[7] For a discussion on factor score indeterminacy see Brown (2006, p. 37).

of quality of life. Lastly, a multi-factor CFA model was specified to investigate the linkages between the components of quality of life.

2.3.2 Measures

In order to measure the quality of life of the respondents in the sample, we selected indicator variables of quality of life based on the adopted theoretical approaches, the dimensions and indicator variables included in the reviewed indices (see Section.2.1) and the availability of indicator variables in the data set. Furthermore, if indicator variables were closely correlated we selected the variable which was the most closely related to the latent variable (dimensions of quality of life), thus with the highest communality,[8] as revealed by EFA. The dimensions of quality of life covered in the analysis by the selected indicator variables were: 'housing and infrastructure (basic services)', 'social relationships', an 'economic dimension', 'education', 'health', 'governance', 'safety' and 'global satisfaction with life'.[9]

To measure 'housing and infrastructure' the following indicator variables were included in the data set, and selected for inclusion in the analysis: 'type of dwelling', 'type of sanitation', 'electricity used for lighting', 'satisfaction with dwelling', and 'piped water on the premises'. All these variables are nominal and were recoded into dichotomous variables with one indicating a positive influence on quality of life, for example 'living in a formal dwelling', and zero indicating a negative effect on quality of life, for example 'not living in a formal dwelling'.

To measure the dimension 'social relationships' we selected four indicator variables which were included in the data set: 'satisfaction with time with family', 'satisfaction with time with friends', 'satisfaction with time to do own things' and 'satisfaction with marriage'. The respondents were requested to rate their perceptions on a five-point scale ranging from 'very dissatisfied' to 'very satisfied'.

To measure the dimension related to 'economic factors' we selected the variables as available in the data set: 'work conditions', 'income', 'standard of living', 'satisfaction with amount of

[8] Amount of variance in the indicator explained by the component (see Brown (2006) for a detailed description).
[9] Global satisfaction with life, measures the satisfaction of a person with all spheres of his/her life.

money available', satisfaction with life' and 'perceived social status'. The income variable was recoded to reflect different income categories. The other indicators were rated on a five-point scale ranging from 'very dissatisfied' to 'very satisfied'.

To measure 'education' the only indicator variable available in the data set was 'years of education', thus we included this variable in our selection.

Based on the recommendations of the Stiglitz Report (2009) and the Happiness Report of the UN (2012) we also selected a global satisfaction indicator: 'how satisfied are you with your life', to be validated as a measuring item of quality of life.

We selected three indicator variables to measure the dimension 'health'. Two of the three indicators determined if a person's health kept him/her from doing their daily work or taking part in social activities, and the third indicator measured if the respondent was 'satisfied with their health'. Each of these indicators was measured on a four-point scale ranging from 'never' to 'always'.

For the dimensions of 'safety' we selected three measures which were included in the data set: 'how safe do you feel in the area where you live during the day', 'how safe do you feel in the area where you live after dark', and 'how safe do you feel'. All three indicators were categorical indicators with one indicating 'feeling unsafe' and five indicating 'feeling very safe'.

The final dimension included in the analysis was 'governance', and we selected five variables to be validated. These were included in the data set. The indicators were: 'satisfaction with local government', 'politics is not a waste of time', 'the country is going in the right direction', the 'judiciary is free from influence' and the 'election was free and fair'. These indicators were measured on a five-point scale ranging from 'very dissatisfied' to 'very satisfied'.

Table 5 gives a summary of all the indicators included in the analysis with the relevant descriptive statistics, showing the type of variable and the minimum, maximum, mean and standard deviation of each of the variables.

Table 5: Indicators included in the analysis

Variable	Type	Min	Max	Mean	SD*
Housing and infrastructure					
Type of dwelling	Dichotomous	0	1	0.8505	0.3566
Piped water on premises	Dichotomous	0	1	0.9160	0.2774
Electricity used for lighting	Dichotomous	0	1	0.9050	0.0036
Type of sanitation	Dichotomous	0	1	0.8529	0.3543
Satisfaction with dwelling	Dichotomous	0	1	0.6240	0.4994
Social relationships					
Satisfied with time available for family	Ordinal	1	5	3.9985	0.8878
Satisfied with time available for friends	Ordinal	1	5	3.7534	1.0157
Satisfied with time available for own things	Ordinal	1	5	3.5010	1.0707
Satisfied with marriage	Ordinal	1	5	4.1561	0.0424
Economic Variables					
Work conditions	Ordinal	1	5	3.5117	1.1588
Level of education	Ordinal	1	5	3.6589	0.0127
Income category	Ordinal	1	5	2.3907	0.9315
Satisfaction with standard of living	Ordinal	1	5	3.1952	1.1448
Satisfied with money available	Ordinal	1	5	2.3627	0.0137
Perceived social status	Ordinal	1	5	1.8340	0.8870
Satisfaction with life	Ordinal	1	5	3.1718	0.0153
Education					
Level of education	Ordinal	1	5	3.6589	0.0127
Health					
Satisfaction with health	Ordinal	1	4	3.2115	0.7039
How often does health prevent you from doing your daily work	Ordinal	1	4	3.1700	0.9370
How often does health prevent you from taking part in social activities	Ordinal	1	4	3.1900	0.8720
Safety					
Feel safe in area where you live in the day	Ordinal	1	5	3.9325	0.0140
Feel safe in area where you live after dark	Ordinal	1	5	2.2876	1.3280
Feel safe at home	Ordinal	1	5	4.2874	0.2125
Governance					
Satisfied with local government	Ordinal	1	5	2.9142	0.0144
Politics is not a waste of time	Ordinal	1	5	3.7079	1.0897
Judiciary is free	Ordinal	1	5	3.1100	1.0900
Country is going in the right direction	Ordinal	1	5	3.4100	1.0940
Election was free and fair	Ordinal	1	5	3.9300	0.9360

Source: GCRO (2009)
*SD = standard deviation

In further analyses we used the indicator variables listed in Table 5 to address the primary and the secondary research questions.

4.3 Operational Hypotheses

In this section we derived the operational hypotheses from the literature review as set out in Section 2.2. The hypotheses were set to empirically evaluate the primary and the secondary research questions.

The primary research question tested the validity of the scales measuring the dimensions of quality of life and was assessed against the null hypothesis (H_{0prim}) that there was no relationship between the measuring indicators and their underlying latent constructs (dimension of quality of life), for example, between ‘type of housing’ and the dimension ‘housing and infrastructure’. This hypothesis implied that there was a poor fit between the specified model and the data. In the alternative we assessed a hypothesis (H_{aprim}) which stated that there was a relationship between the observed indicator variables and their latent constructs. This implied that the specified model fit the data well. In the empirical section these hypotheses were tested for each of the dimensions of quality of life.

In order to assess the secondary research question we assessed a null hypothesis (H_{0sec}) stating that there was no relationship between the different dimensions of quality of life. The alternative hypothesis (H_{asec}) stated that there is a relationship between the different dimensions of quality of life. These hypotheses were tested against a full CFA model including all the dimensions of quality of life.

5. RESULTS

In this section the empirical merits of the hypotheses developed in the methodological section are evaluated. The results are discussed in three sections. Firstly, the results from the EFA to determine the uni-dimensionality of the dimensions of quality of life are reported. Secondly, the evaluation of the construct validity of the proposed measures of quality of life is discussed and thirdly, the relationships between the dimensions constituting quality of life, considering the hypotheses developed are examined.

5.1 Evaluation of the uni-dimensionality of the dimensions of quality of life

This section assesses the measures (scales) as set out in the methodological section, using EFA, to ensure that the scales measured the dimensions of quality of life, which they were intended to measure. To test for this we explored if the scales described a single specific dimension of quality of life, thus we tested each scale for uni-dimensionality. Uni-dimensionality suggests that the inter-correlations between items are due to a single, dominant, latent variable. If a scale is uni-dimensional the indicator variables load on a single factor and the error terms of the indicators are independent (Kline 2011). Once uni-dimensionality was established we could assume that the indicator variables that measured a specific dimension of quality of life only loaded on the specific dimension, and that the error terms of the indicator variables were uncorrelated.

Application of EFA

Before submitting the data to EFA we evaluated the normality of the measurement variables.[10] As was expected, the majority of the observed variables were not normally distributed, as it was categorical data. However, we used asymptotic free estimation techniques such as Weighted Least Squares (WLS) and Robust Maximum Likelihood (RML), which were less affected by the skewness of the indicator variables in our EFA and CFA. For this reason, no correction was made for the skewness in the data (Muthen & Muthen 1998-2004 and Flora & Curran 2004).

To extract the factors we used Weighted Least Squares (WLS) with Promax rotation. As mentioned previously, WLS is an asymptotic free estimation technique appropriate for application to categorical data in which the Satorra-Bentler chi-square test statistic is divided by scaling correction to better approximate the chi-square under non-normality (Brown, 2006). Promax rotation allows for correlated factors with no restrictions and the estimation of factor correlations (Muthen & Muthen, 1998-2004).

We submitted each of the scales explaining the dimensions of quality of life as defined in the methodological section to EFA. The dimensions included: ‘housing and infrastructure’, ‘social relationships’ and ‘economical’ dimensions, ‘health’, ‘governance’, ‘safety’ and ‘global life satisfaction’. Although the dimensions of ‘education’ and ‘global life satisfaction have only one measuring indicator each (and thus do not represent a scale), we analysed the correlation between these indicator variables and the other selected variables and found that both were closely related to the ‘economic’ dimension. Therefore we added these variables to the ‘economic’ factor dimension, to be tested for uni-dimensionality.

[10] We used the Kolmogorov-Smirnov test. Used in sample sizes larger than 2000.

EFA results

The results of the EFA are summarised in Table 6. The results show that the measuring items of each of the dimensions of quality of life only loads on its purported factor, which supports the notion that each of the hypothesised dimensions of quality of life is uni-dimensional and the error terms of each of the indicators are independent. Hence each measuring item included in a specific quality of life scale is closely related to this dimension and measures only the specific dimension of quality of life. For example, the items 'satisfaction with family time', 'satisfaction with time spent with friends', 'satisfaction with the time available to oneself,' and 'satisfaction with marriage,' are closely related to the dimension 'social relationship', and measures items only of this specific dimension.

This finding, of uni-dimensionality, is also applicable to the 'economic' dimension which incorporates the indicator variables of 'education' and 'satisfaction with life'. We renamed the dimension and labelled it the 'socio-economic status' dimension (see the definition of socio-economic status as given by the American Psychological Association, 2012).

Table 6: EFA results

Constructs and measurement items	Factor loadings	Eigenvalue	% of variance
Housing and infrastructure			
Type of Dwelling	.645	2.741	54.813
Electricity	.726		
Satisfaction with dwelling	.310		
Sanitation	.763		
Water	.805		
Social relationships			
Satisfaction- time with family	.826	1.987	48.63
Satisfaction- time with friends	.454		
Satisfaction with marriage	.550		
Satisfaction with own time	.469		
Socio-economic Status			
Satisfaction with life	.696	2.945	50.00
Perceived social status	.656		
Satisfaction with money	.602		
Satisfaction with standard of living			
Income category	.603		
Work conditions	.680		
Education	.426		
Health			
Health status prevents you from going to work	.948	2.271	75.688
Health prevents you from taking part in social activities	.966		
Satisfaction with health	.496		
Safety			
Safe during the day	.747	1.827	60.88
Safe at work	.788		
Safe after dark	.408		
Governance			
Country is going in right direction	.676	1.861	37.223
Elections were free and fair	.547		
Satisfaction with local government	.300		
Politics is not a waste of time	.354		
Judiciary is free	.428		

Source: Author's calculations based on the Quality of Life survey (Gauteng City-Region Observatory (GCRO), 2009)

An additional indication of the uni-dimensionality of the indicator variables of each dimension of quality of life can be derived from the eigenvalues of each of the factors. We note that the eigenvalues of the extracted factors of each of the dimensions of quality of life are larger than one (see Table 6), which indicates that only one latent variable is measured. Furthermore, only one eigenvalue greater than one is noted for each dimension, which supports the finding that the different scales measuring the different dimensions of quality of life are uni-dimensional.

Table 6 also shows that the factor loadings of the indicator variables on each of the dimensions (factors) of quality of life are robust and range between 0.3 (satisfaction with local government) [11] and 0.966 (health prevents you from taking part in social activities). The robust loadings of each of the indicator variables on the dimensions which they are purported to measure indicate that the selected measuring items are closely related to the latent variables (dimensions).

To conclude, we determined that each of the scales that measure a dimension of quality of life is uni-dimensional and that the error terms of the indicators are not related. In the next section, based on these findings, we proceed to evaluate the construct validity of each of the scales that measure the different dimensions of quality of life.

2.4.2 Evaluation of the construct validity of the dimensions constituting quality of life using CFA

To address the primary research question, namely to validate the measuring items of the scales that are used to measure the different quality of life dimensions, we assessed the primary hypothesis applicable to the six dimensions of quality of life. The primary hypothesis states that the measuring items included in the scales that measure the quality of life dimensions give a good representation of the underlying dimensions of quality of life. In the next section we determined if the hypothesis is consistent with the data and reported the results found in the analyses.

The specification of the models

In each of the dimensions the first items were used as marker indicators of each construct.[12] Based on the results of the EFA assessing the uni-dimensionality of the scales of the different dimensions of quality of life, we assumed the measurement errors of the indicator variables to be uncorrelated and each indicator variable to load on only one latent factor. All the models explaining each construct were identified, though the dimensions of 'health' and 'safety' were only just identified due to the limited items (i.e. three items) included in the survey to measure the dimensions.

[11] See section 3.1 (factor loadings of 0.3 and more are seen as robust, (Brown, 2006).
[12] This is done to allocate a metric to the latent variable in which it can be measured. The latent variable's metric is set to the same as the marker variable (see Brown, 2006, p. 62).

The application of CFA

CFA is a large-sample technique and allows for estimations of missing data in the model (Tabachnick & Fidell, 2007). After a missing value analysis was conducted it appeared that the missingness in the data was random. According to Allison (2003) it is then permissible to use the maximum likelihood (ML) technique to estimate or impute the values of the missing data (Allison, 2003). Therefore we used ML to estimate the missing variables.

As the items included in the 'housing and infrastructure' dimension are dichotomous and all other indicators/items are categorical, we used asymptotic free estimation techniques including Robust Weighted Least Squares (WLSMV) and Robust Maximum Likelihood (RML) to estimate the specified models. These methods are suitable for dichotomous and categorical data (Muthen & Muthen, 1998–2004 and Flora & Curran, 2004).

Evaluation of the model fit for the different dimensions of quality of life

Next, we evaluated the tenability of each of the six hypothesised models by means of the goodness-of-fit indices as well as by the interpretability and the strength of the resulting parameter estimates. The test statistics we used to evaluate the fit of the model to the data were based on those most often used in the literature. The statistics included the Satorra-Bentler chi-square test, RMSEA, CFI, TLI and the SRMR. The rules of thumb, mentioned in the methodological section (see Table 4), were used as guidelines to evaluate the hypothesised models of the quality of life dimensions. The fit indices of each of the dimensions of quality of life as well as a summary of the rules of thumb as reported in the methodological section are shown in Table 7. Due to the just-identified specification (degrees of freedom = 0) of the 'health' and the 'safety' dimensions, test statistics for these dimensions of quality of life could not be calculated. Therefore the goodness-of-fit of these two dimensions was not evaluated.

Table 7: A summary of the fit indices of the hypothesised dimensions

Construct	Df[1]	SB Chi-square	Prob	RMSEA	CFI	TLI	SRMR/ WRMR[2]
Summary of rules of thumb		0.00	*p <0.05*	<0.5* <0.1**	>0.9	>0.8	<0.6/ <4
Housing and Infrastructure	5	112.553	0.000	0.057	0.997	0.994	1.981
Social Relationships	2	16.856	0.000	0.033	0.992	0.977	0.012
Socio-economic Status	14	883.139	0.000	0.097	0.913	0.870	0.047
Health	0	0.000	0.000	0.000	1.000	1.000	0.000
Governance	5	80.992	0.000	0.048	0.963	0.926	0.022
Safety	0	0.000	0.000	0.000	1.000	1.000	0.000

Source: Author's calculations based on the Quality of Life survey (Gauteng City-Region Observatory (GCRO), 2009)

[1.] Df= Degrees of Freedom, SB Chi-Square = Satorra–Bentler chi-square, Prob = Probability

[2.] WRMR – is similar to the SRMR test statistic, but applies to categorical data

* Good fit

** Mediocre fit

The Satorra-Bentler chi-square statistic of each of the dimensions (except those that were just identified) was relatively high and did not approach zero. Furthermore, all the Satorra-Bentler chi-square indices were statistically significant ($p < .001$). Together, these suggested that the null hypothesis of exact fit had to be rejected for each of the hypothesised dimensions constituting quality of life. Hence, based on the Satorra-Bentler chi-square fit indices, none of the models fit the data perfectly, which was expected as very few models that predict latent variables do so perfectly. As the models did not fit the data perfectly, we proceeded to evaluate the model fit by adjudging the other model fit statistics (Blunch, 2008). In the next section the goodness-of-fit statistics for each dimension of quality of life are discussed to evaluate the tenability of the primary hypothesis.

The first dimension we reported on is the 'housing and infrastructure' dimension. The dimension consists of dichotomous variables and, therefore WLSML was used to estimate the model. The fit indices for the model are reported in Table 7. Considered collectively, the fit indices suggested that the model fit the data well and was within the guidelines of the rules of thumb. We could thus reject the null hypothesis (H_{0prim}) that there is no relationship between the measuring indicators of the dimension 'housing and infrastructure' and the latent construct, 'housing and infrastructure' and accept the alternative hypothesis (H_{aprim}) which states that there is a relationship between the indicator variables and the latent variable. The acceptance of the alternative hypothesis implies that the measurement items such as 'water' and 'electricity' were valid measures of the latent variable 'housing and infrastructure'.

The second dimension we evaluated was 'social relationships'. The CFA fit statistics for the dimension 'social relationships' were all within the requirements to meet good model fit (see Table 7). Therefore, we concluded that the measurement items included in the construct, such as 'time spent with the family', gave a good representation of the data and were valid measures of the latent variable social relationships. We rejected the null hypothesis (H_{0prim}) of poor fit and accepted the alternative hypothesis (H_{aprim}) suggesting that the model fit the data well.

The third dimension evaluated was the 'socio-economic status' dimension. Considered jointly, the fit indices of the 'socio-economic status' dimension suggested that the model fit the data well, as all the indices were in close approximation to the rules of thumb. The RMSEA was somewhat higher than the 0.05 guideline for good model fit but was still less than 0.1, thus within the range of acceptable model fit. Therefore, measuring items such as 'income' or 'satisfaction with work,' are valid measures of the latent variable 'socio-economic status'. Hence, we rejected the null hypothesis (H_{0prim}) of poor fit and accepted the alternative hypothesis (H_{aprim}) of good fit.

Fourthly, we evaluated the 'governance' dimension. All the fit indices reported with regard to 'governance' conformed to the criteria of good model fit (see Table 7). According to these findings we concluded that measuring items such as 'elections are free and fair' and 'the country is going in the right direction' were valid measures of the latent variable of 'governance'. Judging from the test statistics we rejected the null hypothesis of poor fit and accepted the alternative hypothesis of good fit.

To conclude, each of the hypothesised dimensions explaining quality of life fit the empirical data well. Thus the items that we postulated to measure the dimensions of quality of life and which we included in the measurement models were good measures of the latent variables. Stated differently, the model configurations seemed to be congruent with the empirical data. As mentioned in the methodological section, Kline (2011) stated that the tenability of theoretical models should be assessed on global (i.e. goodness-of-fit) and molecular (i.e. model parameter) levels. The next section is dedicated to looking at specific model parameters. To evaluate the model we inspected the direction, significance and magnitude of the parameter estimates which in these models consisted of the factor loadings of each of the measuring items on their purported dimensions of quality of life.

The factor loadings of the indicator variables are shown in Table 8. Table 8 shows both the unstandardised[13] and completely standardised[14] factor loadings of the items. The unstandardised parameters were included in the table as they reflect the original metrics of the indicators, though for the interpretation of the factor loadings the general practice is to interpret the completely standardised factor loadings. The first measuring items in each of the dimensions were used as a marker indicator. That is, the metrics of this measuring item were given to the latent variables therefore the unstandardised parameter of each of the marker indicator variables is equal to one with the p-value of 999.0.

Table 8 shows that all the freely estimated unstandardised and completely standardised parameters were statistically significant ($p < 0.001$). Furthermore, all the measuring items were positively related to their purported dimensions of quality of life, indicating that if any of the measuring items increased, it would have had a positive effect on the quality of life of the respondent. For example, if respondents were more satisfied with the amount of money they had, it is likely that the dimension 'socio-economic status' would improve.

[13] Parameters expressed in the original metrics of the indicators.
[14] Relationships involving standardised indicators and standardised latent variables.

Table 8: Estimations of the unstandardised and completely standardised parameters

Dimensions and measurement items	Un-standardised parameters	*p*-value	Completely standardised parameters	SE**	*p*-value	R^2
Housing and Infrastructure						
Type of Dwelling	1.000	999.0	0.845	0.011	0.000	0.739
Electricity	1.396	0.000	0.910	0.009	0.000	0.841
Satisfaction with dwelling	0.384	0.000	0.518	0.018	0.000	0.326
Sanitation	1.539	0.000	0.925	0.008	0.000	0.855
Water	3.160	0.000	0.980	0.005	0.000	0.993
Satisfaction- time with family	1.000	999.0	0.812	0.015	0.000	0.659
Satisfaction- time with friends	0.635	0.000	0.451	0.017	0.000	0.203
Satisfaction with marriage	0.739	0.000	0.564	0.017	0.000	0.318
Satisfaction with own time	0.705	0.000	0.474	0.016	0.000	0.225
Satisfaction with life	1.000	999.0	0.769	0.008	0.000	0.591
Perceived social status	0.574	0.000	0.621	0.011	0.000	0.385
Satisfaction with money	0.716	0.000	0.615	0.010	0.000	0.378
Satisfaction with standard of living	0.883	0.000	0.741	0.009	0.000	0.549
Income category	0.592	0.000	0.610	0.012	0.000	0.372
Work conditions	0.825	0.000	0.677	0.014	0.000	0.456
Education	0.398	0.000	0.371	0.012	0.000	0.138
Health status prevents you from going to work	1.000	999.0	0.950	0.006	0.000	0.903
Health prevents you from taking part in social activities	1.015	0.000	0.967	0.006	0.000	0.936
Satisfaction with health	0.394	0.000	0.498	0.011	0.000	0.248
Safe during the day	1.000	999.0	0.757	0.012	0.000	0.573
Safe at work	0.982	0.000	0.790	0.013	0.000	0.624
Safe after dark	0.591	0.000	0.409	0.010	0.000	0.187
Country is going in right direction	1	999.0	0.675	0.017	0.000	0.298
Elections was free and fair	0.692	0.000	0.546	0.018	0.000	0.455
Satisfaction local government	0.460	0.000	0.289	0.016	0.000	0.083
Politics is not a waste of time	0.542	0.000	0.267	0.018	0.000	0.135
Judiciary is free	0.646	0.000	0.438	0.016	0.000	0.192

Source: Source: Author's calculations based on the Quality of Life survey (Gauteng City-Region Observatory (GCRO), 2009)
*The probability of 999.0 is due to the indicator marker being set to one
**SE = standard error

To interpret the magnitude of the factor loadings we evaluated the standardised factor loadings as shown in Table 8. The factor loading varied between 0.980 (R^2 = 0.993) for the indicator variable 'water' and 0.267 (R^2 = 0.135) for the indicator variable 'politics is not a waste of time'. The strength of the factor loadings indicated how closely the measuring items were related to the latent variables. If the factor loadings were relatively high it implied that a higher proportion of the variance in the indicator variable was explained by the latent variable. For example, if we squared the factor loading of 'water' (0.980) we derived the true variance[15] explained by the latent variable 'housing and infrastructure', which is 0.993. Thus, 99.3% of the variance was explained, leaving only 0.07% of the variance not explained by the latent variable 'housing and infrastructure'. This suggests that the indicator variable 'water' was a very good measure of the dimension, 'housing and infrastructure'.

According to Brown (2006), factor loadings equal to or more than 0.3 ($R^2 \geq 0.09$) are salient, therefore factor loadings of less than 0.3 ($R^2 < 0.09$) are items that could be considered for elimination except if those items are fundamental to the theory on which the model specification is based. Only two items had factor loadings of less than 0.3, both in the dimension of 'governance', namely, 'satisfaction with local government' (0.289, $R^2 = 0.083$) and 'politics is not a waste of time' (0.267, $R^2 = 0.135$). Although these factor loadings and R-square values of 'satisfaction with local government' were slightly less than the guidelines, both items are statistically significant. Both these indicator measures are generally used as measures of 'good governance' in quality of life measuring instruments, and have been found to be valid measuring items (see the literature review, Section 2.2). The slightly lower factor loadings than the 0.3 guideline indicated that the measuring items were not that closely related to the latent variable 'good governance', as has been found in other countries.

A likely explanation for this is to be found in the specificity of the perceptions and voting patterns of demographic and socio-economic groups in South Africa, associated in particular with the country's history and political economy. This is likely to make the relationships between socio-economic characteristics and perceptions of governance less linear and more complex than is typically the case in other countries. For instance, in South Africa many people with low incomes and relatively poor housing, health, and so on, may nevertheless have more favourable views of government than many people with high incomes and relatively favourable socio-economic characteristics. Even though it seems as if these indicators ('satisfaction with local government' and 'politics is not a waste of time') are not as closely associated with the dimension 'good governance' as in other countries, we did not consider these items for deletion at that point of the analysis. This decision was motivated by the possibility that in a multi-factor model these measuring items might have shown a closer relationship to the all-inclusive concept of quality of life in the GCR.

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[15]The variance not explained by measurement error.

Considering the goodness-of-fit statistics of each of the dimensions of quality of life as well as the results on the estimated factor loadings, it seemed that the hypothesised models fit the data well. Therefore we concluded that the measuring items included in the scales that measured the different quality of life dimensions gave a good representation of the underlying dimensions of quality of life. These results indicated strong empirical evidence in support of the alternative primary research hypothesis (H_{prima}). Therefore, we could use the measuring items as valid measures of quality of life.

5.3 Determining the links between the dimensions of quality of life

In this section we addressed the second research objective: to evaluate the linkages between the different dimensions of quality of life and to determine if the hypothesised relationships, based on the literature review (Section.2) and operationalised in the methodological section (Section 4.3) were supported by the data. For this purpose we included all the validated dimensions into a multi-factor CFA model and evaluated the model fit according to the goodness-of-fit indices and the estimated parameters. The estimated parameters included the factor loadings of the measuring items on the latent variables, and the estimated correlations coefficient between the latent variables. Next, we described the model specification, the application of CFA and the CFA results.

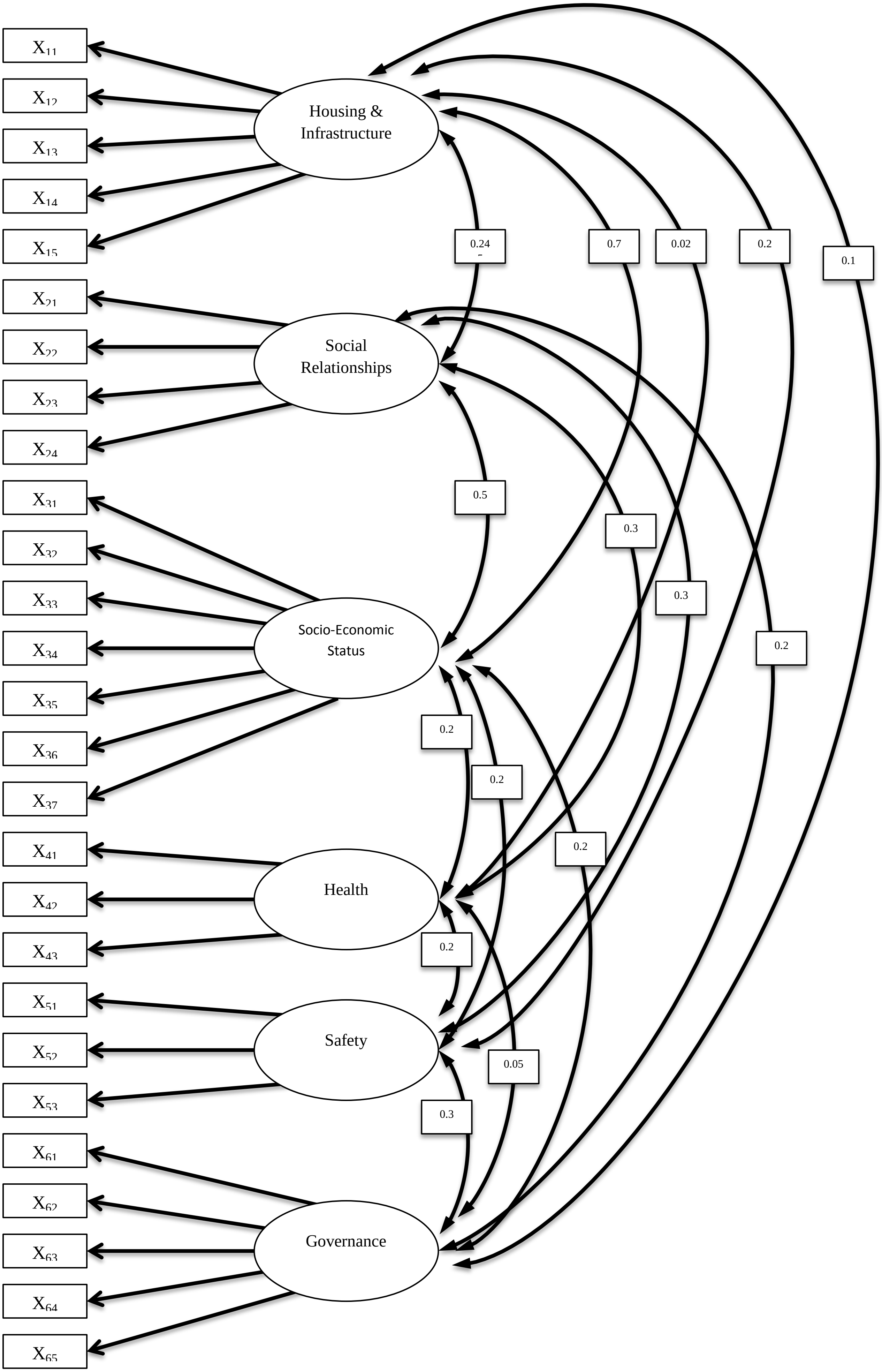
2.4.3.1 Specification of the model

The model included the six dimensions (latent variables) of quality of life which were validated in the previous section. Figure 1 reflects the path diagram of the fully integrated six factor CFA model. The rectangular blocks indicate all the measuring items of each of the latent variables.[16] The ovals in Figure 1 show the six latent variables or dimensions of quality of life. The latent variables were linked to the measuring items with a single headed arrow which shows that each of the factors were uni-dimensional, with all the measuring items of a specific dimension loading only on the dimension it was purported to measure (this specification was based on the findings of the EFA). The error terms of each of the indicator variables are not shown in Figure 1 although they are directly linked to each measuring item. We assumed all the measurement errors to be uncorrelated as was shown in the EFA. Based

[16] The error terms of each of the measuring items are not shown in the figure to simplify the diagram.

on the literature reviewed on the linkages between the different dimensions of quality of life we assumed all latent variables to be correlated. This is indicated by the double headed arrows in Figure.1, which links all the latent variables. Considering the sample size and the number of parameters that were to be estimated we found the specified model to be over-identified with 309 degrees of freedom, and therefore suitable for estimation.

Figure 1: Fully integrated six factor CFA model



As the majority of the indicator variables used in the analysis was ordinal, we used the WLSMV estimator technique, as it was able to provide adjusted weighted least square parameter estimates, robust standard errors, means and variance adjusted chi-square test statistics, which are appropriate for categorical variables.

5.3.2 Results

To evaluate the model we first assessed the overall fit of the model and secondly reviewed the estimations of the model parameters.

The overall model fit

In Table 9 a summary of the rules of thumb to measure the goodness-of-fit (explained in the methodological section) and the absolute, parsimony correction and comparative fit indices of the multi-dimensional CFA model are shown.

Table 9: The fit indices of the six factor model

	Df[1]	**Chi-square**	**Prob**	**RMSEA**	**CFI**	**TLI**	**WRMR**
Summary of rules of thumb		Close to 0.00	*p<0.05*	<0.5* <0.1**	>0.9	>0.8	<4
Full six factor CFA model	309	6553.301	0.000	0.055	0.874	0.857	3.895

Source: Author's calculations based on the Quality of Life survey (Gauteng City-Region Observatory (GCRO), 2009)
[1]Df – Degrees of freedom
*Goof fit
**Mediocre fit

The chi-square, a measure of perfect fit, was 6553.301 and statistically significant (*p*-value<0.001), thus the null hypothesis of a perfect fit was rejected as expected, as most models do not fit data perfectly. The WRMR which is an additional measure of absolute fit was 3.895. This is a fairly newly developed test statistic, and, according to Muthen and Muthen (1998-2004), the reliability of the statistic still needs to be researched, though a relatively small value of less than four seems to be acceptable. According to this recommendation the WRMR statistics indicated a good model fit.

The CFI, one of the incremental fit indices, was 0.874. Although this is slightly below the 0.9 rule of thumb, as it is in close proximity to the guideline, we accepted it as an indication of adequate model fit (see Bentler and Hu (1999) in this regard). The other reported incremental fit index, the TLI, was within the guideline given by Hair et al. (1998) for adequate fit.

The RMSEA, an index adjusted for model parsimony, was 0.055 and within the requirements of a good fit model (Bentler & Hu, 1999). Considered collectively, the fit indices suggested that although not all the indices were in the optimal ranges, the majority were within the guidelines set by the rules of thumb. We therefore concluded that the final model fit the data well.

In the second part of the evaluation of model fit we assessed the estimations of the model parameters. Firstly we reviewed the estimated factor loadings of each of the indicator variables on the latent variables, and secondly we reviewed the estimated correlations' coefficients showing the links between the different dimensions of quality of life.

Results on the estimated parameters: factor loadings

In Table 10 all unstandardised and completely standardised factor loadings (including SE and *p*-values) as well as the R-square values of the full CFA model are presented. The unstandardised factor loadings were included in Table 10 as these showed the original metrics in which the measuring items were measured as well as giving an indication of the items used as marker indicators. As the latent variables do not have units of measurement, the general practice is to fix the latent variables' metric to the first indicator variable; this is indicated by the factor loading of the marker variable being equal to one ($p = 0.999$) (see Table 10).

All the unstandardised factor loadings and the completely standardised loadings were statistically significant ($p<0.001$). Furthermore, all the factor loadings were positively related to their different purported dimensions of quality of life as was shown in the models to validate the dimensions. The completely standardised loadings of the items on the dimensions were robust and varied between 0.378 for the indicator 'politics is not a waste of time' to 0.992 for the indicator 'water'. The factor loadings of the indicators 'politics is not a waste of time' (0.378) and 'satisfaction with local government' (0.389) in the multi-factor

CFA model were more than the guideline set by Brown (2006) of 0.3 (R^2 = 0.09). This is in contrast to the finding in the previous section on the validation of the 'governance' dimension of quality of life, where the factor loadings were less than 0.3. The findings on these indicators in the multi-factor CFA model indicated the stronger relationship between these indicator variables and the total concept of quality of life. This finding supported the decision to retain these indicator variables in the specified model.

In completely standardised solutions, as those shown in Table 10, the metrics of both the indicators variables and the latent variables were standardised (i.e. the mean = 0.0 and the SD = 1.00). Thus the factor loadings in a completely standardised solution could be interpreted in the same way as standardised regression coefficients. For example, a one standardised score increase in the dimension 'health' is associated with a 0.528 (see Table 10) standardised score increase in the 'satisfaction with health' variable. The associations between all the standardised latent variables and their purported indicator variables could be similarly interpreted.

Table 10: Factor loadings of the full CFA model

Constructs and measurement items	Unstan-dardised	*p*- value	Completely standardised	SE	*p*- value	R-Square
Type of Dwelling	1.000	0.999*	0.850	0.009	0.000	0.723
Electricity	1.074	0.000	0.913	0.008	0.000	0.834
Satisfaction with dwelling	0.858	0.000	0.730	0.013	0.000	0.533
Sanitation	1.075	0.000	0.91	0.006	0.000	0.836
Water	1.167	0.000	0.992	0.007	0.000	0.984
Satisfaction time with family	1.000	0.000	0.675	0.011	0.000	0.486
Satisfaction time with friends	0.844	0.000	0.498	0.011	0.000	0.248
Satisfaction with marriage	0.749	0.000	0.472	0.014	0.000	0.223
Satisfaction with own time	0.119	0.000	0.626	0.013	0.000	0.392
Satisfaction with life	1.000	0.000	0.721	0.009	0.000	0.520
Perceived social status	0.649	0.000	0.659	0.010	0.000	0.434
Satisfaction with money	0.684	0.000	0.551	0.012	0.000	0.304
Satisfaction with standard of living	0.894	0.000	0.703	0.010	0.000	0.494
Income	0.663	0.000	0.641	0.011	0.000	0.410
Work conditions	0.864	0.000	0.671	0.016	0.000	0.450
Education	0.486	0.000	0.425	0.011	0.000	0.180
Health prevents taking part in work	1.000	0.000	0.742	0.015	0.000	0.550
Health prevents from social activities	1.005	0.000	0.748	0.016	0.000	0.559
Satisfaction with health	0.735	0.000	0.726	0.017	0.000	0.528
Safe at home	1.000	0.000	0.750	0.015	0.000	0.563
Safe at work	0.849	0.000	0.677	0.015	0.000	0.459
Safe after dark	0.709	0.000	0.538	0.019	0.000	0.289
Country is going in right direction	1.000	0.000	0.628	0.015	0.000	0.394
Elections were free and fair	0.637	0.000	0.468	0.014	0.000	0.219
Satisfaction local government	0.657	0.000	0.389	0.015	0.000	0.152
Politics is not a waste of time	0.698	0.000	0.378	0.015	0.000	0.143
Judiciary is free	0.600	0.000	0.440	0.015	0.000	0.200

Source: Author's calculation based on Quality of Life Note:
*`The probability of 999.0 is due to the indicator marker being set to one

Considering both the model fit statistics and the estimates of the parameters of the factor loadings of the model, the model suggested a good fit to the data. Therefore we proceeded to evaluate the estimated parameters of the correlations coefficients between the dimensions of quality of life.

Results on the estimated parameters: correlations between latent variables

In this section we addressed the second research objective of the paper: to evaluate the linkages between the different dimensions of quality of life. The second research objective was addressed by evaluating the estimated parameters of the correlation coefficients and their statistical significance against the hypotheses set in the methodological section. This is the first study of its kind in South Africa and one of the first internationally that evaluates a fully integrated model of quality of life to determine the linkages between the different latent variables. The values of the correlation coefficients between the latest variables could only be estimated by CFA, as the latent variables were not directly observable, but were underlying constructs. The correlation coefficients between the latent variables are indicated in the square blocks in Figure.1 and also summarised in Table 11.

Table 11: The correlation coefficients of the latent variables of quality of life

	Housing and infrastructure	Social Relationships	Socio-Economic Status	Health	Governance	Safety
Housing and infrastructure	1					
Social Relationships	0.201***	1				
Socio-Economic Status	0.679***	0.527***	1			
Health	0.023	0.262 ***	0.264 ***	1		
Governance	0.098***	0.208***	0.033*	0.052**	1	
Safety	0.197 ***	0.297 ***	0.298 ***	0.224***	0.296 ***	1

Note: *** = p< 0.01; ** = p<0.05; *p = < 0.10

As a guideline to determine the strength of the association between the dimensions we used the rules of thumb summarised in Table 12, as suggested by Cohen (1988).

Table 12: Rules of thumb regarding the strength of correlations

Correlation coefficients (r)	Type of relationship
$0.02 \leq r \leq 0.29$	Weak relationship
$0.03 \leq r \leq 0.49$	Moderate relationship
$0.05 \leq r < 1.00$	Strong relationship

Source: Cohen (1988)

All the interrelationships between the different dimensions of quality of life, except for one, were positive and statistically significant. The exception was the estimated correlation between 'housing and infrastructure' and 'health' which was not statistically significant (see Table 12). Therefore the alternative hypothesis (H_{asec}), which states that there is a relationship between the dimensions of quality of life, was accepted, except for the relationship between 'housing and infrastructure' and 'health' in which we accepted the null hypothesis (H_{0sec}) of no relationship between these variables.

The finding that the relationship between 'housing and infrastructure' and 'health' was not statistically significant differs from the findings in the literature. The reviewed literature shows that there is a relationship between the dimensions although the relationship is weak (see Section 2) (Dalstra, et al., 2006). It is plausible that although this study did not reveal a direct relationship between the dimensions 'housing and infrastructure' and 'health' there might have been an indirect relationship based on an underlying third factor, such as income. Furthermore, a probable reason for the relationship between 'housing and infrastructure' and 'health' that was not confirmed in this sample was because many of the young, healthy respondents in the sample did not reside in houses or flats (seen as formal housing), but rather in the back yards of formal houses, in hostels and in informal dwellings (GCRO, 2010), thus showing healthy respondents living in informal dwellings.

Furthermore, the relationship between the dimensions 'governance' and 'social relationships' (the correlation coefficient (r) = 0.208) was weak and only statistically significant at a 10% level. A positive relationship implied that social relationships of an individual such as time spent with family and friends might be related to the interrelationships between individuals and government, such as taking part in elections or having a favourable view of the local government. Although it is plausible that good social relationships are related to a person's improved interaction with government it is likely that if such a relationship exists, the relationship will probably be weak. This weak relationship does not only manifest between the dimensions 'governance' and 'social relationships' but also between 'governance' and all the other dimensions of quality of life. The same reasons for these weak relationships discussed earlier are possibly also applicable to the other relationships. As governance relates to the interaction of individuals with government this 'interaction' might possibly be related to indicators such as an individual's health, type of housing or satisfaction with life, though it is likely to be weak. The only relationship that might be stronger is the relationship between a measure of governance such as 'the belief that the judiciary is free' and an indicator variable such as 'safety'.

Although the results showed that the majority of the relationships between the dimensions of quality of life are positive and statistically significant there were some relationships that were much stronger than others. Strong relationships exist between 'socio-economic status' and the dimensions 'housing and infrastructure' and 'social relationships'. A positive relationship was shown in this research, and while no causality was proven we could argue that it is likely that respondents with relatively high socio-economic status would be more likely to reside in formal housing with basic services. If the relationship between the dimensions can be shown to be causal it can be argued that policy decisions which improve 'socio-economic status' could also improve the 'housing and infrastructure' of the respondents.

Table 12 also shows that a strong positive relationship existed between the dimensions 'socio-economic status' and 'social relationships' (r=0.527). Although in this study no causality between the dimensions was proven, if the relationship was in fact causal, a possible explanation could have been that respondents with good social relationships might have had access to better work opportunities and the ability to earn higher levels of income, which would be consistent with the literature (Coburn, 2000; Stiglitz et al. 2009).

Table 11 shows weak relationships between the dimension 'housing and infrastructure' and the dimensions 'safety' (r=0.197) and 'social relationships' (r=0.197). We could argue that though this study does not prove any causality between the dimensions it is likely that the weak relationship between 'housing and infrastructure' and 'safety' could possibly be explained by the high crime rates reported in the GCR that affect respondents in all types of housing.

The weak relationship between 'housing and infrastructure' and 'social relationships' emphasises that improved surroundings including housing and basic services might have had a positive effect on social relationships, although no causality was proven in this study. Furthermore, we could make a case that such a relationship was possibly weak and that other variables such as employment status, culture and religion might have been of more relevance in describing the association.

As the majority of the linkages between the dimensions of quality of life were positive it seemed that the improvement in any one of the dimensions would be correlated with an improvement in any of the other dimensions, although causality between these dimensions had not been established and could thus only be based on what was shown in the relevant literature.

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