UNIVERSIDADE FEDERAL DO PARANÁ

KARINA REIS NAKAMURA

MULTIDIMENSIONAL POVERTY AMONG THE ELDERLY: EVIDENCE FROM BRAZILIAN LONGITUDINAL STUDY OF AGING DATA (ELSI-BRAZIL)

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Orientadora: Prof. Dra. Kênia Barreiro de Souza

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação DESENVOLVIMENTO ECONÔMICO da Universidade Federal do Paraná foram convocados para realizar a arguição da dissertação de Mestrado de **KARINA REIS NAKAMURA**, intitulada: **MULTIDIMENSIONAL POVERTY AMONG THE ELDERLY: EVIDENCE FROM BRAZILIAN LONGITUDINAL STUDY OF AGING DATA (ELSI-BRAZIL)**, sob orientação da Profa. Dra. KÊNIA BARREIRO DE SOUZA, que após terem inquirido a aluna e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.

A outorga do título de mestra está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

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Aos meus avós, que adorariam ter uma neta mestra.

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"Long story short, I survived."

— Taylor Swift

RESUMO

O conceito de pobreza multidimensional supõe que a pobreza dependa não apenas da renda, mas que considere privações em outros aspectos. Para os idosos, mensurar a pobreza multidimensional é crucial já que este grupo está sujeito a desafios únicos, como os relacionados a saúde e inclusão social. Medidas de pobreza multidimensional, portanto, podem ajudar a capturar a extensão das privações dos indivíduos de forma mais completa. O objetivo desta dissertação, portanto, foi criar uma medida de pobreza multidimensional para os idosos brasileiros. Foram utilizados os dados do Estudo Longitudinal da Saúde dos Idosos Brasileiros (ELSI-Brasil). A pesquisa conta com um questionário com perguntas direcionadas a essa população, a partir das quais foi possível identificar quais são as dimensões que mais impactam a vida dos idosos, utilizando uma combinação das técnicas de Análise Fatorial e Análise de Cluster. Os fatores resultantes da Análise Fatorial foram: Saúde e Funcionalidade, Psicossocial, Padrão de vida e Sintomas Depressivos. Os escores fatoriais obtidos foram usados para agrupar os idosos entre multidimensionalmente pobres ou não. Por fim, uma regressão log-log complementar foi utilizada para analisar quais características podem afetar a probabilidade de um idoso ser pobre. De forma geral, os resultados indicam que os indivíduos classificados como pobres financeiramente e aqueles identificados como pobres multidimensionalmente não são apenas grupos distintos, mas também vivenciam a pobreza por meio de mecanismos fundamentalmente diferentes. Essa distinção é evidente no fato de que os indivíduos financeiramente pobres tendem a apresentar baixos escores nos fatores latentes que impactam significativamente aqueles em situação de pobreza multidimensional. Ademais, os resultados da regressão sugerem que a pobreza multidimensional parece ter um componente etário, em que a probabilidade de ser pobre cresce com a idade, enquanto o mesmo não pode ser afirmado para a pobreza monetária. Esses resultados reforçam a necessidade de que os idosos sejam tratados em abordagens mais amplas de pobreza que sejam capazes de revelar sua vulnerabilidade em múltiplas dimensões.

Palavras-chave: Pobreza multidimensional, Idosos, Análise Fatorial, Análise Cluster.
Classificação JEL: I32, J14, C38, C25 .

ABSTRACT

The concept of multidimensional poverty supposes that poverty depends not only on income, but that it should consider deprivations in other aspects. For the elderly, measuring multidimensional poverty is crucial since this group is subject to unique challenges, such as ones related to health and social inclusion. Multidimensional poverty measures, therefore, can help capture the extension of individuals' deprivations to a fuller extent. The goal of this dissertation was to create a multidimensional poverty for the Brazilian elderly. Data from the Brazilian Longitudinal Study of Aging (ELSI-Brazil) were used. The research contains a questionnaire with questions directed to this population, from which it was possible to identify the dimensions that impact the lives of the elderly the most, using a combination of Factor Analysis and Cluster Analysis techniques. The resulting factors from the Factor Analysis were: Health and Functionalities, Psychosocial, Living Standards and Depressive Symptoms. The factor scores were used to cluster the elderly as multidimensionally poor or not. At last, a complementary log-log regression was used to analyze which characteristics can affect the probability of an elder to be poor. Generally, results suggest that the individuals classified as financially poor and those identified as multidimensionally poor are not only distinct group, but they also live poverty through fundamentally different mechanisms. This distinction is evident by the fact the financially poor individuals tend to present low scores on the latent factors that impact significantly those who are multidimensionally poor. Furthermore, regression results suggest that multidimensional poverty seems to have an age component, in which the probability of being poor increases with age, while the same cannot be affirmed for monetary poverty. These results reinforce the necessity that the elderly are treated in broader approaches to poverty that are able to reveal their vulnerability in multiple dimensions.

Keywords: Multidimensional poverty, elderly, Factor Analysis, Cluster Analysis.

JEL Classification: I32, J14, C38, C25.

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1 INTRODUCTION

Poverty is, according to Ray (1998), the most visible characteristic of underdevelopment. The concept of poverty can be defined generically as the incapacity to attend to the needs of an individual or family adequately. In this sense, an individual can be considered poor when they do not have the means to live adequately within the social context they find themselves in (ROCHA, 2003).

The most traditional poverty measure is the monetary poverty line, in which individuals or families are either classified as poor or non-poor. In theory, if an individual lives with an income above the poverty line, they can allocate their resources to attend to their set of basic needs (THORBECKE, 2013). According to Ray (1998), making use of a fixed notion of poverty lines can be considered unsustainable. Also in criticism of the traditional approach to poverty, Thorbecke (2013) states that the monetary approach does not consider that some attributes cannot be bought in traditional markets; and, apart from that, that there is no guarantee that everyone that has income above a poverty line are non-poor.

Having an inadequate income is, according to Sen (2010), a strong condition for a poor life, but not the only one. The author suggests that poverty should be viewed as a relative deprivation of basic capabilities — defined by Sen (1979) as an individual's ability to do certain basic things, such as moving, attending their nutritional requirements, to be clothed and sheltered. According to Sen (2010), the age, among other characteristics, is one of the factors that can increase their difficulty in earning income and, consequently, can hinder their ability in converting income into capabilities. This suggests that the "real"poverty can be more intense than what is observed when only income is taken into account. (SEN, 2010)

Sen's capability approach has, according to Alkire (2005), two main components: functionings and freedom. Functionings are things of which owning or realizing are valued by the person, which can vary from person to person; and the freedom to reach what is desired is considered a capability. (SEN, 2010). Ergo, an individual can be considered poor if they are deprived of the freedom to reach certain valued functionings.

In this context, the capability approach has been used as a theoretical background for evaluating elderly poverty. According to Yeung e Breheny (2016), there is evidence that economic living standards tend to matter less in terms of well-being with the increase of age. In the same line, Amarante e Colacce (2022) argue that, since the needs of the elderly differ from those of the 'average' individual, evaluating poverty for this group should be done separately. Doing so also permits that the multidimensional poverty indexes reflect the capabilities valued by the elders themselves. (VENKATAPURAM; AMUTHAVALLI THIYAGARAJAN, 2023; MÄKI-OPAS; PIEPER; VAARAMA, 2022)

According to the 2010 Census, 20,590,591 Brazilians were of at least 60 years old, as opposed to the 32,113,490 in 2022 (IBGE, 2011, 2023). This, linked to an increase of life expectation - which grew from 71.1 years in 2000 to 76.6 years in 2024, according to IBGE (2018) - denote that the demographic transition, which is observed in other countries when they reach higher levels of development, has already happened in Brazil (DE LIMA; KONRAD, 2020).[1]

Projections made by IBGE estimate that the elderly population in Brazil could amount to 19% of the total population by 2030 and reach 30% in 2060. Therefore, the elderly population tends to become a growing parcel of the population. Attention to their quality of life and level of poverty is essential, especially given the unique characteristics of Brazil, it being one of the most unequal countries in the world, united with the fact it has the fifth-largest population worldwide (IBGE, 2018).

Given the size and specific needs of this population, there is an urgent need to establish public policies aimed at their well-being. This necessitates the development of comprehensive and focused indicators tailored to the elderly. In this context, the idea that a series of capabilities can be transformed into variables in which individuals accumulate deprivations is the core concept of multidimensional poverty (LUZZI; FLÜCKIGER; WEBER, 2008). As stated in Alkire (2008), measures of multidimensional poverty provide more precise information on people's capability deprivation, especially when compared to other empirical exercises that oversimplify the capability approach.

Despite recent advances, some unanswered questions remain in the field of multidimensional poverty, such as, how to measure it and, primarily, which dimensions are important in the study of multidimensional poverty (ALKIRE, 2008; THORBECKE, 2013). Sen (2004) argues against the adoption of a fixed list of capabilities — or dimensions. To the author, researchers should choose the relevant dimensions for their analysis. This, however, leaves another open question: the selection of relevant dimensions (ALKIRE, 2008).

At the same time, there has been growing interest regarding elderly multidimensional poverty, with studies that set out to investigate how specific aspects of old-age life such as healthcare, social support and interaction, and pensions, for example, could impact elderly poverty and well-being (HU; HAN; LIU, 2022; CHEN; LEU, 2022; CIHLAR; MICHEEL; MERGENTHALER, 2023; AMARANTE; COLACCE, 2022; HWANG; NAM, 2020; LI; KE; SUN, 2023). The same cannot be assessed when it comes to literature around multidimensional poverty among the elderly in Brazil. While there are studies on multidimensional poverty in Brazil as a whole, specific focus has not been given to the elderly. (BARROS; CARVALHO; FRANCO, 2006; COSTA; COSTA, 2014; SILVA et al., 2016).

[1] Demographic transition is defined by Coale (1989) as a change in the reproductive behavior within a society once they reach higher levels of development where birth and death rates are equally low, as opposed to less developed societies in which the average life expectation is lower, as well as birth rates. The phenomenon was, however, experienced in countries such as Brazil, despite the fact that these countries are still developing.

The aim of this work is to create a multidimensional poverty measure for the elderly in Brazil in order to have a better understanding of what deprivations affect this group, as well as how multidimensionally poor individuals differ from the non-poor. A comparison between multidimensional and monetary poverty will also be performed in an effort to see if and how this multidimensional poverty measure differs from traditional (monetary) poverty measures and manages to explore aspects that can impact the lives of the elderly that are not captured by monetary poverty.

With that in mind, the present study makes use of the Brazilian Longitudinal Study of Aging (ELSI-Brazil) and the two available waves of the research, collected in 2015-2016 and 2019-2021, respectively. ELSI-Brazil belongs to a group of studies that focus on evaluating the aging process of a population, as well as its health and socioeconomic determinants. (LIMA-COSTA et al., 2023)

To do so, the methods used in this study comprised: Factor Analysis, where a group of 81 relevant variables were selected to uncover the underlying factors that constituted multidimensional poverty for the population of interest, the elderly. The resulting factor scores of each individual on the underlying factors were then applied in a Cluster Analysis to separate the individuals into groups of those who are poor and non-poor. This allows for us to evaluate how each group fares on the factors of multidimensional poverty uncovered previously, and which of the factors impact their lives the most.

The proposed method intends to overcome some of the issues previously cited in regard to multidimensional poverty. The adoption of factor analysis methods allows the information available in the database to be used to identify poverty, without resorting to arbitrary poverty lines (DEKKERS, 2008).

These results were then followed by the application of a complementary log-log model where the dependent variable was a binary variable that depicted if the individual was poor or not, and the selected explanatory variables used were social-economic factors that had not been previously included in the analysis such as age, gender, race, and education.

Results found in this study were that the factors that make up multidimensional poverty for the elderly in Brazil were: Health and Functionalities, Psychosocial, Living Standards and Depressive Symptoms. Factor scores estimated also suggest that with age, the average scores increase for Health, Psychosocial and Living Standards, but that Depressive Symptoms act in the opposite direction. At last, the regression results show that multidimensional poverty age is an important component that influences how likely the elderly are to being poor. However, the same relationship cannot be found for monetary poverty.

This study is structured into five sections. Following this introduction, the second section presents a literature review that covers both the theoretical and methodological aspects of multidimensional poverty, along with empirical evidence related to poverty among the elderly.

The third section details the data used and the methods applied in the analysis. In the fourth section, the results of the study are discussed. Finally, the fifth section offers concluding remarks and reflections on the findings.

2 LITERATURE REVIEW

This literature review aims to provide a comprehensive overview of multidimensional poverty, covering theoretical aspects of the issue, but focusing on its methodological approaches and empirical evidence. Special emphasis is placed on studies concerning the elderly and the methods chosen for this study, i.e., factor and cluster analysis. Given the limited research on multidimensional poverty in Brazil among the elderly, this review also highlights studies employing factor and cluster analysis to examine poverty in other contexts, illustrating the potential and relevance of these methods for the current study.

2.1 THEORETICAL ASPECTS

Poverty concepts that take into account not only income, but other aspects of the individuals' and family lives are addressed in pioneering works from the 1970s such as Townsend (1979) and Sen (1976). In these works, the authors criticize analyses that consider poverty unidimensionally, where the object of study is monetary poverty. Townsend (1979) argues that it is necessary to consider that people's needs are relative to the society they belong to, as well as the period in time they live in. These needs are not limited by monetary income, but also from other expectations that are imposed by the several systems (labor, educational and economic, for example) that are part of the individuals' lives.

The discussion around poverty is brought forth by Sen (1976, 1979, 2010), with the introduction of the capability approach. According to Sen (2010), poverty can be characterized as a deprivation of basic capabilities. These are defined as one's ability to do certain things such as moving around, attending to their nutritional needs and taking part of their communities' social life (SEN, 1979).

As per Alkire (2005) e Wagle (2009), the capability approach can also be seen through a lens of means and ends. Wagle (2009) posits that the functionings are the ends, or the beings and doings of an individual in terms of the life they wish to lead; while capabilities are the means to achieve those functionings. These aspects are connected to freedom - that is, the understanding that capability is also the freedom to achieve the desired functionings. This means, therefore, that people can, in fact, have the same set of capabilities, but also pursue different sets of functionings, depending on what is valuable to them (WAGLE, 2009).

Sen (2010) affirms that the true notion of poverty can be understood through the capability approach, given that it is more sensible to the well-being of the individuals, and that, as has been argued before, functionings can differ depending on the context and individuals being considered.

In this sense, Alkire (2005) argues that social arrangements in general should be measured based on the freedom people have to achieve the functionings valued by them. Therefore, the capability approach is a framework that can be used to conceptualize the evaluation of poverty, though it is not considered a theory for poverty measurement (SHUBHABRATA; RAMSUNDAR, 2012).

The capability approach can be considered as a theoretical basis for multidimensional poverty Alkire (2008) e Shubhabrata e Ramsundar (2012). Multidimensional poverty supposes that poverty depends on both monetary and non-monetary variables (BOURGUIGNON; CHAKRAVARTY, 2003), and, in the same sense, the capability approach's concepts of capabilities and functionings are intrinsically related to attributes apart from income to understand well-being and poverty. According to Anand e Sen (2003), a person can live above a poverty line that is defined in terms of income, but be deprived in other aspects, such as education and health. This leads to a need of evaluating poverty by a multidimensional view. In other words, considering that an individual or family's poverty can be impacted by several dimensions.

This conceptual framework allows for the analysis to be adapted in a case-dependent manner. Sen (2010) argues that some groups, such as the elderly, have different needs, and therefore, capabilities. Evaluating elderly poverty through a multidimensional perspective may enhance the understanding of the concept, given that this group is vulnerable to unique challenges, such as mobility and health (GOTOH; KAMBAYASHI, 2023). These challenges may hinder the ability of the old-age population to achieve the capabilities valued by them, and, in turn, impact their quality of life. (VENKATAPURAM; AMUTHAVALLI THIYAGARAJAN, 2023; MÄKI-OPAS; PIEPER; VAARAMA, 2022)

Therefore, the capability approach allows for the analysis to focus on what the elderly population in itself values as their functionings and capabilities, moving on from focusing only on monetary poverty and taking into account other aspects of elderly life, apart from illnesses and disabilities related to aging Yeung e Breheny (2016). According to Venkatapuram e Amuthavalli Thiyagarajan (2023), measuring functionings of the elderly through the capability approach is a crucial step in understanding elderly health and wellbeing and to make progress in these aspects.

2.2 METHODOLOGICAL ASPECTS

Some key empirical studies around multidimensional poverty propose methodologies for its measurement. The Alkire-Foster (A-F) method, by Alkire e Foster (2011), has become the most widely used method for multidimensional poverty evaluation. It has two poverty cut-offs: one for each dimension, and one to determine if a person is multidimensionally poor. While some dimensions are traditionally used in the A-F method, such as income, health and education, others can be added depending on the nature of the research.

Several studies have applied the A-F method, as it has been heralded as the most 'mature' multidimensional poverty measure (CHEN; LEU, 2022). Works that seek to not only understand poverty and the dimensions that constitute it, but how, for example, vulnerable groups such as children, migrant workers, and people living in rural areas are multidimensionally poor and what affects their lives (CHEN; LEU, 2022; FONTA et al., 2019; CHEN; TANG, 2023; ZHANG; MA; WANG, 2021).

The Multidimensional Poverty Index (MPI) has also become a popular measuring tool for poverty. It has been constructed based on the A-F method, but is stricter in the dimension choice aspect. Since it has been structured similarly to the Human Development Index, the dimensions considered in the MPI are health, education, and living standards. The MPI is preferred to be used when measuring acute poverty (ALKIRE; SANTOS, 2014). The structuring of the index helps to compare results between periods and different regions and countries. Papers making use of the MPI have sought to investigate elderly poverty and the impact of armed conflict and happiness on the multidimensional poverty of individuals (LOAIZA QUINTERO; MUÑETÓN SANTA; VANEGAS LÓPEZ, 2018; STROTMANN; VOLKERT, 2018; AMARANTE; COLACCE, 2022).

While the Alkire-Foster method is widely used in the literature, it has its shortcomings. Amarante e Colacce (2022), for example, critiques that the MPI approach depends on the discretion of the researcher when determining the components of the index; and Iglesias et al. (2017) found that, while A-F methods paint a clearer picture, confirmatory factor analysis was found to be better at empirically testing the theoretical framework.

Other methodological approaches have also been used to measure multidimensional poverty. One of those is applying fuzzy measures (OTTONELLI; MARIANO, 2014; GARCÍA VÉLEZ; NÚÑEZ VELÁZQUEZ, 2022; FORTINI et al., 2019; KIM, 2015). Diniz e Diniz (2009) argues in favor of this since it helps reduce the level of arbitrariness when it comes to the choice of relevant dimensions, which is one of the considered shortcomings of stricter measures such as the MPI. Though the approach has also been gaining popularity, Handastya e Betti (2023) argues that it also relies on arbitrary choices made by the researcher to distinguish the poor from the non-poor.

Some studies also propose new indexes and methodologies for multidimensional poverty measurement, such as Burchi et al. (2021), Kana Zeumo, Tsoukiàs e Somé (2014) and Merz e Rathjen (2014), that strive to overcome issues with traditional measuring methodologies. Burchi et al. (2021), for example, proposes their index with the argument that the MPI, for example, cannot account for inequality among the poor or intra-household inequality and that the A-F as a whole implies the use of arbitrary choices.

The method proposed for this study aims to counter some issues regarding more traditional methodological approaches to evaluating multidimensional poverty. Factor and cluster analysis, when applied together, allow for some degree of liberty so that the data can speak for itself (LUZZI; FLÜCKIGER; WEBER, 2008). Using these methods reduce the need and amount of arbitrary choices made by the researcher when determining the dimensions of multidimensional poverty Dekkers (2003). Those were the methods applied in this research, described in more detail in the Data and Methods section.

Some of the studies that make use of this measurement of poverty are detailed in the section below (LUZZI; FLÜCKIGER; WEBER, 2008; DEKKERS, 2003; DEKKERS, 2008; UGUR, 2016; CARUSO; SOSA-ESCUDERO; SVARC, 2015). Most of them uncover financial and material deprivation, issues with the neighborhood and social exclusion as underlying dimensions of poverty. Their results are then used to evaluate several aspects of poverty, such as the risk of being poor, Luzzi, Flückiger e Weber (2008); what factor causes multidimensional poverty, Dekkers (2008); and compare multidimensional poverty measures with financial poverty ones, Dekkers (2003).

2.3 EMPIRICAL EVIDENCE

The issue of elderly multidimensional poverty has not been studied at large in Brazil. There is, however, evidence on the issue that can be found in related studies. In general, these studies show that the elderly in Brazil are more vulnerable and multidimensionally poor than the rest of the population. Box 1 shows a summary of studies that measured multidimensional poverty, the methods they used and dimensions that constituted their measures, as well as the countries and population of interest.

The seminal article proposing a multidimensional poverty index for Brazil was Barros, Carvalho e Franco (2006). They bring forward an index similar to the Human Poverty Index (HPI) with data from the National Household Sample Survey (from Portuguese, Pesquisa Nacional por Amostra de Domicílios - PNAD) for each family covering the years of 1993 to 2003. The results found that families with an elderly member, as well as with children or pregnant women, are more vulnerable. Evidence from this study also suggests that the elderly are only second to people living in rural areas in terms of poverty.

Also using PNAD data, for the years of 2006 to 2012, Silva et al. (2016) adopt the method proposed by Bourguignon e Chakravarty (2003) and find that when compared to other age groups, the elderly are the ones who suffer with deprivation the most. In terms of multidimensional poverty, though there was a decrease in the index along the years of the study, the reduction of multidimensional poverty among the elderly was of 1.6%, while other age groups observed a reduction of, on average, 3%. [2]

Similarly to Silva et al. (2016), Silva, Sousa e Araujo (2017) focus on the North region of Brazil to analyze multidimensional poverty for the years of 2006 to 2013 with data from PNAD. Their results show that the elderly were the group with the higher multidimensional poverty and

[2] The method proposed by Bourguignon e Chakravarty (2003) proposes the measurement of poverty adapting the Foster-Greer-Thorbecke index while making use of a matrix of the attributes being considered and a vector of the 'minimally accepted limits' of each attribute, where more weight is considered to people with higher levels of deprivation and to dimensions with bigger deprivation gaps. This method intends to measure the incidence levels of poverty of each dimension.

with the lower decrease in the measure along the years studied. In a similar exercise for the state of Minas Gerais, Costa e Costa (2014) calculate the MPI with local data from the Pesquisa por Amostra de Domicílio of the João Pinheiro Foundation for the year of 2011. The authors note that the elderly of the state were subject to a higher incidence and intensity of multidimensional poverty.

Though the empirical evidence around the topic is scarce in Brazil, there has been a growing interest in multidimensional poverty among the elderly in the literature. Studies with focus on this group take into account and look to evaluate how aspects of old-age life, such as healthcare, pensions, and social interactions impact their poverty in a multidimensional approach. (HU; HAN; LIU, 2022; LI; KE; SUN, 2023; CHEN; LEU, 2022; CIHLAR; MICHEEL; MERGENTHALER, 2023).

Bieszk-Stolorz e Dmytrów (2023) aim to evaluate well-being among the elderly in Western European countries for 2015 and 2020 based on Eurostat data. While their condition has, in general, improved, the researchers note that the change was not significant between the years analyzed. They also argue that the standard of living in post-soviet countries is lower than in EU countries. Similarly, for a group of Latin American countries, Amarante e Colacce (2022) compare their MPIs using data from the Longitudinal Social Protection Survey Harmonized Regional Database (LSPS). Their results suggest that health has the highest level of deprivation among the sample. They also show that women are more multidimensionally poor than men, and poverty increases with age. Hwang e Nam (2020) also evaluate how gender and age affect poverty, this time for South Korea with the 2015 Korea Welfare Panel Study, and found, through the application of the dual-cutoff method based on Alkire e Foster (2011), similar results where the tendency of decreasing poverty is more moderate for women, also emphasizing the importance of health.

In several of these works, health comes up as an important factor that determines multidimensional poverty. Li, Ke e Sun (2023) show that access to long-term care insurance in the long term reduces multidimensional poverty of older adults in Taiwan, using panel data from the China Health and Retirement Longitudinal Survey, also applying the dual cut-off method proposed by Alkire e Foster (2011).

Another aspect important in multidimensional poverty among the elderly is support. In a study about old-age Germans using the German Health Update 2014/2015 dataset to apply confirmatory factor analysis, Cihlar, Micheel e Mergenthaler (2023) found that social support improves life satisfaction. The more an elder is vulnerable, the bigger the impact of social support on their satisfaction. In turn, Tan, Dong e Zhang (2023) evaluate the impact of intergenerational support for the Chinese elderly through the use of a binary logit regression model with data from the 2018 Chinese Longitudinal Health Longevity Survey. They achieve similar results, in which emotional support plays a key role in the reduction of poverty.

Social participation also seems to play a key role in multidimensional poverty among the elderly. With data for the years of 1999 and 2003 from the Taiwan Longitudinal Study on Aging (TLSA), Chen e Leu (2022) adopted the Alkire-Foster method to evaluate the dynamics of multidimensional poverty in Taiwan, and found that social participation was an influential contributor to poverty in the country.

While other dimensions of life have been noted as important to multidimensional poverty, traditional aspects such as income and material deprivation also show up as dimensions that impact the life of the elderly. Chan e Wong (2020) adopt a structural equation modelling (SEM) on the data from a project called "Trends and Implications of Poverty and Social Disadvantages in Hong Kong: A Multi-Disciplinary and Longitudinal Study", and show that material deprivation have a significative impact on the subjective perception of the elderly in relation to poverty.

On another note, the relationship of pensions and multidimensional poverty has also been studied. Solaymani, Vaghefi e Kari (2019) evaluate multidimensional poverty among retirees in Malaysia, using data from the Malaysian Employee Provident Fund. They applied the Alkire-Foster method and found that 84% of the retirees were considered multidimensionally poor. Deprivation was high in dimensions such as health insurance, owning a car and education. Zhang e Imai (2024) take a different approach. The authors seek to understand if a new pension scheme in China reduced elderly poverty. The paper used panel data from the China Health and Retirement Longitudinal Study, for the years of 2011 to 2015. Based on a fixed effects model adopted with a propensity score matching approach, it was found that the pension scheme did reduce multidimensional poverty among the elderly in rural areas.

Other vulnerable groups have also been given focus in the evaluation of multidimensional poverty. Trani, Biggeri e Mauro (2013) aims to examine multidimensional poverty for Afghan children. The relevance of their research is argued based on the fact that the country has not only been subject to the impacts of war, but also political issues and droughts. By applying the Alkire-Foster method, the authors analyzed ten dimensions of child poverty: health, care and love, material deprivation, food security, social inclusion, education, freedom from exploitation, shelter and environment, autonomy and mobility. Their results suggest that, though poverty levels were high in the country as a whole, regardless of gender, children living in rural areas were more vulnerable to multidimensional poverty.

Wüst e Volkert (2012) also sought to understand child poverty. The authors made use of the 26th version of the German Socioeconomic Panel and evaluated the domains of education/leisure, health, social participation and income also using the Alkire-Foster method. Their results show that the education of parents or caretakers can have significative impacts on the child’s likelihood to be deprived multidimensionally. In an effort to understand how disability can affect multidimensional poverty, Trani et al. (2015) carried out surveys in Morocco and Tunisia and applied the Alkire-Foster method. They found that people with disabilities, especially girls, women and those who lived in rural areas, were more prone to being multidimensionally poor.

In a general sense, multidimensional poverty has been at the forefront of poverty research

(MOHAQEQI KAMAL; BASAKHA; ALKIRE, 2024). While this area of study has witnessed a significant growth and maturing of its methodological practices, D'Attoma e Matteucci (2024) argue that efforts to evolve the practices beyond the Alkire-Foster method that, though widely used, has its share of limitations. The authors also point to the relative lack of studies on regions apart from Europe and Asia. Similarly, when it comes to studies focused on the elderly, though the topic has received renewed interest, it has not been translated, geographically, into focus outside of Europe and Asia.

The proposed method for this study is a two-step procedure that combines results for Factor Analysis (FA) and Cluster Analysis (CA) — discussed in detail in the Data & Methods section, following Dekkers (2003), Dekkers (2008) and Luzzi, Flückiger e Weber (2008). Earlier studies that sought to uncover underlying factors that impacted poverty, however, can be traced back to Whelan et al. (2001) and Nolan e Whelan (1996).

Nolan e Whelan (1996) sought to understand the relationship between deprivation and income, and made use of FA methods to uncover what aspects impacted poverty for Irish families. The resulting factors were deprivation on basic items, secondary items, and housing items. The study did not seek to estimate multidimensional poverty, but was a building block for following studies. With these results, the authors used Ordinary Least Squares regression on the determinants of the scores on each factor. Similarly, Whelan et al. (2001) used a similar approach to understand the relationship between monetary income and life-style deprivations, making use of FA to estimate how this relationship impacted households' perceptions of economic strain, for several countries in the European Union. The dimensions of poverty in this instance are basic life-style deprivations, secondary life-style deprivations, housing facilities, housing deteriorations, and environmental problems.

Dekkers (2003) builds on this approach and unites FA previously used in the aforementioned studies with CA methods, with a different objective. The authors argue that the previous methods suppose previously which individuals are poor and which are not, and argues that, by uniting both FA and CA, they are able to find the latent structure based on the results of the estimations and not *a priori* imposed thresholds. Moreover, according to Dekkers (2003), making use of the suggested two-step approach permits that the factors hold the same weight and that dimensions for multidimensional poverty are not impacted by having more variables in comparison to others and that making use of factor scores solves the problem with standardizing variables in the clustering process. The analysis was complemented with a survival analysis model to help explain poverty better. The procedure was applied for seven European countries, and found common underlying factors that compose poverty are material deprivation and housing circumstances.

Following the same methodology, Dekkers (2008) used the Panel Set of Belgian Households for the years 1994 to 2000. The underlying factors of multidimensional poverty in that instance were material deprivation, social deprivation, and psychological health. The author also ran a complementary log-log model of the probability of a non-poor individual becoming poor in up to seven years. The indicators that increase the likelihood of being poor were not having a job, not being Belgian, having poor health, low education, and living with another poor individual.

At last, Luzzi, Flückiger e Weber (2008)'s approach is very similar to Dekkers (2003). Using the Swiss Household Panel data from 1999 to 2003. The uncovered factors of multidimensional poverty were financial poverty, poor health, bad neighborhood, and social exclusion. The analysis was complemented with a complementary log-log model, where characteristics such as being divorced and unemployed showed up as strong predictors of the individual being multidimensionally poor.

This dissertation makes use of methods proposed by Dekkers (2003), Luzzi, Flückiger e Weber (2008) and Dekkers (2008) to create a multidimensional poverty measure, but brings the discussion further by focusing on the elderly, as, according to Sen (2010), more vulnerable groups such as the elderly should be given special attention by researchers. The research will also provide evidences on multidimensional poverty for the elderly in Brazil, which is somewhat scarce.

BOX 1 – EMPIRICAL STUDIES ON MULTIDIMENSIONAL POVERTY

Authors	Country	Data	Years	Methods	Focus	Dimensions
Trani, Biggeri e Mauro (2013)	Afghanistan	National Disability Survey in Afghanistan	2004 and 2005	A-F method	Children	Health, care, family assets, food security, social inclusion, education, freedom from exploitation, shelter, personal autonomy and mobility
Wüst e Volkert (2012)	Germany	German Socioeconomic Panel	2009 and 2010	A-F method	Children	Education/leisure, health, social participation, income poverty,
Hu, Han e Liu (2022)	China	China Family Panel Survey	2012, 2014 and 2016	A-F method	Elderly	Standard of living, health, social inclusion, subjective well-being
Li, Ke e Sun (2023)	China	China Health and Retirement Longitudinal Survey	2012 to 2018	A-F method	Middle-aged and elderly	Income, living consumption, material well-being, social participation, health, psychological well-being
Amarante e Colacce (2022))	Chile, Colombia, Paraguay, El Salvador and Uruguay	Longitudinal Social Protection Survey	2012, 2013 and 2015	A-F method (MPI)	Elderly	Education, labor market and social security, health and housing
Tan, Dong e Zhang (2023)	China	Chinese Longitudinal Healthy Longevity Study	2018	Song et al (2019)	Elderly	Economic poverty, health poverty, rights poverty and spiritual poverty
Cihlar, Micheel e Mergenthaler (2023)	Germany	German Health Update	2014 to 2015	Confirmatory factor analysis	Elderly	Income poverty, limitations, multimorbidity, mental problems and living alone
Barros, Carvalho e Franco (2006)	Brazil	PNAD	1993 and 2003	Synthetic indicator based on IDH	General population	Vulnerability, access to knowledge, access to labor, resource scarcity, child development, living needs

Silva et al. (2016)	Brazil	PNAD	2006 to 2012	Bourguignon and Chavravarty (2003)	General population	Food and water, communication and information, education, housing conditions, health, labor and demographics
Hwang e Nam (2020)	South Korea	Korea Welfare Panel Study	2015	Counting approach	General population	Money, health, housing, employment, social protection and social relations
Chan e Wong (2020)	Hong Kong	Trends and Implications of Poverty and Social Disadvantages in Hong Kong		Structural Equation Modeling	General population	Deprivation, social exclusion and subjective poverty
Dekkers (2003)	Denmark, Belgium, France, UK, Italy, Portugal and Finland	European Community Household Panel	1996 to 2000	FA + CA	General population	Material position and housing circumstances
Dekkers (2008)	Belgium	Panel Set of Belgian Households	1994 to 2000	FA + CA	General population	Material deprivation, social deprivation and psychological health
Luzzi, Flückiger e Weber (2008)	Switzerland	Swiss Household Panel	1999 to 2003	FA + CA	General population	Financial poverty, poor health, bad neighborhood, social exclusion
Bersisa e Heshmati (2021)	Ethiopia	Ethiopian Socioeconomic Survey	2011 and 2014	based on A-F method	General population	Consumption expenditure, health facilities, education, housing facilities, asset ownership and energy use
Ugur (2016)	Turkey	Survey of Income and Living Conditions	2010	FA + CA	General population	Financial deprivation, housing deprivation and health deprivation
Costa (2003)	Brazil	PAD	2011	MPI	Minas Gerais state	Education, health, standard of living,

Silva, Sousa e Araujo (2017)	Brazil	PNAD	2006 to 2013	Bourguignon and Chavravarty (2003)	North region	Food and water, communication and information, education, housing conditions, health, labor and demographics
Trani et al. (2015)	Morocco and Tunisia	Primary data collection	2013 to 2014	A-F Method	People with disabilities	Health, education, employment, household-level material well-being, social participation, psychologial well-being and physical security
Solaymani, Vaghefi e Kari (2019)	Malaysia	Employee Provident Fund	2016-2017	A-F method	Retirees	Health, education, living standard and economic activity
Zhang e Imai (2024)	China	China Family Panel Studies	2010 to 2018	A-F method	Rural population	Education, health, living standard, food security and income
Bourguignon e Chakravarty (2003)	Brazil	PNAD	1981 and 1987	Bourguignon and Chavravarty (2003)	Rural population	Income and education
Chen e Leu (2022)	Taiwan	Taiwan Longitudinal Study of Aging	1999 and 2003	A-F method	Elderly	Health, ability, medical care, social participation and economic security
Whelan et al. (2001)	European Union	European Community Household Panel	1994	FA	General population	Basic life-style deprivation, second life-style deprivation, housing facilities, housing deterioration, environmental problems
Nolan e Whelan (1996)	Ireland	ERSI Irish Survey	1987	FA	General population	Basic items, secondary items and housing items

SOURCE: Prepared by the author.

3 DATA AND METHODS

This section provides an in-depth examination of the data source utilized in this study, including its design and the information contained within the datasets. Additionally, it delves into the methods employed, factor analysis and cluster analysis, their characteristics and steps taken.

3.1 DATA

Data used in this work is from the Brazilian Longitudinal Study of Aging (ELSI-Brazil), organized and collected by the Osvaldo Cruz Foundation in Minas Gerais (Fiocruz-MG) and the Federal University of Minas Gerais (UFMG). ELSI-Brazil is part of a group of studies based on the Health and Retirement Study (HRS) from the United States, that focuses on evaluating the process of aging within a population, their health and socioeconomic and psychological determinants, with counterparts from China, England, Mexico, among others. [3]

ELSI-Brazil is a nationally representative study and the design of the sampling used three selection stages (municipalities, census tracts and households) and made use of an inverse sampling design. Information regarding the design of the study is explained thoroughly in Lima-Costa et al. (2023) and Lima-Costa et al. (2018). The respondents are adults at least 50 years old from 70 municipalities in the five regions of Brazil. There are two waves of the research: the first one, collected between 2015 and 2016, and the second between 2019 and 2021. They are comprised of, respectively, 9,412 and 9,949 respondents.

The ELSI-Brazil was approved by the Ethics Committee of the Oswaldo Cruz Foundation - Minas Gerais and the process is registered on Plataforma Brasil (CAAE: 34649814.3.0000.5091). Participants signed separate informed consent forms for each of the research procedures and authorized access to corresponding secondary databases.

Table 1 shows selected summary statistics from both waves of the research. A majority of the respondents' households earn between one and five minimum wages in Brazil in both waves. Considering 2025 exchange rates, the minimum wage for 2016 was R$ 880, around US$ 150 and the minimum wage for 2021 was R$ 1.100, roughly US$ 190. The percentage of households with income of less than a minimum wage in Brazil has risen from around 13% to almost 20%. Over 70% of them have 8 or fewer years of schooling. The survey includes several questions on health, which significantly enhance our ability to understand the well-being of the elderly. For instance, about half of the sample has been diagnosed with hypertension, while all selected diseases observed a reduction in diagnosis among the sample.

[3] More information regarding ELSI-Brazil can be found at https://elsi.cpqrr.fiocruz.br/

TABLE 1 – SUMMARY STATISTICS OF THE RESPONDENTS OF ELSI-BRAZIL

Category	Subcategory	First Wave		Second Wave	
		%	SE	%	SE
Age	50-59	43.18	0.0062	41.73	0.0070
	60-69	31.92	0.0058	31.79	0.0059
	70-79	16.73	0.0044	17.77	0.0043
	80-89	7.09	0.003	7.18	0.0028
	90+	1.13	0.0011	1.53	0.0013
Sex	Male	46.05	0.0062	45.61	0.0067
	Female	53.95	0.0062	54.39	0.0067
Region	North	5.56	0.0026	6.68	0.0031
	Northeast	24.10	0.0051	28.16	0.0052
	Southeast	47.19	0.0062	43.24	0.0057
	South	16.55	0.0049	13.30	0.0036
	Mid-West	6.60	0.0025	8.61	0.0027
Schooling	<8 years	73.10	0.0056	71.60	0.0064
	8-11 years	8.26	0.0035	7.40	0.0035
	>12 years	18.64	0.005	21.0	0.0061
Health	Hypertension	52.35	0.0063	49.16	0.0068
	Diabetes	15.77	0.0045	17.75	0.0054
	Depression	18.55	0.0048	13.04	0.0044
	Cancer	5.29	0.0027	4.52	0.0035
Income	<1 MW	12.99	0.0040	19.81	0.0051
	1-5 MW	68.73	0.0058	70.0	0.0062
	5-10 MW	13.03	0.0044	7.72	0.0039
	10-15 MW	3.13	0.0024	1.61	0.0019
	15-20 MW	1.01	0.0014	0.49	0.0010
	20-25 MW	0.38	0.0007	0.25	0.0008
	>25 MW	0.73	0.0011	0.11	0.0005

SOURCE: Prepared by the author with data from ELSI-Brazil
NOTE: Minimum wage (MW) considered as R$ 880 in the first wave an R$ 1.100 in the second wave

Both waves of ELSI-Brazil were collected through two interviews, the first one being the household interviews, with information regarding: 1) house characteristics, including structure, accessibility, sanitation, and adherence of the household to the Family Health Program [4]; 2) assets, that cover ownership of houses, household appliances and vehicles, domestic employees in the household, mortgages, rent, and house market value; 3) household expenses, that go into detail about money spent by the family on groceries, eating out, utility bills, condominium fees, transport, gas, phone and internet bills, leisure, car and household taxes, education, and health insurance; 4) residents' income, where each resident's income in the household is broken down into the possible different streams of income and how much it entails to, including salaries, cash transfers, pensions, income from rent and savings, and whether the household income is sufficient for their monthly expenses. It is important to note that the household interview is answered by any adult that is apt give information regarding the household and its members.

Following the household interview is the individual interview, in which any member of

[4] The Family Health Program is a national health policy first introduced in 1994 as part of the Sistema Único de Saúde (SUS), the public health system in Brazil, in order to aid expansion and consolidation of basic health access. The program proposes the establishment of family health teams, composed of a primary healthcare physicians, nurses, nursing technicians and community health agents to be responsible for around 3,000 individuals.

the household that is at least 50 years old is eligible to answer. The question groups cover information as follows: 1) sociodemographic characteristics, such as marital status, family structure, color, education, and enrollment in extracurricular courses; 2) neighborhood structure and issues, such as violence, sanitation, crime, and perceptions of safety; 3) discrimination, that covers perception and experience with ageism, ableism, racism, religious prejudice, aporophobia, LGBT-phobia; 4) life and health history, with information on the subject's childhood health, poverty, housing, and health history; 5) work and retirement, work history, if the respondent had contributed to the Brazilians' public or private pension schemes, present employment, retirement, after retirement plans; 6) family member's support, that asks if the respondent has given or received help — such as taking care of someone who is sick — from relatives, and if the respondent has given or received financial help; 7) health behaviors, that covers the respondent's behaviors regarding physical activities, sedentary behaviors, eating habits, alcohol consumption and smoking; 8) women's health, with information on reproductive health, periods, pregnancies, miscarriages, and children; 9) general health and diseases, with questions regarding health perception, sight problems, broken bones, accidents such as falls, chronic diseases, e.g. diabetes, high blood pressure, heart diseases, and several other ailments that impact the elderly more prominently, frailty's phenotype, exhaustion, sleep quality, pain; 10) oral health, if they have their natural teeth, any pain, prosthesis, implants or issue with their teeth; 11) functioning, that cover the individual's ability to perform basic, instrumental and advanced activities related to day-to-day living; 12) cognition, with memory tests; 13) cognition by a proxy respondent to evaluate other's perception of the elderly in question' memory; 14) depressive symptoms, such as loneliness and pleasure for life; 15) psychosocial, that asks about social relations and support, subjective well-being and if they have gone through stressful events, religiousness, and autonomy; 16) use of medicine, if the respondent's uses any medicine regularly, how much is spent on them and if it is hard to get a hold of them; 17) use of health services, if they use private health insurance, how much they pay for it, recent doctor's visits and hospitalizations, and money spent on health.

Health measurements and tests were also taken by the study, such as anthropometric tests, weight, height, and blood pressure. They also carried out walking, grip strength, and balance tests. Although not available in the data set provided by Fiocruz, blood samples were collected on the first wave, as well as saliva samples for DNA testing on the second. (LIMA-COSTA et al., 2023; LIMA-COSTA et al., 2018)

The datasets of ELSI-Brazil were initially raw, containing inconsistencies and missing values. To ensure usability and reliability of the datasets to reach the objective of this study, thorough data cleaning and organization were performed by removing duplicates, handling missing data and standardizing entries.

In short, the information available in the ELSI-Brazil datasets provides a comprehensive overview of life among the elderly in Brazil, with focus on aspects that impact their lives directly. The broadness of the information allows for a more comprehensive analysis of poverty among the Brazilian elderly.

3.2 METHODS

Having established that poverty is a multidimensional issue, where individuals can accumulate deprivations across various aspects, and that it is advisable that the evaluation of poverty be done with as little subjective choices as possible, the present two-step procedure aims to achieve that goal.

The first step consists on making use of factor analysis (FA). It is often applied when researchers have a large set of observations and intend to find if the dataset contains common factors, which allows for the reduction of information being dealt with. FA is done through the calculation of a correlation matrix, where items with a high correlation with each other are understood to be influenced by a common factor. Common factors are defined as unobservable constructs that influence the variables being used. Having established the factors, it is possible to analyze the factor loadings, which provide information on the strength and direction of influence that these factors have on the original variables. (FABRIGAR; WEGENER, 2011).

The second proposed step consists of applying a cluster analysis (CA) method based on the factor scores resulted from FA. Cluster analysis allows for the separation of the data into groups of more or less similar observations — for example, people. The aim of this method is to have groups as different as possible, containing observations as similar as possible within these groups. The two-step procedure will estimate multidimensional poverty, and was used by Dekkers (2003), Dekkers (2008), and Luzzi, Flückiger e Weber (2008) with that goal. Given the survey at hand, this procedure allows the data to speak for itself, as per Luzzi, Flückiger e Weber (2008). In this case, factor analysis could help determine what constitutes poverty, and the cluster analysis will discern which individuals from the sample are poor and what differs them from the non-poor individuals.

A third method is used in this study. In addition to the two-step procedure proposed to measure multidimensional poverty, a complementary log-log model is used with the clusters that resulted from the CA and a number of variables not previously included, in order to evaluate what are the socioeconomic determinants of multidimensional poverty.

The present section relies heavily on Hair et al. (2018) for the detailed description of the methods being applied in this dissertation. Fabrigar e Wegener (2011), Garson (2022) and Hennig et al. (2020) were also used to support the detailing of these methods. In the case of complementary log-log models, the discussion relies on Agresti (2012) and Dunn, Smyth et al. (2018).

3.2.1 Factor Analysis

As per Garson (2022), it is advisable to, when making use of factor analysis methods, apply exploratory factor analysis (EFA) to construct a base model, especially if the researchers are interested in uncovering the underlying structure of a dataset, without assuming prior theory. EFA methods are also useful to test the optimal number of factors and help weed out weak indicators.

Factor analysis methods are commonly used to analyze patterns within complex datasets and to reduce these datasets into smaller, condensed factors while minimizing information loss, in an attempt to uncover the latent structure of the dataset. (HAIR et al., 2018)

Mathematically, factor analysis can also be defined through a model such as, in matrix notation:

$$x = \Lambda f + u + \mu \tag{3.1}$$

In which x is a random vector of length $(p \times 1)$ that includes all variables, Λ is a matrix of factor loadings with size $(p \times k)$ and both $f(k \times 1)$ and $u(p \times 1)$ are random vectors as well. The latter vectors represent the common and unique factors that influence the variables in the dataset, respectively. (LUZZI; FLÜCKIGER; WEBER, 2008; MARDIA, 1979)

Extracting the latent factors in a dataset can be done through several methods, but they follow, in general, the same methodological procedures. When designing a factor analysis, Hair et al. (2018) suggests that, the primary requirement is the construction of a correlation matrix. With that in mind, the best-fitted variables for this case are metric variables. If non-metric variables are to be included in the analysis, it is suggested that they should be transformed into dummy variables.

Another option for the use of different types of variables is to construct alternative correlation matrices that provide better results, as opposed to the commonly used Pearsonian correlation matrices. As is the case of this dissertation, where most variables of interest are ordinal variables, it is advised to construct polychoric correlation matrices. (OLSSON, 1979; GARSON, 2022)

Sample size is also of importance when applying factor analysis. Hair et al. (2018) suggest that a sample should, preferably, have 100 or more observations. The ratio of observations to variables should be, according to the authors, 10:1.

Before applying factor analysis in itself, it is advised to test the dataset's factorability - if the dataset is in fact comprised of underlying factors and if it is possible to reduce them into these factors effectively. A commonly applied measure is the Kaiser-Meyers-Olkin (KMO) test, a measure of sampling adequacy that ranges from zero to one, one being when the variable is perfectly predicted by other variables in the dataset of interest. The measure can increase as the sample size, average correlation and number of variables increase, as well as if the number of factors decreases. (GARSON, 2022; HAIR et al., 2018)

According to Garson (2022), a dataset's KMO should be 0.60 or higher for either the dataset in general. This threshold can be expanded to the individual variables as well, and it is advised that any variables with an MSA lower than 0.60 should be dropped. Hair et al. (2018) propose that MSAs with values of 0.8 or higher are meritorious; 0.6 or above, mediocre and below 0.5, unacceptable.

After confirming that the dataset at hand can be adequately factored, the next step is to select the preferred factor extraction model. The most common are principal component analysis (PCA) and common factor analysis, also known as factor analysis, the latter being the method of choice in the present work. These methods differ mainly through the use of different variances when extracting the factors. A factor's variance is the total dispersion of values for a variable when compared to its mean.

The variance for a variable can be split into three parts: Common variance, which is shared by all variables in the data being analyzed; unique variance is, on the other hand, the variance associated with a single variable and that is not represented in the correlations among variables. The unique variance of a variable is consequently divided into two: unique specific variance, that is the variance that is related to unique aspects of the variable and error variance, that remains unexplained by neither the correlation among variables, nor the specific characteristics of a variable, being derived from measurement error or random components in the data, for example. PCA methods make use of total variance when extracting factors, while FA is based on the variables' common variance measures. (HAIR et al., 2018)

The number of factors chosen should be the best combination of variables, where it accounts for more variance than any other combination of variables. In the best combination, the first extracted factor is the one that best summarizes the linear relationships in the dataset, while the second is the second-best, and so on. Furthermore, the factors should be orthogonal to each other — that is, the second factor should be the linear combination of variables that account for the most variance still unexplained after extracting the first factor and removing its effects. (HAIR et al., 2018)

According to Fabrigar e Wegener (2011), the optimal choice of the number of factors is one of the still unresolved challenges within exploratory factor analysis, with vast literature devoted to developing mechanisms to indicate the number of factors to use in EFA. While no single tool is indicated to be used on their own, it is advisable to apply a mix of them to achieve a more trustworthy result. Among the most commonly used stopping rules for choosing the number of factors to be extracted are: the Kaiser criterion, the scree test, the parallel analysis and the percentage of variance criterion, of which the first three were used in this study.

The Kaiser criterion, also known as the latent root criterion, involves calculating the eigenvalues for all variables being factored and counting how many of these values are equal or higher than one, with this sum being the indicated number of factors to be extracted. If the dataset has a large number of variables, the Kaiser criterion may extract too many factors. In this case, Hair et al. (2018) suggest that this criterion should be used as a starting point in selecting the number of variables.

The scree test Cattell (1966) creates a graph with the same eigenvalues calculated in the Kaiser criterion. According to this test, the number of factors to be extracted is the one that precedes, graphically, the last major drop in eigenvalues. (FABRIGAR; WEGENER, 2011) In other words, as Hair et al. (2018) put, one should use the inflection point, also known as elbow, to select the number of factors.

Parallel analysis is considered as a middle ground in terms of subjectiveness when compared to the use of scree plots and the Kaiser rule. This criterion compares eigenvalues from a sample data with those obtained from simulated random data, and the number of factors indicated should be the sum of eigenvalues from the real data that are higher than the random sample.

The percentage of variance criterion is based on reaching a specified cumulative percentage of total variance upon extracting successive factors. This ensures that the factors will explain at least a specified amount of variance, although a threshold is not established. In the social sciences, it is common to consider solutions that account for at least 60% of the total variance as satisfactory.

With the preliminary steps taken, the first beginning step into applying factor analysis methods is to estimate a factor matrix, which will contain the factor loadings for each variable on each factor. In other words, factor loadings are the correlation between each variable to each factor. Having higher loadings suggests that the variable in case is representative of the factor, and they also help in the interpretation of the role each variable plays into the factor's definition.

Since loadings are the correlations between variable and factor, the variance for each variable can be calculated as usual, by getting the squared loading. The higher the loadings, the more important they are. Hair et al. (2018) suggests that factor loadings of less than 0.10 can be considered null when evaluating factor structure; loadings between 0.3 and 0.4 meet the minimal acceptable level for structural interpretation; 0.5 or higher are practically significant and those above 0.7 indicate a well-defined structure. Though these values are useful benchmarks for defining a factor structure, the authors point out that smaller loadings might need to be included if given a larger sample size or a large number of variables being analyzed.

Having examined the factor matrix in its entirety, the following step is to construct the factor structure by placing each variable on the factor where it has the highest holdings following a selected threshold, which can be based on the literature or chosen by the researcher. This step is in theory simple if each variable is significant to a single factor. If that is not the case and cross-loading occurs, where a variable has significant factor loadings in multiple factors, this issue can be solved through applying different rotation methods — explained below — to improve variable distribution among the factors. If the problem persists, the variable in question might have to be excluded from the analysis. Yong e Pearce (2013) argues, on the other hand, that the researcher may retain the variable with cross-loading if it seems that it is naturally related to both factors; if the variable makes for a more difficult interpretation, then it can be considered for exclusion.

If needed, factor solutions can be rotated with the goal of simplifying and improving the interpretation of the solutions by allowing simpler and more meaningful solutions to be found while reducing ambiguities. Hair et al. (2018) argues that factor rotation may be the most important tool when interpreting factors. Rotating factors means that the reference axis for each factor is turned around its origin to find new positions, while redistributing the variances to make the solution more meaningful. The most common types of factor rotation are orthogonal, in which the axes are fixed at 90 degrees, and oblique rotation. The latter, where the axes are not necessarily kept at 90 degrees to rotate, is considered more flexible and realistic, given it does not suppose factors are not correlated, as orthogonal rotations does.

Some statistics can be used to grasp model fit and how well it represents the original correlation matrix used in the FA. Root Mean Square of Residuals (RMSR) measures the difference between the original and the reproduced correlation matrices, where a lower value indicates a better fit. Garson (2022) suggests that, by rule of thumb, RMSR indexes lower than 0.05 indicate a good fit. Mean item complexity measures how each variable contributes to simple factor structure, where simpler models make them more easily interpretable. According to Garson (2022), a model with mean item complexity of <1.5 fits the criterion. Complexity can also be calculated for each variable. Fit based off diagonal values is a type of pseudo-r2 measure, which can be defined as, per Garson (2022):

$$(1 - resid^2/cor^2) \tag{3.2}$$

Where *resid* values belong to the residual matrix, and *cor* ones belong to the correlation matrix. This measures how well the off-diagonal elements of the correlation matrix are reproduced in the factor model. The closer to 1, the better the model fit in this instance.

Other useful measures to consider when evaluating FA model fit and structure are communality, uniqueness. Communality is the sum of the squared factor loadings in all factors for a specific variable, which show the importance of each factor in explaining the variance of each variable. Garson (2022) argues that communalities should not be too low, but that this may happen if there are several observations and variables included in the FA; while uniqueness is simply 1 - communality. These values provide insight into the reliability of the factor structure.

Upon analysis of the results, there may arise a need to re-specify the model by removing non-significant variables from the analysis; changing rotation methods; changing the number of factors being extracted or even changing the extraction method to reach the best solution possible. To validate the model, replication, or the application of a confirmatory analysis is suggested.

3.2.2 Cluster Analysis

Cluster Analysis (CA) methods are a group of multivariate data analysis tools in which the main objective is to discover groups within data sets by aggregating observations into clusters based on their characteristics and how similar the observations are to each other. Most often, CA methods are applied with the aim of either achieving data reduction or generating hypotheses. Similarly to FA, CA evaluates the data structure, often in an exploratory manner, to better understand the data. However, these methods differ in the fact that CA groups observations based on distance or similarity measures, while FA groups variables using correlation measures. (HENNIG et al., 2020; HAIR et al., 2018; JOHNSON; WICHERN et al., 2002)

Separating observations into clusters should produce results that are internally homogeneous — in other words, observations within the same cluster should be as similar to each other as possible — while simultaneously being externally heterogeneous — as in, clusters should be as different to each other as possible. Graphically, this means that objects that belong to the same cluster should be plotted close to each other, while different clusters should be distant to each other. (HAIR et al., 2018)

CA methods do not necessarily assume assumptions about the group structure or number of groups. Similarly, CA methods are not necessarily statistically heavy, despite having strong mathematical properties. This means they do not depend on probability models. (JOHNSON; WICHERN et al., 2002; HAIR et al., 2018) Hair et al. (2018) assert that CA models should have a strong conceptual basis to be able to deal with issues that may arise, especially since CA methods will create clusters regardless of whether the data have an inherent structure in itself.

The research design for CA should take a few issues into consideration before putting the methods into action. First, CA methods supply better results if a single type of variables — either metric or nonmetric — are put into use, though methods can handle if mixed variables are used. The cluster variate — in other words, the group of variables being used in the analysis — faces bigger issues with the increase of variables. This issue can be dealt with the use of other data reduction methods, such as exploratory factor analysis. Applying EFA methods prior to CA can also aid with multicollinearity, which can bring implicit weighing to the variables and observations in the sample, by using factor scores resulting from EFA. (HAIR et al., 2018)

Cluster variates are mathematical representations of the set of chosen variables that are used to compare similarities between objects. As opposed to other multivariate techniques, the cluster variate is defined by the researcher.(HAIR et al., 2018)

As is with other multivariate data analysis methods, CA methods should consider the issue of sample size, though not for statistical inference, but because there exists a trade-off between sample size and representation. Hair et al. (2018) argues that the researcher should make sure the sample used is a good representation of the population in question.

Another issue to take note is if the data should be standardized to calculate the similarities, since the CA methods are somewhat sensitive to different scales among variables, and having variables with larger dispersions might affect the results. To scale variables, one can make use of the most common method of standardization, which is to subtract the mean and divide the by the standard deviation of each variable, reaching a mean of 0 and a standard deviation of 1. This makes the analysis easier, and helps to diminish effects of the scale differences within and across variables. (HAIR et al., 2018; HENNIG et al., 2020)

If all variables follow the same scale, then standardizing is not necessary. This is the case in this dissertation, since the data used in the CA are the resulting factor scores (HENNIG et al., 2020). According to Dekkers (2003), the use of factor scores negates the need for standardizing variables.

The methodological procedure for CA methods proceeds with the calculation of similarity measures for each pair of observations. This allows for the comparison of each observation with any other in the sample, based on the characteristics it holds. There are several ways to calculate similarity in a data set, but the most common are distance measures, where the proximity of two observations indicates how similar they are to each other. According to Hair et al. (2018), distance measures actually represent how dissimilar two observations are. In this sense, higher distance measures indicate dissimilarities between observations.

Among distance measures, the Euclidean distance is the most popular and is the one used in this study. To get the Euclidean distance between two observations, one must have its coordinates to be able to calculate the length of the hypotenuse of a right triangle. The distance can be summed as:

$$d(X,Y) = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \tag{3.3}$$

The resulting distance measure calculated for the sample can be displayed as a similarity matrix, in which each observation's distance to the other observations in the data set is shown. The similarity matrix, in conjunction with the selected variables, are then used to derive the clusters. Hair et al. (2018)

Clusters are then derived through partitioning procedures, of which the most common are hierarchical and non-hierarchical clustering procedures. While non-hierarchical clustering procedures depend on the researcher making an *a priori* decision regarding the number of clusters, assigning each observation to one of the specified clusters. On the other hand, hierarchical clustering procedures will combine observations into a tree structure, following a series of $n-1$ clustering decisions. The latter kind of procedures can be divisive, in which all observations begin by belonging to the same cluster, and are successively divided until each observation belongs to its own cluster. Following an inverse logic, agglomerative methods begin with each observation being its own cluster.Then, the most similar objects are grouped, and so on, until all observations belong to a single cluster. A type of clustering procedure, average-linkage, was used in this study, discussed below. Hierarchical procedures can be graphically demonstrated in a dendogram, which shows how the clustering designation is made, though they can become increasingly hard to decipher in large data sets. (HAIR et al., 2018; JOHNSON; WICHERN et al., 2002)

There are several clustering algorithms, each differing in how they define similarity to merge clusters when using agglomerative procedures. Among the most common are single-linkage, complete-linkage, and average-linkage. In the single-linkage procedure, similarity is defined as the shortest distance between any object in one cluster and any object in another. In contrast, complete-linkage considers the longest distance between observations in two clusters. The average-linkage procedure differs from the first two by avoiding reliance on extreme values; it defines similarity between clusters as the average distance between all individuals in one cluster and all individuals in another. This approach tends to produce clusters with smaller variations and more balanced within-cluster variance, and it was eventually used in this study.

To select the number of clusters, a stopping rule must be put into use. They allow the comparison of solutions to reach a final, optimal one. Stopping rules generally concern the trend of change of heterogeneity — that is, how different observations from the same cluster are from each other — across solutions to identify when marked changes happen.

Among the stopping rules available for CA methods, there are those that measure heterogeneity changes, as well as those that measure heterogeneity directly. These stopping rules work as indices to aid in determining the validity of the cluster solution. (HAIR et al., 2018; CHARRAD et al., 2014)

There are several rules proposed with this goal, among those, one of the most common is the pseudo F statistic. First introduced by Caliński e Harabasz (1974), this statistic was originally brought forward to aid researchers in selecting the number of clusters optimally while reducing computational load, specially in taxonomy studies.

The optimal number of clusters (q) resulting from the pseudo F statistic maximizes $pseudo-f(q)$. This can be defined as below, according to Charrad et al. (2014):

$$pseudo-f(q) = \frac{trace(B_q)/(q-1)}{trace(W_q)/(n-q)} \tag{3.4}$$

Where q stands for number of clusters, n is the number of observations. The term B_q is the between-group dispersion matrix for q clusters, defined as:

$$B_q = \sum_{k=1}^{q} nk(c_k - \overline{x})\top \tag{3.5}$$

Similarly, W_q is the within-group dispersion matrix for q clusters

$$W_q = \sum_{k=1}^{q} \sum_{i \in C_k} (x_i - c_k)(x_i - c_k)\top \quad (3.6)$$

The pseudo t^2 statistic is also widely adopted among CA applications. It is derived from the Duda-Hart rule, proposed by Duda e Hart (1973), to decide if a cluster should be split into two smaller clusters by comparing the within-cluster sum of squared errors ($Je(1)$) with the within-cluster sum of squared errors when the cluster is split into two sub-clusters ($Je(2)$) in a simple ratio, $Je(2)/Je(1)$. In other terms,

$$Duda = Je(2)/Je(1) = W_k + W_l/W_m \quad (3.7)$$

In which W_m is the within-cluster squared error in the case of a single cluster, and W_k and W_l stand for the within-cluster squared errors of the sub-clusters. The pseudo t^2 index derives from the Duda-Hart rule and is defined as, according to Charrad et al. (2014):

$$pseudo{-}t^2 = \frac{W_m - W_k - W_l}{\frac{W_k + W_l}{n_k + n_l - 2}} \quad (3.8)$$

The selection of optimal number of clusters in this case should take into account the pseudo t^2 index and, if there is a jump of the pseudo t^2 at q clusters, then the optimal number of clusters is $q+1$.

In this dissertation, both the pseudo-t^2 and the pseudo-f statistic were used to reach the optimal number of clusters. In our case, the indexes propose differing numbers of clusters, Luzzi, Flückiger e Weber (2008) and Dekkers (2008) suggest finding a middle ground. With the optimal number of clusters suggested, the researcher should focus on verifying if the solution is valid. Ideally, the clusters should be significantly different from each other, and this can be checked through the cluster centroid, that is, a mean profile of the cluster for each variable of the analysis to evaluate how each cluster fares in each variable of interest. If a cluster solution shows no discernible difference between clusters in their mean profile, it might be an indicator of the need to re-specify the model, for example.

3.2.3 Complementary log-log models

A third method is proposed for this dissertation, a complementary log-log model, in which the results of the Cluster Analysis are considered the dependent variable, and several characteristics of interest other than those in previous methods are the independent variables. Complementary log-log models belong to the family of generalized linear models, of which the most common are binary response models, such as logit, probit, and the model used here, complementary log-log. These models are useful when the dependent variable of interest represents a proportion, and complementary log-log is particularly useful in the case where the proportion of zeroes and ones is heavily skewed. (AGRESTI, 2012; DUNN; SMYTH et al., 2018)

Some studies that applied complementary log-log models in similar contexts to the present work are Luzzi, Flückiger e Weber (2008), Dekkers (2008) and Dekkers (2003).

Modeling binary response data demands alternative regression procedures, as they face restrictions that are not easily solved when applying linear probability models. A binomial regression model can be defined generically as:

$$\pi_i = F(x_i'\beta) \tag{3.9}$$

In which π_i represents a probability - that ranges between 0 and 1 -, F denotes a cumulative distribution function and the predictor of a vector of variables $x_i'\beta$ that can be represented at any given value. This model faces restrictions due to the fact that both of the terms are not subject to the same range of values. A solution to this problem is to transform the probability on the left side into odds of the model as to remove its range restriction, while also modeling this transformation as a linear function. The model can be transformed:

$$F^{-1}(\pi_i) = x_i'\beta \tag{3.10}$$

The inverse F^{-1} is called a link function. Among the most common of the possible transformation are logit and probit links. However, the transformation proposed in this work is the complementary log-log, which uses a Gumbel cumulative distribution function. Complementary log-log link can be described, according to Dunn, Smyth et al. (2018) as:

$$\eta_i = log(-log(1-\pi_i)) \tag{3.11}$$

With that, the regression model for binary data with complementary log-log links is defined as:

$$log(-log(\pi_i)) = x_i'\beta \tag{3.12}$$

Though similar, complementary log-log models differ from logit and probit mainly because the latter are symmetry. While logit and probit are symmetric around 0.5, where the probability π_i reaches 0 at the same rate it reaches 1 - complementary log-log approaches 0 gradually and 1 more sharply. This characteristic makes it particularly useful for modelling binary responses that are highly skewed towards one outcome, as is the case in this dissertation. The resulting coefficients in the complementary log-log models can be understood as the effects the covariates have on the latent variable. (AGRESTI, 2012)

Complementary log-log models are especially useful in the case that the dependent variables being examined are binary, and that the number of zeroes and ones are highly skewed towards one outcome. This is the case of the results being found so far, where the number of multidimensionally poor people in the samples is much lower than the number of those who are not poor. Having such skewed outcomes for the dependent variable may reduce the quality of the results if more traditional binary response models, such as logit and probit, are used.

The variables used in the complementary log-log models adopted in this work are: gender, age, marital status, number of children, education, working status, retirement, race, mother's education and if the individual lives in a rural or urban area. These are common variables used in the literature to help determine the socioeconomic determinants of poverty, and will be used with the same goal here. (LUZZI; FLÜCKIGER; WEBER, 2008; DEKKERS, 2008).

4 RESULTS

This section is split into two parts: the first describes the results found when estimating the multidimensional poverty following the FA and CA methods presented in the Data & Methods section; the second section follows with the detailing of the determinants of multidimensional poverty as it was previously estimated, with the use of the complementary log-log regression model.

4.1 ESTIMATING MULTIDIMENSIONAL POVERTY

4.1.1 Factor Analysis

The procedures described in the Data and Methods section were implemented. Although ELSI-Brazil has two waves collected in different years, both samples were pooled due to the lack of access to individual identifiers. Originally, 150 variables of the around one thousand variables present in the original samples were selected based on their suitability to the methods being used, and their similarity to variables used in previous studies employing comparable methodologies.

Of the original 150 variables, 25 were discarded due to a high number of NA responses. Since FA requires complete observations to compute, these variables were dropped to maximize the number of observations included in the FA. The remaining 125 variables were used in a first iteration of the EFA, and 44 were also dropped since they did not present loadings of at least 0.4 in any factor and thus, were not fit for the method, as explained in the Data & Methods section. This first iteration contained several variables related to the diagnosis of diseases, specially those most predominant in the elderly population, but only three variables had significant loadings: if the respondent had undergone hip replacement surgery, experienced a stroke, or been diagnosed with Parkinson's disease.

Chosen variables were altered so that higher values meant a worse situation for the respondent. In practice, observations with the most negative scores will signify that the person in question is better off regarding the factor. Alterations were also made to variables from the disability section — in the first wave of the research, most questions from this section had the answers in a scale, in which 1 represented no difficulty and 4 represented being unable to do said action; whereas in the second wave, the answers were simplified to being binary. To make sure the variables are useful in this study, the first wave disability variables were transformed into binary, as to match the rest of the answers.

The second iteration of the EFA took 81 variables into consideration, described below, in Table 2. Of the 19,361 respondents of the ELSI-Brazil questionnaire, 14,930 observations were used after omitting any NA responses. The results of the KMO test show an overall MSA of 0.93, which suggests that the data set is highly factorable. None of the variables have an individual MSA lower than 0.6, which, according to Garson (2022), would indicate the need to drop the variable in question.

Although this study focuses on the elderly—defined in Brazil as individuals aged 60 and older—the sample includes all respondents, including those under 60, to maximize the number of observations. However, robustness checks were conducted to assess whether the extended sample could reliably be used to draw conclusions about the elderly population.

TABLE 2 – DESCRIPTIVE STATISTICS VARIABLES USED IN FA

CODE	VARIABLE	MIN	MAX	MEAN	SD
a8	Street's house is paved*	0	1	0.205	0.404
b9	Own a refrigerator*	0	1	0.011	0.105
b15	Own dishwasher*	0	1	0.988	0.11
b17	Own microwave*	0	1	0.440	0.496
b19	Own color TV*	0	1	0.032	0.176
b21	Own VHS/DVD/similar*	0	1	0.623	0.485
b23	Own landline*	0	1	0.621	0.485
b25	Own mobile phone line*	0	1	0.898	0.302
b27	Own air-conditioner*	0	1	0.843	0.364
b29	Own computer*	0	1	0.677	0.468
b32	Own cable TV*	0	1	0.684	0.465
b35	Own any vechiles*	0	1	0.577	0.494
b38	Hired domestic workers*	0	1	0.919	0.273
f17	Would like to move from current house	0	1	0.200	0.4
g4_1	Has been a victim of discrimination in a medical setting	0	1	0.08	0.272
g4_2	Has been a victim of discrimination in social gatherings	0	1	0.032	0.177
g4_3	Has been a victim of discrimination in the workplace	0	1	0.025	0.155
g4_4	Has been a victim of discrimination in the family	0	1	0.034	0.181
g4_5	Has been a victim of discrimination due to place of living	0	1	0.035	0.184
n1	Health status	1	5	2,600	0.909
n24	Has surgery to replace a hip joint	0	2	0.010	0.114
n52	Had a stroke	0	1	0.039	0.194
n62	Has Parkinson's disease	0	1	0.006	0.077
o2	Currently need dental treatment	0	1	0.492	0.5
p6	Trouble walking 1km continuously	0	1	0.341	0.474
p7	Trouble walking 100m	0	1	0.190	0.392
p8	Trouble climbing several flights of stairs	0	1	0.517	0.5
p9	Trouble climbing one flight of stairs	0	1	0.275	0.447
p10	Trouble sitting still for 2 hours	0	1	0.282	0.45
p12	Trouble stooping, kneeling or crouching	0	1	0.492	0.5
p13	Trouble extending arms above shoulder	0	1	0.175	0.38
p14	Trouble pulling/pushing large objects	0	1	0.280	0.449
p15	Trouble lifting and carrying weights heavier than 5kg	0	1	0.316	0.465
p16	Trouble picking up a coin from a table	0	1	0.083	0.275
p17	Trouble doing personal hygiene	0	1	0.031	0.174

Continued on next page

CODE	VARIABLE	MIN	MAX	MEAN	SD
p20	Trouble preparing a hot meal	0	1	0.045	0.207
p24	Trouble using any type of transportation	0	1	0.141	0.348
p26	Trouble doing shopping	0	1	0.107	0.309
p28	Trouble using phone	0	1	0.086	0.281
p30	Trouble taking/managing medication	0	1	0.079	0.27
p22	Trouble managing money	0	1	0.059	0.235
p33	Trouble performing light housekeeping	0	1	0.087	0.282
p35	Trouble performing heavy housekeeping	0	1	0.282	0.45
p37	Trouble getting across from a room	0	1	0.037	0.189
p40	Trouble getting dressed	0	1	0.068	0.251
p43	Trouble taking a shower	0	1	0.030	0.169
p46	Trouble eating	0	1	0.010	0.1
p49	Trouble getting in and out of bed	0	1	0.054	0.227
p55	Trouble using the bathroom	0	1	0.020	0.141
p70	Kept contact with other people in the last 12 months*	0	1	0.280	0.449
p71	Visited friends/family in the last 12 months*	0	1	0.254	0.435
p72	Had friends/family over in the last 12 months*	0	1	0.285	0.451
p73	Went out with other people in the last 12 months*	0	1	0.562	0.496
p76	Used the computer in the last 12 months *	0	1	0.776	0.417
p77	Drove in the last 12 months *	0	1	0.729	0.445
p80	Went on a short trip in the last 12 months *	0	1	0.641	0.48
r2	Felt depressed most of the time in the last week	0	1	0.221	0.415
r3	Felt that things were more difficult most of the time in the last week	0	1	0.424	0.494
r4	Felt sleep was not restful in the last week	0	1	0.383	0.486
r5	Felt happy most of the time *	0	1	0.203	0.403
r6	Felt lonely most of the time	0	1	0.267	0.442
r7	Felt pleasure most of the time *	0	1	0.203	0.402
r8	Felt sad most of the time	0	1	0.287	0.452
r9	Felt unable to keep going most of the time	0	1	0.280	0.449
s38	Feels free to make future plans (frequency)*	1	3	0.622	0.718
s40	Does things they wish to (frequency)*	1	3	0.649	0.633
s42	Can look for activities they enjoy (frequency)*	1	3	0.704	0.697
s43	Health prevents from doing what they'd like (frequency)	1	3	1,830	0.742
s44	Financial problems prevent from doing what they'd like (frequency)	1	3	2,090	0.721
s45	Wait enthusiastically for each (frequency)*	1	3	0.438	0.631
s46	Feels life has a meaning (frequency)*	1	3	0.272	0.524
s47	Likes what they do (frequency)*	1	3	0.245	0.475
s48	Likes to be in the company of other people (frequency)*	1	3	0.295	0.516
s49	Feels happy about what has lived (frequency)*	1	3	0.336	0.55
s50	Feels full of energy (frequency)*	1	3	0.442	0.582
s51	Likes to do new things (frequency)*	1	3	0.413	0.587
s52	Feels satisfied with achievements (frequency)*	1	3	0.315	0.512
s53	Thinks life is full of opportunities (frequency)*	1	3	0.379	0.555
s54	Feels optimistic about the future (frequency)*	1	3	0.409	0.594
t1	Takes medicine regularly or continuously	0	1	0.689	0.463

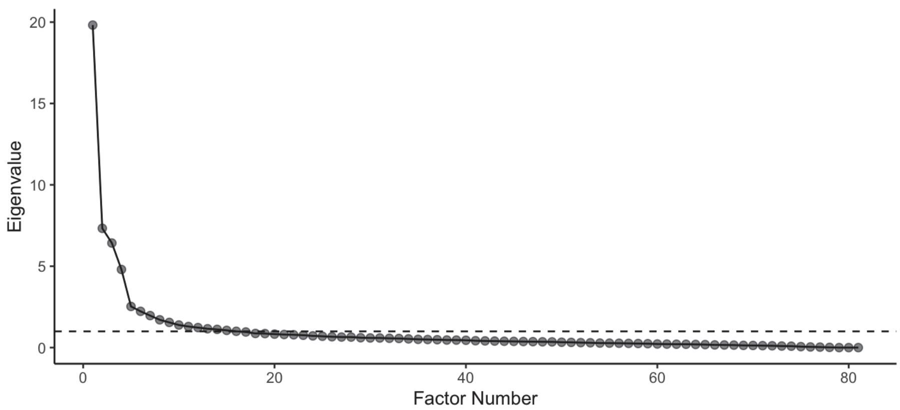
Continued on next page

CODE	VARIABLE	MIN	MAX	MEAN	SD
u1	Covered by private health insurance	1	2	0.215	0.411

SOURCE: Prepared by the author with data from ELSI-Brazil

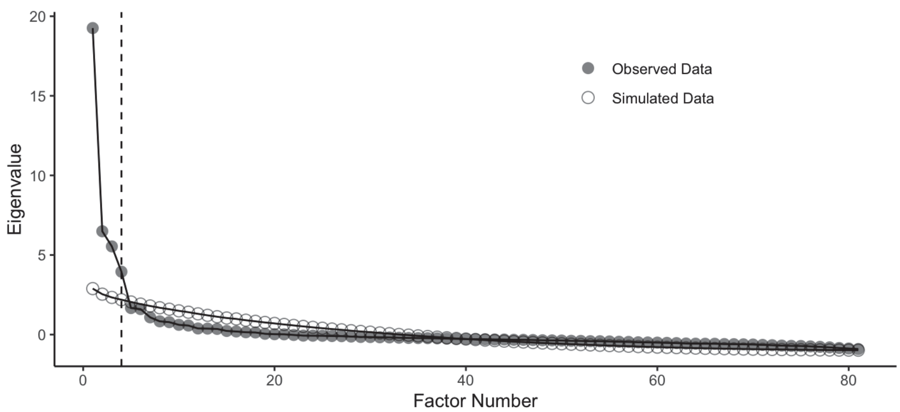
Following in the steps for EFA is the choice for the number of factors to be extracted. The criteria applied in this study, as suggested by the literature and discussed in the previous section, include the Kaiser criterion and the scree test. The Kaiser criterion suggests selecting 28 factors, as 28 variables had eigenvalues over 1. Since the data set contains many variables, this result is considered as a starting point. The scree plot, built with the eigenvalues, shows that the 'elbow' — or the number of factors that precede the last major drop, graphically — indicates the existence of four factors, as shown in Figure 1. The results of the parallel analysis also suggest that four is the optimal number of factors, as displayed in Figure 2.

FIGURE 1 – SCREE PLOT



SOURCE: Prepared by the author with data from ELSI-Brazil

FIGURE 2 – PARALLEL ANALYSIS PLOT



SOURCE: Prepared by the author with data from ELSI-Brazil

Factor Analysis was thus performed with four factors. The coefficient estimation method used in this study was ULS, a minimal residual method, as suggested by Knol e Berger (1991). A *promax* rotation was also used, which is a type of oblique rotation method (HENDRICKSON; WHITE, 1964). The resulting loadings are presented in Table 3. The first factor presents high loadings on variables regarding health, such as *Health status*, *Had surgery to replace hip joint*, *Had a stroke* and *Has Parkinson's disease*, as well as most variables that cover functionalities of the individual, such as *Trouble waking*, *Trouble doing personal hygiene* and *Trouble performing housekeeping*, for example. In short, the first factor can be summed as regarding Health and Functionalities. The second factor presents high loadings on variables that are related to the respondent's own psychosocial evaluation in regards to their life, such as *Does things they wish to*, *Likes what they do* and *Feels optimistic about the future* and it can be labeled as Psychosocial. The third factor is related to ownership of goods in general, specially house appliances, as well as participation in paid activities. Some of the variables with high loadings on the third factor are *Own computer*, *Owns any vechiles*, *Went out with other people*, *Went on a short trip*. Indeed, this factor could be labelled as Living Standards. At last, the fourth factor presents variables with high loadings on questions about episodes of discrimination in several instances and depressive symptoms, such as *Felt depressed most of the time*, *Felt unable to keep going*. As such, this factor may be named Depressive Symptoms.

TABLE 3 – FACTOR LOADINGS

Var	MR1	MR2	MR3	MR4	Var	MR1	MR2	MR3	MR4
a8	0.013	0.117	0.498	0.015	p33	0.895	-0.016	-0.023	-0.002
b9	-0.142	-0.058	0.556	0.135	p35	0.827	0.02	-0.086	-0.007
b15	-0.064	-0.194	0.547	0.193	p37	0.883	-0.001	0.013	-0.132
b17	-0.024	-0.123	0.7	0.093	p40	0.843	-0.127	-0.098	0.115
b19	-0.078	-0.006	0.561	-0.034	p43	0.918	-0.091	-0.085	0.014
b21	-0.05	0.132	0.457	-0.183	p46	0.766	-0.021	-0.011	0.041
b23	-0.061	-0.087	0.682	0.021	p49	0.863	-0.081	-0.023	0.016
b25	-0.052	-0.037	-0.52	0.198	p55	0.901	-0.072	-0.034	-0.003
b27	-0.001	-0.016	0.472	0.05	p70	-0.039	0.169	0.536	-0.198
b29	0.002	-0.037	0.805	-0.087	p71	0.171	0.207	0.36	-0.149
b32	0.03	-0.075	0.606	0.035	p72	0.02	0.177	0.413	-0.035
b35	0.014	0.02	0.61	-0.02	p73	0.185	0.071	0.575	-0.062
b38	-0.257	0	0.501	0.168	p76	0.174	-0.038	0.777	-0.163
f17	-0.024	-0.02	-0.04	0.426	p77	0.255	0.047	0.453	-0.019
g4_1	0.018	-0.078	-0.051	0.576	p80	0.108	0.118	0.454	-0.097
g4_2	-0.072	0.015	-0.024	0.549	r2	0.118	0.176	-0.027	0.682
g4_3	-0.204	-0.043	-0.066	0.613	r3	0.153	0.056	-0.027	0.649
g4_4	-0.017	-0.014	-0.032	0.58	r4	0.207	0.044	-0.072	0.563
g4_5	-0.079	-0.047	0.017	0.579	r5	0.031	0.377	-0.03	0.525
n1	0.425	0.097	0.129	0.162	r6	0.077	0.161	0.008	0.646
n24	0.401	-0.028	-0.086	-0.139	r7	0.062	0.421	0.055	0.41
n52	0.402	-0.02	0.007	0.037	r8	0.104	0.193	0.003	0.697
n62	0.43	0.001	-0.066	-0.128	r9	0.218	0.148	0.116	0.501
o2	-0.008	-0.063	-0.014	0.38	s38	-0.004	0.54	0.015	-0.038
p6	0.764	0.109	0.004	-0.102	s40	0.046	0.526	-0.007	0.017
p7	0.796	0.12	0.009	-0.142	s42	0.019	0.547	-0.012	0.011
p8	0.723	0.073	0.002	-0.033	s43	0.47	0.015	0.121	0.066
p9	0.753	0.066	0.078	-0.08	s44	0.117	-0.052	0.156	0.357
p10	0.459	-0.053	0.005	0.214	s45	-0.072	0.652	0.026	-0.014
p12	0.737	-0.031	-0.087	0.069	s46	-0.094	0.782	0.054	0.031
p13	0.607	-0.019	-0.013	0.156	s47	-0.07	0.846	-0.006	-0.033
p14	0.779	0.048	0.001	0.004	s48	-0.116	0.657	0.024	0.013
p15	0.772	0.031	-0.025	0.051	s49	-0.126	0.696	-0.047	0.106
p16	0.554	0.052	0.103	-0.025	s50	0.128	0.729	-0.099	0.071
p17	0.809	-0.041	0.017	0.041	s51	0.051	0.724	-0.059	-0.119
p20	0.873	-0.036	-0.004	-0.04	s52	-0.069	0.826	-0.056	0.049
p24	0.88	-0.125	-0.019	0.034	s53	-0.057	0.759	-0.018	0.011
p26	0.829	-0.064	0.052	0.045	s54	-0.001	0.727	-0.081	0.067
p28	0.498	-0.127	0.276	0.074	t1	0.421	0.044	-0.215	-0.052
p30	0.531	-0.116	0.114	0.164	u1	0.085	0.056	-0.599	-0.087
p22	0.582	-0.075	0.058	0.118					

SOURCE: Prepared by the author with data from ELSI-Brazil

Other FA statistics show a good RMSR index, which is 0.05, at the limit of what is considered a good fit. Mean item complexity also is within bounds, being 1.2 (1.5 is the suggested threshold); as well as the fit based off diagonal values, that is 0.96 in this instance, while authors suggest it should be as close to 1 as possible. (GARSON, 2022) Table 4 shows that the cumulative variance for the model in question is 0.45, which is quite low for the standard suggested by Garson (2022), 0.60. The EFA was also applied for a subsample that excluded individuals who were younger than 60 years old, to verify if the factor structure changed significantly for both samples. The factor loadings, detailed in Appendix A show that the factor structure does not change much between the two groups. Hence, the original results that included all respondents were used in this study in order to make use of the full sample.

TABLE 4 – VARIANCE

	Factor 1	Factor 2	Factor 3	Factor 4
SS loadings	16.368	7.138	7.017	5.771
Proportion Var	0.202	0.088	0.087	0.071
Cumulative Var	0.202	0.290	0.377	0.448
Proportion Explained	0.451	0.197	0.193	0.159
Cumulative Proportion	0.451	0.648	0.841	1

SOURCE: Prepared by the author with data from ELSI-Brazil

Table 5 presents the values for communalities, uniqueness and complexity measures for the FA model at use. The communalities in general seem to be low for the usual standards for social sciences, but Garson (2022) suggests that this might happen in instances with a high number of either variables and observations, which is the case of the data being used. Complexity for each variable indicates how well the variable in question correlates to a simple factor structure, where if the value is one, then the variable loads well into only one factor. While the values for complexity in the sample are usually higher than one, most do not seem to load highly on two factors.

Factor structure results found in this work shows some resemblance to studies that applied the same methods, though these were not focused on multidimensional poverty for the elderly population. Dekkers (2008) found, for Belgium, that the underlying factors impacting multidimensional poverty were Material Deprivation, Social Deprivation and Individual Psychological Health. A similar case is described in Luzzi, Flückiger e Weber (2008), where the dimensions for poverty in this instance for Switzerland were Financial Poverty, Poor Health, Bad Neighborhood and Social Exclusion. In turn, Dekkers (2003) found only two common factors for several European countries, that were Material Conditions and Living and Housing Conditions.

Some dimensions uncovered in this dissertation are also considered in other works (BARROS; CARVALHO; FRANCO, 2006; SILVA et al., 2016; COSTA; COSTA, 2014) with different methods for Brazil, such as living standards and health, which could indicate the importance of these factors in the Brazilian context

The FA results are also in concordance with studies that do focus on the elderly, but that apply other methods for multidimensional poverty evaluation. Issues regarding social participation

TABLE 5 – COMMUNALITY, UNIQUENESS, AND COMPLEXITY OF FA

Var	Communality	Uniqueness	Complexity	Var	Communality	Uniqueness	Complexity
a8	0.231	0.769	1.113	p33	0.781	0.219	1.002
b9	0.301	0.699	1.279	p35	0.659	0.341	1.023
b15	0.32	0.68	1.549	p37	0.724	0.276	1.045
b17	0.475	0.525	1.1	p40	0.705	0.295	1.112
b19	0.295	0.705	1.047	p43	0.778	0.222	1.037
b21	0.252	0.748	1.528	p46	0.595	0.405	1.008
b23	0.432	0.568	1.051	p49	0.709	0.291	1.02
b25	0.303	0.697	1.317	p55	0.762	0.238	1.016
b27	0.227	0.773	1.025	p70	0.353	0.647	1.499
b29	0.627	0.373	1.028	p71	0.273	0.727	2.516
b32	0.366	0.634	1.042	p72	0.239	0.761	1.376
b35	0.381	0.619	1.005	p73	0.44	0.56	1.265
b38	0.268	0.732	1.751	p76	0.667	0.333	1.197
f17	0.171	0.829	1.029	p77	0.347	0.653	1.606
g4_1	0.325	0.675	1.054	p80	0.279	0.721	1.358
g4_2	0.28	0.72	1.04	r2	0.612	0.388	1.199
g4_3	0.333	0.667	1.255	r3	0.526	0.474	1.129
g4_4	0.324	0.676	1.009	r4	0.44	0.56	1.315
g4_5	0.308	0.692	1.052	r5	0.497	0.503	1.83
n1	0.351	0.649	1.611	r6	0.528	0.472	1.155
n24	0.131	0.869	1.35	r7	0.464	0.536	2.078
n52	0.17	0.83	1.022	r8	0.643	0.357	1.199
n62	0.156	0.844	1.228	r9	0.489	0.511	1.687
o2	0.138	0.862	1.059	s38	0.288	0.712	1.011
p6	0.602	0.398	1.077	s40	0.295	0.705	1.018
p7	0.647	0.353	1.111	s42	0.305	0.695	1.004
p8	0.544	0.456	1.025	s43	0.299	0.701	1.177
p9	0.603	0.397	1.06	s44	0.205	0.795	1.662
p10	0.308	0.692	1.445	s45	0.407	0.593	1.029
p12	0.542	0.458	1.049	s46	0.604	0.396	1.042
p13	0.446	0.554	1.134	s47	0.675	0.325	1.017
p14	0.635	0.365	1.008	s48	0.408	0.592	1.067
p15	0.631	0.369	1.014	s49	0.463	0.537	1.123
p16	0.361	0.639	1.092	s50	0.601	0.399	1.12
p17	0.666	0.334	1.011	s51	0.513	0.487	1.078
p20	0.72	0.28	1.008	s52	0.649	0.351	1.031
p24	0.736	0.264	1.044	s53	0.55	0.45	1.013
p26	0.71	0.29	1.026	s54	0.527	0.473	1.042
p28	0.39	0.61	1.769	t1	0.174	0.826	1.548
p30	0.381	0.619	1.396	u1	0.343	0.657	1.102
p22	0.396	0.604	1.138				

SOURCE: Prepared by the author with data from ELSI-Brazil

seem to be a preponderant feature in multidimensional poverty among the elderly population, as they are dimensions that were used to measure multidimensional poverty in Hwang e Nam (2020), Li, Ke e Sun (2023), Chen e Leu (2022) e Cihlar, Micheel e Mergenthaler (2023), for example. Psychological well-being and living standard are common dimensions in studies regarding the elderly as well. They are considered in Li, Ke e Sun (2023), Cihlar, Micheel e Mergenthaler (2023), Solaymani, Vaghefi e Kari (2019) e Zhang, Ma e Wang (2021).

Though it belongs to its own dimension in Chen e Leu (2022), functionalities has been discussed among the elderly, which are included in the Health and Functionalities factor in the present work, using questions regarding Basic Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL), a group of tasks of differing levels of physical exertion that help build a picture of how a person is faring regarding these activities and their independence to do so.

Table 6 shows correlation coefficients between the four factors. All factor seem to be mildly correlated with each other, presenting lower correlations only between the Depressive Symptoms factor with Psychosocial and Financial Deprivation. None of the factor have a negative correlation with others. In general, these results show similarity to Luzzi, Flückiger e Weber (2008) e Dekkers (2008), with low, but positive correlations among factors.

TABLE 6 – INTER FACTOR CORRELATIONS

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1.00	0.30	0.27	0.34
Factor 2	0.30	1.00	0.24	0.17
Factor 3	0.27	0.24	1.00	0.12
Factor 4	0.34	0.17	0.12	1.00

SOURCE: Prepared by the author with data from ELSI-Brazil

4.1.2 Cluster Analysis

Following FA results, CA used the factor scores to evaluate how similar the respondents in the sample are to each other and how they can be split considering their inherent characteristics. The factor scores were not standardized to reduce discrepancy in the values, since the use of factors already imply a standardization of the variables being used. The distance measured applied was the Euclidean, the most common distance measure, and the clustering method used was the average method, which is a measure that, compared to single and complete linkage clustering algorithms, avoids relying on extreme values and results in more well-balanced clusters, as was discussed previously on the Data and Methods section.

To select the optimal number of factors, the pseudo-f and pseudo-t^2 indices were applied, and those were presented in Table 7. The pseudo-f index should be maximized, which occurs with five clusters. The pseudo-t^2 index exhibits a jump, as mentioned in the Data and Methods section at the third cluster, which would indicate a four-factor solution. Similar discrepancies in the optimal number of clusters have been found by Luzzi, Flückiger e Weber (2008) e Dekkers (2008). In this case, Luzzi, Flückiger e Weber (2008) suggests finding a compromise in which the general rules for the indices are followed, as is the case for the five factors solution since it is preceded by a high pseudo-t^2 index, despite it not being the highest index provided.

TABLE 7 – STATISTICS FOR DETERMINING NUMBER OF CLUSTERS

Cluster	Pseudo-F	Pseudo-t^2
1		50.316
2	50.316	7.034
3	31.289	2253.287
4	775.129	737.466
5	790.786	91.996
6	664.647	2.094
7	554.859	331.963
8	532.734	785.473
9	586.891	15.245
10	524.972	48.696

SOURCE: Prepared by the author with data from ELSI-Brazil

The average scores of the four factors, shown in Table 8, suggest that the largest cluster, the first one, scores low on all factors, indicating they are not impacted negatively by variables that belong in the factor. The second and third clusters imply that individuals that belong to these groups are somewhat affected by some factors: the second factor has an average score of 4.77 in the first factor, that represents health and functionalities; and 1.41 in the fourth factor, the one regarding discrimination and depressive symptoms. A third cluster, smaller than the second, indicates a deprivation specially high in the third factor, ownership of goods and participation in paid activities, with a slightly smaller average score on the discrimination and depressive symptoms factor.

Though the optimal solution presented by the tests was of five clusters, the fourth and fifth show only two and one individuals, respectively. These clusters can be considered as outliers, since they are very small. (LUZZI; FLÜCKIGER; WEBER, 2008; DEKKERS, 2008) Therefore, it is assumed that the cluster with the most individuals is the first cluster, which is corroborated with the fact that their mean score shows negative results for all factors. This implies that only around 3% — considering both clusters 2 and 3 — of individuals from the sample are multidimensionally poor, a somewhat low proportion for Brazil, though similar results have been found in Luzzi, Flückiger e Weber (2008). Dekkers (2008) also find more than two clusters with different characteristics regarding multidimensional poverty.

Although multidimensional poverty measures have been gradually accepted in the literature, monetary poverty is still a useful, simpler and the most commonly used way to visualize poverty. As Sen (2010) argues, having an inadequate income is a strong condition to living a poor life, though it is not unique.

TABLE 8 – AVERAGE SCORE ON EACH FACTOR

Clusters	Factor 1	Factor 2	Factor 3	Factor 4	Obs.	%
1	-0.0963	-0.0296	-0.0574	-0.0407	14499	97.11%
2	4.778	1.208	0.988	1.413	281	1.89%
3	0.279	0.564	3.746	1.179	147	0.99%
4	6.663	1.322	1.997	7.081	2	0.01%
5	0.220	4.423	0.583	5.360	1	0.00%

SOURCE: Prepared by the author with data from ELSI-Brazil

With this in mind, Costa (2003) proposes that it is useful to compare both measures. If they do not show significant differences with each other, then the traditional monetary poverty measure should be preferred as it is the simplest approach. On the other hand, if the measures present different sets of individuals considered poor, then a closer to look to both measures should be given as to find what is the most adequate one between the two.

For example, Bersisa e Heshmati (2021) analyzes both uni and multidimensional poverty in Ethiopia, and found that multidimensional poverty incidence was not only higher (80% as opposed to 36% of unidimensionally poor households) but that the monetary measure in use understated the extent of poverty and all aspects it impacted lives of the poor. Similarly, Luzzi, Flückiger e Weber (2008) also compares poverty determinants for Switzerland, and though results seem to be similar, the authors found that different aspects such as marital status and having children, for example, impact the likelihood of being poor in the two measures.

For this sample, the incidence of unidimensional income-based poverty is at 6.10%, considering poor those that the household income per capita is below R$ 154 for respondents from the first wave and R$ 178 for the second wave, which is the poverty line determined by the Brazilian Federal Government for 2015 and 2019, respectively, so that families are eligible to receive cash transfers. (UNICEF, 2023)

In comparison, those considered multidimensionally poor consist of 2.88% of the respondents used in this analysis, while the financially poor are around double that. While these results are not comparable with each other, since they consider different aspects — the multidimensional poverty measure is a relative one, while financial poverty is an absolute measure — they show, according to Dekkers (2008) that the risk of being financially poor is usually higher than being multidimensionally poor, and these results are in concordance with the literature that applied the same methods.

Table 9 shows that only 50 individuals from the sample are considered both multidimensionally and financially poor; 860 are only financially poor, and 378 are only multidimensionally poor. Among the elderly in the sample, 1.84% of them were multidimensionally poor, while 2.73% were financially poor. When comparing average factor scores for these four groups, it is clear that those who are not poor in any measure show lower factor scores — and therefore lower deprivations in the four underlying factors uncovered in this study. Individuals who are poor in both measures have higher average factor scores, especially in the third factor, that covers Living

Standards, as expected. In the case of the individuals who are only financially poor, all average factors are close to zero, with low negative averages for Health and Functionalities and Depressive Symptoms and low positive averages for Psychosocial and Living Standards, which can mean that this group is not heavily affected by any factor of the analysis. At last, those who are only multidimensionally poor show higher averages on the Health and Living Standards factors.

It is also important to note that there is no clear pattern that shows that belonging to the poor cluster would indicate being financially poor; and that being financially non-poor would not mean a person is faring well in the factors selected for multidimensional poverty evaluation. A similar result was found in (LUZZI; FLÜCKIGER; WEBER, 2008).

TABLE 9 – AVERAGE SCORES FOR MULTIDIMENSIONAL AND FINANCIALLY POOR INDIVIDUALS

Group	Factor 1	Factor 2	Factor 3	Factor 4	Obs.
Financially Poor	-0.114	0.119	0.031	-0.017	860
Multidimensionally Poor	3.418	0.971	1.846	1.310	378
Financially and Multidimensionally Poor	1.807	1.107	2.609	1.506	50
Not Poor	-0.095	-0.039	-0.063	-0.042	13,639

SOURCE: Prepared by the author with data from ELSI-Brazil

Although the focus of this study is on elderly poverty, the sample includes individuals of at least 50 years old. When comparing average factor scores by age group on Table 10, the youngest groups — individuals aged from 50-59 and from 60-69 — show negative scores on most factors, which implies they are not deprived in them. As the individuals get older, their average factor scores also increase, especially on the Health and Living Standards factors, which suggest these factors grow in importance as the individuals grow older. It is also of note, however, that the Depressive Symptoms factor presents negative scores starting from the 60-69 age group, implying this factor does not influence multidimensional poverty as much for older individuals.

TABLE 10 – AVERAGE FACTOR SCORES BY AGE GROUP

Age	Factor 1	Factor 2	Factor 3	Factor 4	Multidimensionally Poor	Financially Poor
50-59	-0.145	-0.057	-0.121	0.199	153	502
60-69	-0.068	-0.031	-0.017	-0.043	109	259
70-79	0.191	0.077	0.159	-0.208	109	111
80-89	0.559	0.236	0.273	-0.349	47	36
90+	0.969	0.405	0.723	-0.243	10	2

SOURCE: Prepared by the author with data from ELSI-Brazil

4.2 SOCIOECONOMIC DETERMINANTS OF MULTIDIMENSIONAL POVERTY

While having established the underlying factors regarding multidimensional poverty is important, this does not imply that the socioeconomic determinants of multidimensional poverty are known yet. For that, the next step of this dissertation is to estimate what variables influence if someone is to be considered poor or not, with the use of a complementary log-log model, described above in the Data and Methods section.

Independent variables included in the model should be reasonable causes of poverty, as per Luzzi, Flückiger e Weber (2008). In their study, variables related to human capital, age, gender, nationality, household consumption, marital status, among others, were included, as well as several dummy variables in an attempt to capture the effect of different years on poverty. Here, the variables selected for the complementary log-log model were: gender, age, marital status, number of children, education, race, and mother's education, as well as dummy variables regarding whether the individual is retired, working, and if the respondents live in an urban area. Descriptive statistics for the chosen variables can be found in the Appendix B.

For the education variable, where answers ranged from 'never went to school' to having a doctorate, education levels were split into groups: from 0 to 8 years, which entails elementary education, 9 to 11 years, which relates to high school and above 12 years, any number of years having attended a college or university. Mother's education original possible responses were split differently into having unfinished or finished elementary, middle, high school or had a college degree. These answers were also standardized into the aforementioned groups: from 0 to 8 years; from 9 to 11 and 12 upwards years of education. The number of children variable consists of the number of children the respondent had throughout their lifetime.

Results for the regression are shown in Table 11. Four different regressions were estimated with the aim of visualizing the landscape of poverty among the elderly in Brazil more broadly. Costa (2003) argues for the comparison of multidimensional and monetary poverty measures, especially in the cases that the measures seem to categorize different people in the different measures in order to find the better approach. With that in mind, the same variables were used in four different regression models with either different poverty measures as dependent variables, or different age groups being considered. The first is considered multidimensional poverty as a dependent binary variable with the entire sample; the second regression used monetary poverty as a dependent variable. Regressions three and four are heterogeneity checks and differ from the first two in the fact that they only consider individuals of at least 60 years old. The Akaike Information Criterion shows, upon first glance, that the multidimensional poverty models are better than their counterparts, since lower AICs indicate better models.

The results show that some variables are consistent in their effects on both poverty measures. Firstly, the Intercept suggests that the likelihood of being poor for those with the reference categories, such as being White and Single, is low in all models. Having children seems to increase the probability of being poor; and actively working by the time of answering the research acts to reduce poverty in all measures. The models also show that, in general, men are more likely to be poor than women. In turn, Marital Status acts in similar ways for both measures of poverty and for both age samples: the estimates show that being married reduces the likelihood of being poor, and being widowed when compared to single individuals. However, distinct differences show up in other instances, that suggest how the profile of poor individuals changes not only between multidimensional and monetary poverty, but also between age samples.

TABLE 11 – COMPLEMENTARY LOG-LOG MODEL

	Multidimensional	Monetary	Multidimensional (60+)	Monetary (60+)
	(1)	(2)	(3)	(4)
Gender	0.362***	0.269***	0.107	0.230*
	(0.116)	(0.082)	(0.153)	(0.129)
Age				
50-59	−0.958**	0.447		
	(0.397)	(0.718)		
60-69	−1.505***	0.270	−1.641***	0.176
	(0.388)	(0.715)	(0.392)	(0.719)
70-79	−1.227***	0.017	−1.299***	0.002
	(0.384)	(0.718)	(0.384)	(0.720)
80-89	−1.021**	−0.124	−1.056***	−0.106
	(0.402)	(0.739)	(0.401)	(0.739)
Race				
Black	0.356*	0.016	0.082	−0.138
	(0.190)	(0.134)	(0.258)	(0.211)
Brown	0.329**	−0.044	0.334**	−0.097
	(0.128)	(0.085)	(0.161)	(0.130)
Yellow	0.752	−0.233	0.738	−0.258
	(0.590)	(0.576)	(0.721)	(0.713)
Indigenous	0.953***	−0.515	0.930**	−1.307
	(0.312)	(0.385)	(0.428)	(1.007)
Children	0.064***	0.082***	0.056***	0.053**
	(0.018)	(0.016)	(0.022)	(0.025)
Marital Status				
Married	−0.702***	−0.586***	−0.676***	−0.662***
	(0.167)	(0.111)	(0.238)	(0.184)
Divorced	0.015	−0.168	0.061	−0.384*
	(0.194)	(0.134)	(0.271)	(0.221)
Widowed	−0.407**	−0.336**	−0.374	−0.432**
	(0.201)	(0.152)	(0.251)	(0.208)
Urban area	−0.722***	−0.014	−0.855***	0.636***
	(0.127)	(0.120)	(0.161)	(0.244)
Education				
12+ years	−0.881***	0.262*	−0.361	0.772***
	(0.331)	(0.145)	(0.374)	(0.193)
9-11 years	−0.703***	0.099	−0.956***	0.256
	(0.195)	(0.099)	(0.330)	(0.161)
Working	−0.796***	−0.798***	−0.728***	−0.666***
	(0.161)	(0.093)	(0.259)	(0.168)
Retired	0.105	−1.341***	−0.220	−1.243***
	(0.144)	(0.104)	(0.188)	(0.129)
Mother's Education				
12+ years	−11.940	0.907***	−12.362	1.049**
	(249.919)	(0.301)	(397.417)	(0.431)
9-11 years	−0.089	0.347	−0.748	0.528*
	(0.514)	(0.215)	(1.016)	(0.320)
Constant	−1.765***	−2.398***	−1.160**	−2.824***
	(0.453)	(0.737)	(0.498)	(0.786)
Observations	12,158	12,158	7,169	7,169
Log Likelihood	-1,402.561	-2,406.772	-843.153	-1,127.569
Akaike Inf. Crit.	2,847.123	4,855.543	1,726.306	2,295.138

SOURCE: Prepared by the author with data from ELSI-Brazil
NOTE: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Reference categories is White for Race, Single for Marital Status and <8 years for Education and Mother's Education.

For instance, the likelihood of being multidimensionally poor appears to increase with age. Since the reference category for Age is 90+, all other age groups are less likely to be poor, with high levels of significance. The same cannot be stated for monetary poverty, where Age does not seem to have a statistically significant impact on it. Similar results are found for Race, which appears to be a strong predictor for multidimensional poverty, especially for individuals who are Indigenous and Brown; while only being Indigenous seems to impact monetary poverty with some significance. The only race who does not show significance in any estimation is Yellow. In short, the regression estimates here suggest that while multidimensional poverty has a strong Age and racial component, the same cannot be said for monetary poverty.

Living in either rural or urban areas also impact the likelihood of being poor in differing manners. While, for both samples, living in an urban area reduces the probability of being poor with significance; it actually increases the likelihood of bring financially poor for individuals aged 60 years old and up.

Similar results can be found for education, where it acts to reduce multidimensional poverty. The more education, the less likely someone is to be poor, as is usually expected. Interestingly, mother's education, a common variable used in poverty studies, is not statistically significant for multidimensional poverty. For monetary poverty, however, mother's education seems to increase the likelihood of being poor, with even stronger coefficients for the elderly.

Being retired reduces the likelihood of being financially poor in both models. However, it does not have a significant impact on multidimensional poverty. Notably, for individuals aged 60 and over, being retired, gender and mother's education do not have a significant impact on the likelihood of being multidimensionally poor, as opposed to the estimation for monetary poverty. This suggests that, among the elderly, factors typically associated with poverty determination lose their significance. Consequently, individuals who experienced differing probabilities of poverty at younger ages become equally likely to be poor in old age.

When compared to results found by Luzzi, Flückiger e Weber (2008), the picture of multidimensional and monetary poverty seem to differ. While in this dissertation, the results provide somewhat different results, with some categories acting in opposite ways in the different measures of poverty, Luzzi, Flückiger e Weber (2008) found a much more similar aspect. This can go to show that, for the elderly in Brazil, the aspects of multidimensional poverty differ strongly from traditional monetary poverty measures when poverty is analyzed including the unique aspects covered in this research. These results are also in accordance to the argument made by Sen (2010) that 'real' poverty is more intense than what traditional measures of poverty show.

Table 10 already suggested that not only the financially and multidimensionally poor were different individuals, but that what made them poor or not was intrinsically different, given how the financially poor score low on the latent factors that indeed affected those who were multidimensionally poor, and that landscape is further supported by the results found on the regressions previously presented.

5 FINAL REMARKS

The goal of this dissertation was to develop a multidimensional poverty measure for the elderly in Brazil to better understand the deprivations they face and the factors influencing their likelihood of being poor. Additionally, the multidimensional measure was compared to a traditional monetary poverty metric. To achieve this, a united factor and cluster analysis approach was employed, allowing poverty thresholds to emerge from the data rather than being arbitrarily defined.

The ELSI-Brazil research consisted of nearly a thousand variables, many of those that covered aspects of importance to the life of the elderly, which helped to construct the multidimensional poverty measure considering variables that may not have been included otherwise.

Results show that the factors included in multidimensional poverty among the elderly in Brazil were: Health and Functionalities, Psychosocial, Living Standards and Depressive Symptoms. Considering both clusters of multidimensional poor individuals, they show that the factors that had the highest weight on the measure were Health and Functionalities and Depressive Symptoms, which act in accordance to the literature on the elderly and what aspects of life impact them the most.

A complementary log-log model was estimated to understand better what other characteristics of the individuals impacted the likelihood of them being poor, which aided in creating a bigger picture of what aspects could affect people in the aforementioned factors that created a measure for multidimensional poverty. Regression estimates show that monetary poverty does not seem to have an age component; as opposed to multidimensional poverty, where the likelihood of being poor grows with age.

The findings of this study provide significant insights for public policies, particularly in the context of Brazil's aging population. Policies such as the Continuous Benefit Program (Programa de Prestação Continuada) - a cash transfer program that provides a minimum wage monthly to low-income elderly individuals -, while crucial, primarily address monetary poverty issues, and, as it was discussed in this study, such policies may not be able to deal with the multidimensional deprivation challenges the elderly are subject to.

With that in mind, the results found in this dissertation suggest that public policies aimed at the elderly should adopt a more holistic approach that integrates health, psychosocial well-being and social inclusion when dealing with elderly poverty. For example, policies that focus on enhancing the quality of life of the elderly, such as age-friendly urban planning and community engagement, could be effective in addressing elderly poverty. Expanding and improving existing policies such as the Living Program (Programa Viver) - of which its main goal is to help to promote an active and healthy aging of the population - also can help reduce the impact of the latent factors of multidimensional poverty uncovered here.

Although ELSI-Brazil data does bring to light interesting insights in terms of multidimensional poverty, it is still limited to those aged 50 years old and up. Future research could include data from the National Health Survey (Pesquisa Nacional de Saúde), which provides a representative sample of the entire Brazilian population. However, it is important to note that the National Health Survey is more limited in terms of the number of variables. Notwithstanding, it would be valuable to investigate whether, among the comparable variables, the results remain consistent. In other words, is there a need to develop a poverty measure specific to the elderly, or can a general poverty measure be adapted to incorporate aspects that are particularly relevant for this age group?

Finally, this study showcased the importance of treating elderly poverty through a multidimensional lens while demonstrating the impact of health, psychosocial and economic factors have on the lives of the elderly. Adopting more inclusive and target policies can better address the vulnerabilities this group is subject to and improve their quality of life.

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APPENDIX A – FACTOR LOADINGS FOR SAMPLE 60+

Var	MR1	MR3	MR2	MR4	Var	MR1	MR3	MR2	MR4
a8	-0.018	-0.08	0.487	-0.03	p22	0.647	-0.093	0.044	0.073
b9	-0.123	-0.081	0.569	0.107	p33	0.916	-0.023	-0.051	-0.058
b15	-0.035	-0.204	0.609	0.21	p35	0.818	0.01	-0.114	-0.011
b17	0.001	-0.11	0.703	0.07	p37	0.91	0.007	-0.038	-0.183
b19	-0.053	-0.013	0.585	0	p40	0.855	-0.109	-0.135	0.062
b21	-0.041	0.138	0.466	-0.167	p43	0.95	-0.065	-0.114	-0.073
b23	-0.028	-0.058	0.697	-0.032	p46	0.777	-0.01	-0.021	-0.047
b25	-0.07	-0.051	-0.462	0.169	p49	0.873	-0.074	-0.053	-0.027
b27	0.01	-0.046	0.505	0.057	p55	0.928	-0.059	-0.087	-0.099
b29	-0.021	-0.003	0.798	-0.048	p70	-0.036	0.199	0.492	-0.169
b32	0.04	-0.081	0.627	0.04	p72	0.012	0.173	0.372	-0.007
b35	0.012	0.027	0.604	0.017	p73	0.179	0.073	0.532	-0.027
b38	-0.252	0.011	0.511	0.139	p76	0.152	-0.006	0.766	-0.086
f17	-0.018	-0.034	-0.025	0.405	p77	0.306	0.02	0.433	0.021
g4_1	-0.012	-0.098	-0.023	0.62	p80	0.121	0.141	0.392	-0.104
g4_2	-0.128	-0.009	0.026	0.65	r2	0.151	0.152	-0.006	0.637
g4_3	-0.282	-0.096	0.024	0.703	r3	0.199	0.05	-0.003	0.57
g4_4	-0.089	-0.02	-0.008	0.663	r4	0.247	0.029	-0.037	0.481
g4_5	-0.108	-0.057	0.043	0.66	r6	0.107	0.125	0.041	0.598
n1	0.415	0.107	0.106	0.122	r7	0.091	0.391	0.061	0.323
n59	0.131	0.172	-0.193	0.384	r8	0.131	0.162	0.029	0.65
p6	0.762	0.102	-0.034	-0.104	r9	0.257	0.133	0.134	0.431
p7	0.791	0.128	-0.027	-0.135	s38	0.01	0.523	0.013	-0.05
p8	0.726	0.074	-0.026	-0.079	s40	0.054	0.52	0.018	-0.007
p9	0.759	0.076	0.047	-0.103	s42	0.013	0.549	-0.004	0.021
p10	0.451	-0.063	0.018	0.197	s43	0.454	-0.008	0.098	0.05
p12	0.733	-0.044	-0.092	0.053	s45	-0.067	0.672	0.03	0.004
p13	0.618	-0.026	-0.007	0.108	s46	-0.112	0.791	0.048	0.059
p14	0.777	0.063	-0.021	-0.024	s47	-0.079	0.864	0.008	-0.031
p15	0.78	0.021	-0.029	0.038	s48	-0.149	0.675	0.028	0.011
p16	0.565	0.073	0.1	-0.049	s49	-0.105	0.716	-0.056	0.077
p17	0.83	-0.043	0	-0.026	s50	0.121	0.74	-0.096	0.039
p20	0.891	-0.052	-0.025	-0.085	s51	0.038	0.739	-0.061	-0.121
p24	0.896	-0.137	-0.068	0.005	s52	-0.082	0.858	-0.048	0.015
p26	0.869	-0.065	0.017	-0.008	s53	-0.062	0.785	-0.02	-0.017
p28	0.521	-0.14	0.261	0.028	s54	0.009	0.74	-0.076	0.031
p30	0.589	-0.126	0.084	0.101	u1	0.084	0.044	-0.614	-0.056

SOURCE: Prepared by the author with data from ELSI-Brazil

APPENDIX B – DESCRIPTIVE STATISTICS OF VARIABLES USED IN COMPLEMENTARY LOG-LOG REGRESSION

	MIN	MAX	MEAN	SD
Age	50	109	63.810	9.445
Race	1	5	2.078	1.009
Gender	0	1	0.427	0.495
Marital Status	1	4	2.375	0.906
Children	0	33	3.390	2.513
Education	1	18	6.696	4.343
Retired	0	1	0.552	0.497
Working	0	1	0.317	0.465
Mother's Education	1	6	1.732	1.042
Rural Area	0	1	0.846	0.361

SOURCE: Prepared by the author with data from ELSI-Brazil