ANALYZING THE MULTIDIMENSIONAL STRUCTURE OF POVERTY IN ARGENTINE HOUSEHOLDS°

ANÁLISIS DE LA ESTRUCTURA MULTIDIMENSIONAL DE LA POBREZA EN LOS HOGARES ARGENTINOS

*Adrian Moneta Pizarro**

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Abstract

A key issue in the design of multidimensional poverty measures is whether they should include a monetary poverty indicator. A common argument for treating income poverty separately from non-monetary poverty is that they reflect distinct dimensions of the phenomenon. This study explores the multidimensional structure of poverty in Argentina and assesses whether monetary poverty should be considered an additional indicator of multidimensional poverty using generalized structural equation modeling (GSEM). Drawing on categorical data from the Permanent Household Survey (EPH), it applies a generalized confirmatory factor analysis (GCFA) model and a GSEM with a second-order factor. The GCFA assumes that monetary poverty constitutes a dimension of poverty, while the GSEM posits that monetary poverty causes non-monetary poverty. The findings indicate that both models fit the data well; however, the results more strongly support the view that non-monetary factors serve as indicators of a higher-order dimension and that non-monetary poverty, as a whole, is driven by monetary poverty. Furthermore, the results reveal that monetary poverty is not a perfect predictor of non-monetary poverty, as its indicators capture different aspects of the phenomenon. These findings highlight the need for public policies that not only target monetary poverty but

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* Facultad de Ciencias Económicas, Universidad Nacional de Córdoba, Argentina. ORCID https://orcid.org/0000-0003-0431-6304. E-mail: adrianmoneta@unc.edu.ar

also incorporate specific strategies to address non-monetary deprivation, fostering a more comprehensive and effective approach to reducing multidimensional poverty in Argentina.

Keywords: multidimensional poverty, monetary poverty, generalized structural equation modeling, Argentina
JEL Codes: C38, I32

Resumen

Una cuestión controversial y de gran interés para el diseño de medidas de pobreza multidimensional es la inclusión de un indicador de pobreza monetaria. Uno de los argumentos más frecuentes a favor de mantener la pobreza de ingresos separada de la pobreza no monetaria es que reflejan dimensiones diferentes del fenómeno. Este trabajo explora la estructura multidimensional de la pobreza en Argentina e investiga si la pobreza monetaria debería ser considerada como otro indicador de pobreza multidimensional, utilizando modelos de ecuaciones estructurales generalizados (GSEM). Con datos categóricos de la Encuesta Permanente de Hogares (EPH) de Argentina, se analizan un modelo de análisis factorial confirmatorio generalizado (GCFA) y un GSEM con un factor de segundo orden. El modelo GCFA postula la hipótesis tradicional de que la pobreza monetaria es sólo una dimensión más de la pobreza, mientras que el GSEM apoya la hipótesis de que la pobreza monetaria es una causa de la pobreza no monetaria. Los resultados muestran que los datos se ajustan bien en ambos casos, pero que es más plausible considerar a los factores no monetarios como indicadores de una dimensión de orden superior y que esta pobreza no monetaria, en su conjunto, es explicada por la pobreza monetaria. También muestran que la pobreza monetaria no es un predictor perfecto de la pobreza no monetaria y que sus indicadores miden aspectos diferentes. Esto sugiere la necesidad de desarrollar políticas públicas que no sólo consideren la pobreza monetaria, sino que también integren estrategias específicas para mitigar las privaciones no monetarias, promoviendo así un enfoque más holístico y efectivo en la lucha contra la pobreza multidimensional en Argentina.

Palabras clave: pobreza multidimensional, pobreza monetaria, modelos de ecuaciones estructurales generalizados, Argentina
Códigos JEL: C38, I32

INTRODUCTION

The multidimensional approach to poverty, increasingly recognized by researchers, governments, and society, considers poverty a complex phenomenon involving multiple deprivations, with monetary poverty being only one of them (Salecker et al., 2020). This perspective contrasts with the traditional one-dimensional view, which defines poverty solely in terms of insufficient monetary income. While monetary poverty remains the most widely used method for identifying and measuring poverty—classifying individuals as poor if their income is insufficient to purchase a basic basket of goods and services—it relies on the premise that direct monetary transfers to the poorest households can effectively alleviate poverty (Gasparini et al., 2013). However, assuming that monetary income is the sole determinant of deprivation is overly simplistic. A vast body of research supports that poverty is a multidimensional phenomenon requiring analysis across multiple domains (López & Safojan, 2014; Santos et al., 2015; Santos & Villatoro, 2018; Gasparini et al., 2021; Arévalo & Paz, 2015; Gallardo et al., 2021). This perspective acknowledges that deprivation and exclusion can manifest in various aspects crucial to human well-being, such as health, education, access to basic services, housing, and food security. By conceptualizing poverty as a set of interrelated deprivations across different aspects of life, the multidimensional approach provides a more comprehensive framework for addressing its complexities and mitigating social exclusion (Ravallion, 2011).

Adopting a multidimensional approach to poverty requires determining which dimensions should be considered, a question closely linked to the specific definition of poverty (Kim, 2016). According to Walker (2015), while poverty is often easily recognized, defining its exact scope remains a challenge. Although there is broad consensus on the multidimensional nature of poverty, significant disagreement persists about which dimensions should be incorporated (Ntsalaze & Ikhide, 2018; Kim, 2016) and how they interrelate (Chan & Wong, 2020).

In this context, a key question in the design of multidimensional poverty measures is whether they should include a monetary poverty indicator. A common argument for distinguishing income or consumption poverty from non-monetary poverty is that they represent different dimensions of the phenomenon (Santos et al., 2015). While current income captures cyclical fluctuations in welfare related to the labor market, non-monetary measures of multidimensional poverty reflect deprivations associated with more stable and structural conditions, such as inadequate housing and unfavorable socio-environmental factors.

Empirical studies indicate that monetary poverty measures are imperfect predictors of non-monetary poverty (Bader et al., 2016; Bourguignon et al., 2010; Roelen, 2017, 2018; Roelen et al., 2009, Roelen et al., 2012; Ruggeri et al., 2003; Wang et al., 2016). For example, an analysis of the mismatch between income poverty and the multidimensional poverty index in Chile found that while 20.4% of the population experienced multidimensional poverty and 14.4% suffered from income poverty, only 5.5% were classified as poor under both measures (Ministry of Social Development, 2015). Additional evidence from Latin America further suggests that monetary and multidimensional poverty do not necessarily overlap (Santos et al., 2010; ECLAC, 2013). For the particular cases of Chile and Peru, see also Ruggeri Laderchi (1997). These discrepancies may arise because these two measures capture different aspects of poverty or due to variations in how each indicator is defined and calculated. Understanding the causes of these mismatches and their policy implications remains an important area for further research (UNDP, 2019).

The most widespread approach to addressing the challenge of dimension selection is to adopt a normative framework, such as the Alkire-Foster axiomatic counting methodology (Alkire & Foster, 2011). Methods such as this one rely on subjective decisions regarding dimension definitions and indicators, which are based on socio-political agreements and data availability. Their advantages include the ability to capture the joint distribution of deprivations, identify individuals experiencing poverty, and summarize multidimensional poverty measurement in a single indicator (Alkire et al., 2015).

Statistical techniques offer an alternative proposal to solving the problem of identifying poverty dimensions. Advocates of these methods emphasize their potential to explore the complex nature and structure of poverty by deriving insights directly from the data. Alkire et al. (2015) categorized these techniques into two broad groups: descriptive methods and latent variable modelling approaches. The first group comprises cluster analysis (CA), principal component analysis (PCA), and multiple correspondence analysis (MCA), which are primarily used for dimension reduction. The second group encompasses factor analysis (FA), latent class analysis (LCA), and structural equation models (SEM). According to Walker (2015), this second group can be further subdivided: methods such as FA and LCA aim to identify poverty dimensions, whereas SEM is predominantly employed to test theoretical relationships between dimensions. In SEM, poverty dimensions and their interrelationships are specified in advance based on theoretical frameworks or prior exploratory analyses. These predefined relationships are then tested against the data to assess their validity.

The normative approach is not the most appropriate to analyze whether income-based poverty and non-monetary poverty represent the same construct or distinct dimensions of the phenomenon, as it assumes that dimensions are predetermined. In contrast, statistical methods seem more suitable for this purpose (Nájera Catalán & Gordon, 2020).

In Argentina, the absence of a regular and systematic official measurement of multidimensional poverty stems from a lack of consensus on its composition and limitations in available data sources. Establishing a multidimensional poverty measurement system would be essential to addressing the complexities of poverty more effectively. Unlike traditional measures focused exclusively on monetary indicators, such a system would offer a more comprehensive view of poverty, enabling policymakers to identify critical areas requiring intervention. Recognizing that poverty extends beyond economic scarcity to include a lack of opportunities and access to essential services, this approach would support the design of more holistic and effective policies. These policies could simultaneously alleviate monetary poverty and tackle non-monetary deprivations, thus promoting more equitable and sustainable development.

In addition, a robust multidimensional measurement system would serve as a valuable tool for accountability and policy evaluation. Disaggregated data reflecting various dimensions of poverty would enable governments and organizations to monitor the impact of their interventions and adjust their strategies in response to changes in living conditions. In conclusion, implementing such a system in Argentina is not only crucial for a deeper understanding of poverty but also for the development of inclusive, effective, and responsive public policies that address the needs of the most vulnerable populations.

Significant progress has been made in studying and measuring multidimensional poverty in Argentina. However, the question of whether monetary poverty should be included in a multidimensional poverty index remains unresolved and highly relevant. In Argentina, analyses of multidimensional poverty have predominantly focused on the development of composite indicators, where poverty is represented as a linear combination of independent factors constructed using PCA, a method more suited for continuous indicators. This approach overlooks the potential of a reflective measurement model, which conceptualizes poverty dimensions as latent, unobservable variables, and indicators as particular manifestations of these dimensions, often correlated with one another. Additionally, the reliance on PCA fails to account for the fact that most available indicators are binary variables.

Several studies, including those by Conconi and Ham (2007), Conconi (2011), Carrazán Mena et al. (2011), and Gasparini et al. (2013), provide examples of descriptive techniques, basically PCA, for identifying poverty dimensions. On the other hand, the works of Fagnola and Moneta Pizarro (2021) and Moneta Pizarro and Satorres Bechara (2021) exemplify the use of FA as an alternative approach.

There are no records in Argentina of the application of more appropriate techniques, such as SEM, to explore the relationships between poverty dimensions. Furthermore, methods that account for the binary nature of available data, for example, the generalized structural equations models (GSEM), have not been employed. While the existing research in Argentina represents significant progress in analyzing multidimensional poverty, it does not establish hypotheses to investigate the interrelationships among its dimensions. Most of these studies are grounded in Sen's capabilities approach (1984, 1985, 1992, 2000), which provides a valuable conceptual framework for the hypothesis of multidimensionality. However, this framework has primarily been used to support the notion of multidimensional poverty rather than to develop theoretical models that elucidate causal relationships or confirm its multidimensional structure.

This paper demonstrates how SEM can be implemented to examine the multidimensional structure of poverty in Argentina and to investigate whether monetary poverty should be considered another indicator of multidimensional poverty. Given the categorical nature of the available data, the generalized version of these models, GSEM, is used. Specifically, a generalized confirmatory factor analysis (GCFA) model is compared with a full GSEM that includes a second-order factor. The GCFA model assumes that each factor corresponds to a distinct dimension of poverty without proposing causal relationships among them. In contrast, the GSEM includes structural relationships and simultaneously tests two alternative hypotheses. First, it posits the unidimensionality of the non-monetary dimension of poverty, where the non-monetary factors serve as first-order indicators of a single higher-order construct. Second, it suggests that non-monetary poverty, represented by this higher-order construct, is a consequence of monetary poverty. This approach aligns with Walker's (2015) assertion that poverty is not merely the lack of monetary resources needed to meet specific needs but also encompasses the multiple consequences of such scarcity, including deficiencies in education, healthcare, housing, and employment—factors that collectively represent non-monetary poverty. Additionally, this paper follows Chan and Wong's (2020) findings from their application of SEM to Hong Kong data, which demonstrated that monetary income significantly influences the non-monetary dimensions of poverty.

I. LITERATURE REVIEW

At the international level, there are several precedents in applying SEM to the analysis of multidimensional poverty, with a stronger focus on developing causal models rather than creating synthetic indices. Notable examples include Di Tommaso (2007) using data from India, Ballon and Krishnakumar (2008) applying SEM to child poverty in Bolivia, Wagle (2009) for Nepal and the United States, Kim (2016) using data from the United Kingdom, Ballon (2018) examining female empowerment in Cambodia, Chan and Wong (2020) with data from Hong Kong, Zhang and Huai (2023) analyzing poverty among farmers in China, and Clausen et al. (2024) exploring the association between multidimensional poverty and depression using data from Peru. However, the models proposed in these studies rely on dimensions and variables that are often adjusted to the specific context of each country or the availability of case-specific data.

Despite the widespread global acceptance of advances in multidimensional poverty studies (Alkire & Santos, 2010, 2013) and the growth of poverty in Argentina, research on this topic remains scarce at the national level (Arévalo & Paz, 2015). Among the key Argentine contributions to the literature, outstanding works include those by Conconi and Ham (2007), Conconi (2011), Santos et al. (2015), Arévalo and Paz (2015), Salvia et al. (2017), Durán and Condorí (2017), Ignacio-González and Santos (2020), Fares et al. (2021), Macció and Mitchell (2023), Sione (2024), and Poggiese and Ibañez Martín (2024). These studies are characterized by their focus on the construction and use of synthetic indicators, such as those developed by Bourguignon and Chakravarty (2003) and Alkire and Foster (2011).

Some noteworthy works applying statistical techniques are of great interest for this research. Key examples comprise the investigations of Conconi and Ham (2007), Conconi (2011), Carrazán Mena et al. (2011), and Gasparini et al. (2013). However, in these cases, factor identification relies on PCA, which neither advances the contrast of structural models nor addresses the discontinuity and non-normality of the variables used as poverty indicators.

Recently, some studies on Argentine multidimensional poverty have incorporated robust FA methods using tetrachoric and polychoric correlation matrices to validate dimensions, thereby addressing issues related to the lack of normality in indicators. The works by Fagnola and Moneta Pizarro (2021), Moneta Pizarro and Satorres Bechara (2021), and Gutiérrez Montecino and Moneta Pizarro (2021) have refined multidimensional poverty indicators derived from the Permanent Household Survey (EPH) through advanced exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) techniques. The model initially proposed by Fagnola and Moneta Pizarro (2021) included 15 indicators distributed across five factors (exclusion, sanitation, health, infrastructure, and economic capacity) based on a single EPH wave (third quarter of 2017). After employing EFA and CFA, the model was refined to 13 indicators grouped into four factors. Moneta Pizarro and Satorres Bechara (2021) extended this work to longitudinal data covering representative periods of different phases of the Argentine economic cycle, enabling the testing of longitudinal invariance in the factor structure. Their proposal expanded to 18 indicators across five factors, but subsequent analyses of consistency, construct validity, and longitudinal invariance resulted in a model with 10 selected indicators across three factors (housing, environment, and income). Finally, Gutiérrez Montecino and Moneta Pizarro (2021) explored multiregional invariance, validating a measurement model with seven indicators and three factors. While these studies represent significant progress in identifying the factor structure of multidimensional poverty in Argentina through robust methods, they do not examine potential relationships between the latent constructs.

At both international and national levels, there is no evidence in the available literature on multidimensional poverty of applications of GSEM, the most advanced version of SEM. GSEM represents a novel approach, particularly suitable for addressing complex data structures (Skrondal & Rabe-Hesketh, 2004).

II. DATA

The study relies on microdata at the household level obtained from the cross-section corresponding to the first quarter of 2022 from the EPH conducted by the National Institute of Statistics and Censuses (INDEC). The sample comprises 16 898 observations from households in 32 urban agglomerates across all regions of the country. While this dataset offers valuable insights, it also presents certain limitations. It is restricted to urban conglomerates with populations exceeding 100 000 inhabitants, and the questionnaire applied was not specifically designed to capture multidimensional poverty characteristics. As a result, the conclusions drawn are constrained by these factors. Furthermore, most of the prospective variables used to construct poverty indicators are dichotomous (e.g., whether the household head is employed or unemployed, whether the family has medical coverage, or whether the housing has running water, among others). This characteristic poses challenges for multivariate analysis, particularly for SEM, which typically requires continuous variables with normal distributions. Nevertheless, this limitation is addressed by using GSEM, a more advanced and appropriate statistical modelling strategy for handling such data.

With respect to the variables, the measurement model validated by Gutiérrez Montecino and Moneta Pizarro (2021) serves as the starting point, as it includes seven indicators grouped into three factors. The first factor pertains to housing infrastructure conditions, with the following indicators:

- Roof: This variable takes the value of 1 if the roof is of low quality (e.g., made of plastic, cardboard, cane, planks, or sheets without ceiling or inner lining) and 0 otherwise.
- Bathroom: This variable takes the value of 1 if the housing does not have a bathroom with drainage inside and 0 otherwise.

The second factor is related to the environment or surroundings of the housing and includes the following indicators:

- Dumpsite: This variable takes the value of 1 if the housing is located less than three blocks from a dumpsite and 0 otherwise.
- Floodable area: This variable takes the value of 1 if the housing is in a floodable area (within the last 12 months) and 0 otherwise.

Finally, the third factor encompasses indicators related to household's economic resources:

- External support: This variable takes the value of 1 if the household receives external monetary or material support, such as subsidies, assistance programs, charity, or similar forms of aid, and 0 otherwise.
- Medical coverage: This variable takes the value of 1 if any member of the household unit does not pay or does not have deductions for medical coverage services and 0 otherwise.
- TFI<TBB: This variable takes the value of 1 if the total family income is less than the total specific basic basket for that household and 0 otherwise.[1]

The first two factors are related to non-monetary dimensions of poverty, while the third factor is strictly associated with the monetary dimension. Descriptive statistics for all these variables are provided in the following table, where the means, since all variables are binary, represent the proportion of observations with a value of 1.

1 This is the standard indicator of monetary poverty (unidimensional) in Argentina. The Total Basic Basket (TBB) represents the cost of a predefined set of goods and services necessary for basic consumption. Households with a total family income (TFI) below the TBB threshold are classified as poor.

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std. dev.
Roof	16 898	0.0728	0.2598
Bathroom	16 898	0.0867	0.2814
Dumpsite	16 898	0.0518	0.2216
Floodable area	16 898	0.0541	0.2262
External support (Ext_supp)	16 898	0.2310	0.4215
Medical coverage (Med_cov)	16 898	0.3628	0.4808
TFI<TBB	14 854	0.3161	0.4650

Source: own elaboration

III. METHODOLOGY

As mentioned earlier, this study applies GSEM techniques, which combine SEM capacities with those of generalized linear models (GLM). Similar to the econometric methods of simultaneous equations, SEM allows simultaneously examining a group of dependency relationships where certain variables act as both predictors and dependent variables. Additionally, SEM provides the ability to estimate and analyze the links among latent (unobservable) variables. These latent variables are theoretical constructs measured through observable variables (Cupani, 2012). Unlike other analytical techniques that represent constructs using a single measurement and without accounting for measurement error, SEM employs multiple indicators for each construct, allowing for the control of specific measurement errors associated with each variable. This approach also facilitates the assessment of the validity of each construct (Ruiz et al., 2010).

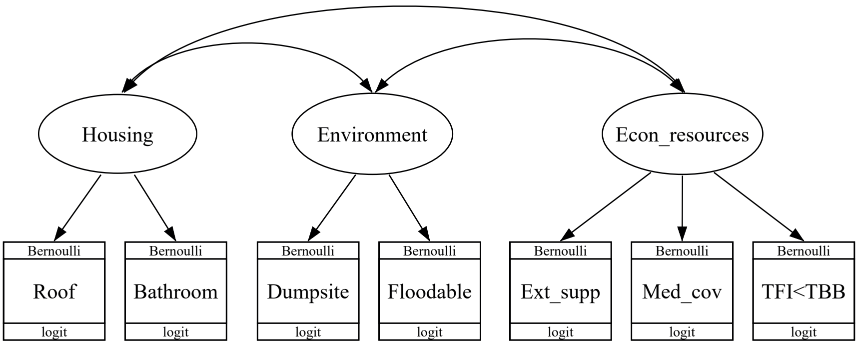
As Kline (2015) explained, every SEM consists of two elements: (a) a measurement model representing the relationships between latent variables and their observed indicators and (b) a structural model describing the interrelationship among the latent constructs. The measurement model evaluates the adequacy of the selected indicators in representing the relevant constructs. On the other hand, the structural model, which is the primary focus of estimation, captures the effects and relationships among the constructs, typically latent variables. Unlike standard regression models, it allows for interconnected effects and loops among variables.

A distinctive feature of SEM is that it includes several statistical tests and a set of goodness-of-fit indicators. The model's fit is achieved when the estimated parameters reproduce the observed covariance matrix as closely as possible (Kahn, 2006). In SEM, model estimation relies on the correlations among the measured variables in a cross-sectional sample. Unlike the least squares method, which reduces the difference between predicted and observed values at the individual level, SEM does so between the covariances observed in the sample and those predicted by the structural model. According to Long (1983), this is why these models are also referred to as covariance structural models. Therefore, the model residuals represent the differences between the observed covariances and those predicted by the theoretical structural model (Ruiz et al., 2010).

By combining SEM with GLM, GSEM allows analyzing response variables that can be continuous, binary, ordinal, count, or multinomial. In addition, it enables the modeling of both normal linear regressions and a wide range of regressions from the exponential family, including Gamma, Logit, Probit, Poisson, Negative Binomial, and their variants (Skrondal & Rabe-Hesketh, 2004). In this research, the presence of binary variables necessitates the use of GSEM rather than SEM.

In this work, a measurement model (without the structural component) with a logit link is first specified, that is, a CFA model adapted for dichotomous or binary response variables (GCFA). As illustrated in Figure 1 below, this model assumes that each latent factor represents one poverty dimension, which can be measured through observable indicators, with the factors potentially being correlated. This initial model is composed of three measurement sub-models, one for each factor. Two observed indicators, roof and bathroom, are used to assess housing conditions; two other observed indicators, dumpsite and floodable area, are considered manifestations of environmental conditions; and three observed indicators measure household's economic resources. The three measurement models are estimated jointly, allowing for correlations among factors. As McGartland Rubio et al. (2001) indicated, the verification of these correlations is usually interpreted as the result of the existence of a higher-order factor. Nevertheless, this may not necessarily be the case, since the correlation could also arise because the factors measure different dimensions of a single construct, poverty in this instance.

Figure 1. GCFA model



Source: own elaboration

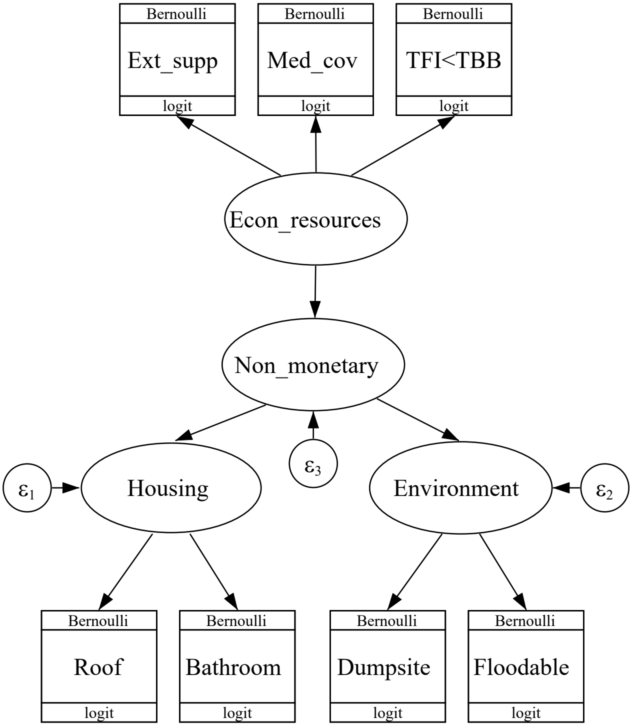
Using matrix notation, this first model can be represented through the measurement Equation (1):

$$\text{logit}[\Pr(w = 1|\xi)] = \Lambda_w \xi \tag{1}$$

where w is the vector of observed indicators, 1 is a vector of ones, ξ is the vector of latent factors (poverty dimensions) with covariance matrix Φ, and Λ_w is the matrix of model coefficients (factor loadings).

Second, a full GSEM is specified, where two factors—housing and environment—represent non-monetary poverty, which is considered a second-order construct. The factor related to economic resources, or monetary poverty, is an exogenous latent variable explaining non-monetary poverty. This model is shown in Figure 2. It should be noted that the measurement indicators for each factor remain the same as those in the first model.

Figure 2. Full GSEM path diagram



Source: own elaboration

The full GSEM can be expressed in matrix form through the following equations:

$$\eta = \mathrm{B}\,\eta + \Gamma\,\tau + \varepsilon \tag{2}$$

$$\mathrm{logit}[\Pr(y = 1|\eta)] = \Lambda_y \eta \tag{3}$$

$$\mathrm{logit}[\Pr(x = 1|\tau)] = \Lambda_x \tau \tag{4}$$

Equation (2) represents the structural part of the model, while equations (3) and (4) correspond to the measurement model for the latent factors. In the structural model, η is the vector of endogenous latent variables (η_1, η_2, η_3), where η_1 and η_2 are the first-order factors (housing and environment) and η_3 is the second-order factor (non-monetary poverty); τ is the only exogenous latent variable (economic resources); B is the 3×3 coefficient matrix for the endogenous latent variables; Γ is a coefficient vector of order 3, with all elements equal to zero except the third, which represents the effect of τ on η_3; and ε is the vector of disturbances ($\varepsilon_1, \varepsilon_2, \varepsilon_3$) associated with the endogenous latent variables in η, with a diagonal covariance matrix Ψ. In the measurement model, y is the vector of indicators used to measure η_1 and η_2; x is the vector of indicators for the measurement of τ; Λ_y and Λ_x are the factor loading matrices; and 1 is a vector of ones.

Both models were estimated using Stata 17 with the maximum likelihood (ML) method, which is the only approach available for GSEM. In the case of the second model, its high complexity presented challenges in achieving convergence during the estimation process. This issue was temporally addressed by modifying the numerical integration method and reducing the number of integration points.

Satisfactory results were obtained using the non-adaptive Gauss-Hermite quadrature model with three integration points. Subsequently, these estimations were utilized as improved initial values to re-estimate the model with the default options. This approach enabled a more accurate solution, achieved through the adaptive Gauss-Hermite quadrature algorithm based on the mean and variance, with seven integration points.

IV. RESULTS

Table 2 presents the estimation results of the pure measurement model (i.e., the GCFA model), which allows assessing the convergent and discriminant validity of the three factors proposed for multidimensional poverty. The results show that all indicators are significantly related to their corresponding latent constructs, supporting the convergent validity of the model. This suggests that the indicator variables of each factor are strongly correlated, sharing a high proportion of variance (Aldás & Uriel, 2017). Furthermore, the covariances among the latent factors are significantly different from zero. Based on the estimated variances and covariances, the correlations obtained are 0.51 between housing and environment, 0.60 between housing and income, and 0.32 between environment and income. These moderate correlation values indicate discriminant validity.

Table 2. Results of the GCFA model

Variables		Coefficient	Std. Err.	z	P>|z|	[95% Conf. Int.]	
Roof							
	Housing	1	(restricted)				
	constant	-4.232543	0.1449429	-29.2	0.000000	-4.516626	-3.94846
Bathroom							
	Housing	0.9593894	0.0813283	11.8	0.000000	0.7999889	1.11879
	constant	-3.85143	0.1272349	-30.27	0.000000	-4.100806	-3.602054
Dumpsite							
	Environment	1	(restricted)				
	constant	-4.199538	0.167694	-25.04	0.000000	-4.528213	-3.870864
Floodable area							
	Environment	1.288781	0.1995092	6.46	0.000000	0.8977506	1.679812
	constant	-4.802548	0.3051847	-15.74	0.000000	-5.400699	-4.204397
External support							
	Economic resources	1	(restricted)				
	constant	-1.809089	0.0375684	-48.15	0.000000	-1.882722	-1.735457
Medical coverage							
	Economic resources	1.474708	0.0745719	19.78	0.000000	1.32855	1.620866
	constant	-1.093027	0.0417698	-26.17	0.000000	-1.174894	-1.011159
TFI<TBB							
	Economic resources	1.263382	0.0554054	22.8	0.000000	1.15479	1.371975
	constant	-1.422182	0.0424695	-33.49	0.000000	-1.505421	-1.338944
var(Housing)		5.305203	0.5600140			4.313697	6.524607
var(Environment)		3.453833	0.5148337			2.578813	4.625756
var(Economic resources)		3.105572	0.1776731			2.776153	3.474079
cov(Housing/Environment)		2.188527	0.2328391	9.4	0.000000	1.73217	2.644883
cov(Housing, Econ. res.)		2.471096	0.1573252	15.71	0.000000	2.162744	2.779448
cov(Environment, Econ. res.)		1.075617	0.1115909	9.64	0.000000	0.8569024	1.294331

Source: own elaboration

In simpler terms, these results show that the proposed measurement for each dimension works very well. Each indicator is clearly linked to the dimension it represents (housing, environment, and economic resources). This means that we are measuring exactly what we intend to measure, and the measure is valid. Moreover, the different types of poverty being assessed are connected, but they are not identical. That is, a household might have poor-quality housing but a good income, or vice versa. This suggests that the model can capture various aspects of poverty.

The significant covariances among the factors confirm the reasonableness of the second-order factor and the structural relationships among the latent variables, making the full GSEM specification plausible. Table 3 exhibits the results of this estimation. According to the measurement model, all indicators in this second model are also significantly related to their corresponding latent factors, with estimated coefficients closely matching those of the pure measurement model. Notably, Table 3 excludes estimated covariances among constructs, since they have been replaced by structural relationships. All structural coefficients were also significant, providing empirical support for the hypotheses proposed for this second model.

The results of this second model reaffirm the findings of the first: each indicator fits perfectly into its corresponding poverty dimension, maintaining the validity of the measurement model. However, the key addition in this model is the way it connects the different dimensions of poverty. For example, it illustrates how the lack of monetary resources influences both housing quality and environmental conditions. This strengthens the plausibility of the proposed relationships between poverty dimensions and provides deeper insight into their causes and consequences. Specifically, it shows that monetary poverty is not an isolated issue; rather, the absence of financial resources exacerbates other forms of deprivation, reinforcing the causal link between the two. As a result, the lack of economic resources creates a cycle of poverty that extends into various aspects of life. Furthermore, the findings suggest that non-monetary deprivation can serve as an indicator of more profound poverty. To effectively combat poverty, addressing income alone is insufficient; improving access to infrastructure and basic services is also critical for providing better opportunities to escape poverty.

Comparing the models with the Akaike (AIC) and Schwarz (BIC) information criteria, the full GSEM demonstrates a better fit. The GCFA model has an AIC of 82658.00 and a BIC of 82789.49, while the GSEM model achieves an AIC of 82657.17 and a BIC of 82788.66. Consequently, the GSEM provides a relatively better fit to the data. In other words, when comparing the simpler GCFA model with the more complex GSEM model, the latter outperforms the former according to both the AIC and BIC. This indicates that the GSEM model offers the best explanation of the data.

Table 3. Results of full GSEM

Variables		Coefficient	Std. Err.	z	P>|z|	[95% Conf. Int.]	
Measurement model Roof							
	Housing	1	(restricted)				
	constant	-4.246725	0.1571272	-27.03	0.000000	-4.554688	-3.938761
Bathroom							
	Housing	0.955539	0.0866052	11.03	0.000000	0.7857958	1.125282
	constant	-3.854903	0.1302366	-29.6	0.000000	-4.110162	-3.599644
Dumpsite							
	Environment	1	(restricted)	-25.51	0.000000	-4.52079	-3.875791
	constant	-4.19829	0.1645436				
Floodable Area							
	Environment	1.289765	0.1964518	6.57	0.000000	0.9047261	1.674803
	constant	-4.803195	0.3025952	-15.87	0.000000	-5.396271	-4.21012
External support							
	Economic resources	1	(restricted)	-45.72	0.000000	-1.887389	-1.732206
	Constant	-1.809797	0.0395883				
Medical coverage							
	Economic resources	1.474086	0.0779903	18.9	0.000000	1.321228	1.626944
	Constant	-1.093534	0.0417848	-26.17	0.000000	-1.17543	-1.011637
TFI<TBB							
	Economic resources	1.263164	0.0579683	21.79	0.000000	1.149548	1.376779
	constant	-1.422828	0.0424854	-33.49	0.000000	-1.506098	-1.339558
Structural model Housing							
	Non-monetary poverty	1			(restricted)		
Environment							
	Non-monetary poverty	0.4383168	0.0493818	8.88	0.000000	0.3415303	0.5351033
Non-monetary poverty							
	Economic resources	0.7941819	0.057259	13.87	0.000000	0.6819563	0.9064074
var(e.Non-monetary poverty)		3.001571	0.4559609			2.228665	4.042523
var(e.Housing)		0.383752	0.3345924			0.0694848	2.119391
var(e.Environment)		2.492091	0.3747607			1.855924	3.346321
var(e.Economic resources)		3.104728	0.1953692			2.744483	3.51226

Source: own elaboration

V. DISCUSSION

The results show that, despite the limitations of the EPH data for multidimensional poverty analysis, it is possible to identify at least three dimensions of poverty: one related to the material conditions of housing, another to environmental factors, and a third to monetary income. However, a more realistic approach is to consider the non-monetary aspects of poverty, such as housing and environmental conditions, as indicators of a higher-order dimension, with non-monetary poverty being explained by the monetary dimension. Thus, empirical evidence supports the identification of two primary dimensions: one associated with the lack of monetary resources and the other with non-monetary deprivations.

In this way, it cannot be excluded that poverty is multidimensional in Argentina, but a structural relationship is supported among its dimensions. This means, as Walker (2015) pointed out, that poverty is manifested not only by the presence of inadequate monetary income but also by the multiple consequences of this absence regarding housing and environment, which are part of a non-monetary dimension of the phenomenon. This conclusion, seeming quite obvious, contradicts much of the literature on multidimensional poverty developed up to present time, which sometimes, both implicitly and explicitly, correlates different poverty factors to distinct dimensions or attributes of a single construct. Kim (2016), for instance, included economic resources as an additional poverty dimension in his model, drawing on the works of Kangas and Ritakallio (1998), Lelli (2001), and Whelan (1993a, 1993b). He affirmed that this is common because these resources can serve other functions related to poverty, such as purchasing healthy food. However, the criticism of such perspectives is that they do not thoroughly explore these links and potential structural relationships among the dimensions. The exception to this may be the poverty trap models, where poverty is characterized as a vicious circle, perpetuated by self-reinforcing mechanisms (Santos, 2014), which allows for causal relationships among its dimensions.

VI. IMPLICATIONS

The implications of these conclusions for future research and public policy designs are that, based on the data used and the evidence found, poverty in Argentina should not be measured with a single multidimensional index, but rather with two: one for monetary poverty and the other for non-monetary poverty. In other words, income poverty should not be combined with other dimensions of poverty, since it is likely the cause of the non-monetary dimensions.

Thus, and contrary to the proposal by Santos et al. (2015), the recommendation to keep income poverty and non-monetary poverty indicators separate is supported. The arguments in favor of this approach are well compiled in the manual of the United Nations Development Programme and the Oxford Poverty and Human Development Initiative of the University of Oxford (UNDP & OPHI, 2019), which state that if the objective is to complement current monetary poverty statistics, including an income dimension introduces unnecessary complexity. In such cases, it is more appropriate to expand the understanding of poverty to include non-monetary dimensions not captured by traditional measures. Among other arguments, the manual emphasizes that monetary and non-monetary indicators capture poverty differently. Monetary indicators are generally considered indirect measures of poverty, focusing on the scarcity of resources for acquiring basic goods and services, while multidimensional indexes based on non-monetary indicators are regarded as direct measures of deprivation, reflecting real lacks in well-being.

However, this study provides another reason to keep monetary and non-monetary poverty measures separate: empirical evidence from the case of Argentina supports the fact that monetary poverty is a good predictor of non-monetary poverty. While there is a noticeable relationship between the indicators of the two types of poverty, suggesting a potential for combining them into a single measure, the correlation is not perfect, as demonstrated by the structural regression of the non-monetary dimension on the monetary one. The partial explanation of non-monetary poverty by economic resources does not imply that they measure the same concept. In contrast, both the GCFA measurement model and the full GSEM treat household economic capacity indicators as manifestations of one construct, while non-monetary indicators reflect other constructs. The empirical evidence presented here confirms that these measures should remain separate, not because they are independent or do not align with the estimation of the poor population, but because it is more plausible, as stated in the full GSEM, that one serves as the cause of the other. These findings contribute constructively to the debate on the relationship between monetary and multidimensional poverty measures, a discussion that is particularly relevant in the Latin American context, as highlighted by Santos et al. (2015).

CONCLUSION

This paper aimed to enhance the multidimensional analysis of poverty in Argentina by emphasizing the need to consider various forms of deprivation beyond monetary income. It also sought to tackle the complexities and challenges associated with determining the specific dimensions to include in multidimensional poverty measures. By addressing these issues, the study contributes to a more comprehensive perspective on poverty and provides insights to improve the effectiveness of poverty alleviation efforts in Argentina.

The methodology employed focused on identifying and selecting relevant dimensions, comparing alternative models to examine their interrelationships, and applying advanced statistical techniques such as GSEM to assess multidimensional poverty in Argentina. Drawing on insights from previous research on robust measurement methods, the study used empirical data from the EPH to validate the proposed models.

The results of this investigation underscored the effectiveness of a multidimensional approach in addressing the complexities of poverty beyond monetary measures. Model testing offered valuable insights into the interconnections between various facets of poverty in Argentina, while empirical validation confirmed the robustness of this approach for capturing its nuances. By exploring different dimensions of deprivation, the research provided evidence on the interconnected nature of poverty and underlined the need of distinguishing the monetary dimension from the non-monetary ones. These findings provide a foundation for developing more accurate multidimensional poverty indicators and designing comprehensive, targeted policies to combat this persistent issue.

In summary, this research on multidimensional poverty not only contributes significantly to the academic literature, but also has important implications for policy and practice. By delving into the complexities of poverty measurement beyond income and exploring the multidimensional aspects of deprivation, the study offers a more thorough understanding of poverty. The findings highlight the importance of adopting a multidimensional approach, which complements traditional monetary measures, for developing poverty indicators and designing effective alleviation programs.

REFERENCES

Aldás, J. & Uriel, E. (2017). *Análisis multivariante aplicado con R* (2nd Ed.). Paraninfo.

Alkire, S., & Foster, J. (2011). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics*, *95*(7-8), 476-487. https://doi.org/10.1016/j.jpubeco.2010.11.006

Alkire, S., Foster, J. E., Seth, S., Santos, M. E., Roche, J. M., & Ballon, P. (2015). *Multidimensional Poverty Measurement and Analysis: Chapter 3 – Overview of Methods for Multidimensional Poverty Assessment*. OPHI Working Paper, 84. https://ophi.org.uk/multidimensional-poverty-measurement-and-analysis-chapter-3-overview-of-methods-for-multidimensional-poverty-assessment/

Alkire, S., & Santos, M. E. (2010). *Acute Multidimensional Poverty: A New Index for Developing Countries*. OPHI Working Paper, 38. https://ophi.org.uk/acute-multidimensional-poverty-a-new-index-for-developing-countries/

Alkire, S., & Santos, M. E. (2013). A Multidimensional Approach: Poverty Measurement & Beyond. *Social Indicators Research*, *112*, 239-257. https://doi.org/10.1007/s11205-013-0257-3

Arévalo, C. & Paz, J. A. (2015). *Pobreza en la Argentina. Privaciones mu´ltiples y asimetrías regionales*. Documento de Trabajo N° 15, Instituto de Estudios Laborales y del Desarrollo Econo´mico (IELDE), Facultad de Ciencias Econo´micas, Jurídicas y Sociales, Universidad Nacional de Salta (UNSa). https://www.economicas.unsa.edu.ar/ielde/index.php/documentos-de-trabajo/167-nro-15-primavera-2015-carla-arevalo-y-jorge-paz-pobreza-en-la-argentina-privaciones-multiples-y-asimetrias-regionales

Bader, C., Bieri, S., Wiesmann, U. & Heinimann, A. (2016). Differences between monetary and multidimensional poverty in the Lao PDR: Implications for targeting of poverty reduction policies and interventions. *Poverty & Public Policy*, *8*(2), 171-197. https://doi.org/10.1002/pop4.140

Ballon, P., & Krishnakumar, J. (2008, august). *A Model-Based Multidimensional Capability Deprivation Index* (Paper). 30th General Conference of the International Association for Research in Income and Wealth, Portoroz, Slovenia. http://old.iariw.org/papers/2008/ballon.pdf

Ballon, P. (2018). A Structural Model of Female Empowerment. *The Journal of Development Studies*, *54*(8), 1303-1320. https://doi.org/10.1080/00220388.2017.1414189

Bourguignon, F., & Chakravarty, S. (2003). The Measurement of Multidimensional Poverty. *Journal of Economic Inequality*, *1*, 25-49. https://doi.org/10.1023/A:1023913831342

Bourguignon, F., Bénassy-Quéré, A., Dercon, S., Estache, A., Gunning, J. W., Kanbur, R., Klasen, S., Maxwell, S., Platteau, J.-P., & Spadaro, A. (2010). Millennium Development Goals: An assessment. In R. Kanbur & M. Spencer (Eds.), *Equity and Growth in a Globalizing World* (pp. 17-39). World Bank.

Carrazán Mena, G., Pagani, P. A. & Sánchez Fernández, D. (2011). *Análisis multivariado de la pobreza en la Ciudad de Salta. Una aproximación a partir del Censo Social 2009-2010*. Documento de Trabajo N° 3, Instituto de Investigaciones Económicas (IEE), Universidad Nacional de Salta. https://www.economicas.unsa.edu.ar/iie/archivos/dt/2011S%C3%A1nchez.pdf

Chan, S. M., & Wong, H. (2020). Impact of Income, Deprivation and Social Exclusion on Subjective Poverty: A Structural Equation Model of Multidimensional Poverty in Hong Kong. *Social Indicators Research*, 152, 971-99. https://doi.org/10.1007/s11205-020-02476-8

Clausen, J., Barrantes, N., Caballero, E., & Guillén, H. (2024). Exploring the Association between Multidimensional Poverty and Depression Using Structural Equation Models. *Applied Research Quality Life*, 19, 727-747. https://doi.org/10.1007/s11482-023-10262-0

Conconi, A. & Ham, A. (2007). *Pobreza Multidimensional Relativa: Una aplicacio´n a la Argentina*. Documento de Trabajo N° 57, Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS), Universidad Nacional de La Plata. http://sedici.unlp.edu.ar/handle/10915/3616

Conconi, A. (2011). *Pobreza Multidimensional en Argentina: Ampliando las Medidas Tradicionales de Pobreza por Ingreso y NBI*. Documento de Trabajo N° 90, Departamento de Economía, Facultad de Ciencias Económicas, Universidad Nacional de La Plata. https://www.depeco.econo.unlp.edu.ar/wp/wp-content/uploads/2017/05/doc90.pdf

Cupani, M. (2012). Análisis de Ecuaciones Estructurales: conceptos, etapas de desarrollo y un ejemplo de aplicación. *Revista Tesis*, *1*, 186-199. https://rdu.unc.edu.ar/bitstream/handle/11086/22039/16.pdf?sequence=1&isAllowed=y

Di Tommaso, M. (2007). Children Capabilities: A Structural Equation Model for India. *Journal of Socio-Economics*, *36*(3), 436-450. https://doi.org/10.1016/j.socec.2006.12.006

Durán, R. J., & Condorí, M. A. (2017). Deprivation Index for Small Areas Based on Census Data in Argentina. *Social Indicators Research*, *141*, 331-363. https://doi.org/10.1007/s11205-017-1827-6

ECLAC (2013). *Social Panorama of Latin America, 2013* (LC/G.2580-P), Santiago de Chile. https://hdl.handle.net/11362/36736

Fagnola, B. & Moneta Pizarro, A. M. (2021). Identificación de la pobreza multidimensional en Argentina con métodos robustos de análisis factorial. *Revista Cuadernos del CIMBAGE*, *23*. https://ojs.econ.uba.ar/index.php/CIMBAGE/article/view/2053

Fares, F. M., Favata, F. & Martínez, R. G. (2021). Una propuesta para la medición de la pobreza multidimensional en la Argentina (2004-2019). *Economía y Desafíos del Desarrollo*, *1*(7), 4-48. https://revistaedd.unsam.edu.ar/?p=1454

Gallardo, M., Santos, M. E., Villatoro, P. & Pizarro, V. (2021). Measuring Vulnerability to Multidimensional Poverty. Documento de Trabajo N 2021-36, Rednie. https://rednie.eco.unc.edu.ar/files/DT/2021-36.pdf

Gasparini, L., Sosa Escudero, W., Marchionni, M., & Olivieri, S. (2013). Multidimensional poverty in Latin America and the Caribbean: new evidence from the Gallup World Poll. *Journal of Economic Inequality*, *11*(2), 195-214. https://doi.org/10.1007/s10888-011-9206-z

Gasparini, L., Santos, M. E., & Tornarolli, L. (2021). Poverty in Latin America. Documento de Trabajo del CEDLAS N284, August, 2021, CEDLAS-UNLP. https://www.cedlas.econo.unlp.edu.ar/wp/wp-content/uploads/doc_cedlas284.pdf?dl=0

Gutiérrez Montecino, D. A., & Moneta Pizarro, A. M. (2021, october). *Invarianza multirregional de la pobreza multidimensional en Argentina* (Paper). XIV Congreso Latinoamericano de Sociedades de Estadística "Laura Nalbarte", Montevideo, Uruguay. https://sue.org.uy/wp-content/uploads/2022/05/Libro_de_resumenes_XIV_CLATSE.pdf

Ignacio-González, F. A., & Santos, M. E. (2020). Pobreza multidimensional urbana en Argentina. ¿Reducción de las disparidades entre el norte grande argentino y centro-cuyo-sur? (2003-2016). *Cuadernos de Economía*, *39*(81), 795-822. https://doi.org/10.15446/cuad.econ.v39n81.76486

Kahn, J. H. (2006). Factor analysis in Counseling Psychology research, training and practice: Principles, advances and applications. *The Counseling Psychologist*, *34*(5), 1-36. https://doi.org/10.1177/0011000006286347

Kangas, O., & Ritakallio, V.-M. (1998). Different methods—different results? Approaches to multidimensional poverty. In H.-J. Andress (Ed.), *Empirical poverty research in a comparative perspective* (pp. 167-203). Ashgate.

Kim, S-G. (2016). What Have We Called as "Poverty"? A Multidimensional and Longitudinal Perspective. *Social Indicators Research*, *129*, 229-276. https://doi.org/10.1007/s11205-015-1101-8

Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling* (4th Ed.). Guilford Press.

Lelli, S. (2001). *Factor analysis vs. Fuzzy sets theory: Assessing the influence of different techniques on Sen's functioning approach*. Discussion Paper Series (DPS) 01.21, Center for Economic Studies, K. U. Leuven. http://www.econ.kuleuven.be/ces/discussionpapers/default.htm

López, C. & Safojan, R. (2014). Un análisis multidimensional de la pobreza: Evidencia reciente de las regiones de Argentina. *Revista de Economía Política de Bs. As.*, *7*, 9-44.

Long, J. S. (1983). Covariance Structure Models: An introduction to LISREL. *Sage University Paper Series on Quantitative Applications in the Social Sciences*, *34*.

Macció, J., & Mitchell, A. (2023). Medición multidimensional de pobreza en ciudades segregadas: evidencia de la ciudad de Buenos Aires. *Revista Desarrollo y Sociedad*, *1*(93), 101-137. https://doi.org/10.13043/DYS.93.3

McGartland Rubio, D., Berg-Weger, M., & Tebb, S. S. (2001). Using Structural Equation Modeling to Test for Multidimensionality. *Structural Equation Modeling*, *8*(4), 613-626. https://doi.org/10.1207/S15328007SEM0804_06

Ministry of Social Development (2015). *Nueva Metodología de Medición de la Pobreza por Ingresos y Multidimensional*. Documentos Metodológicos, 28. Ministerio de Desarrollo Social de Chile. https://observatorio.ministeriodesarrollosocial.gob.cl/storage/docs/casen/2013/Nueva_Metodologia_de_Medicion_de_Pobreza.pdf

Moneta Pizarro, A. M., & Satorres Bechara, A. P. (2021). Estabilidad dinámica de la pobreza multidimensional en Argentina. In R. Pérez Calle, E. Trincado Aznar & E. Gallego Abaroa (Eds.), *Economía, empresa y justicia. Nuevos retos para el futuro* (pp. 1337-1365). Editorial Dykinson S.L. https://www.dykinson.com/libros/economia-empresa-y-justicia-nuevos-retos-para-el-futuro/9788413773261/

Nájera Catalán, H. E., & Gordon, D. (2020). The Importance of Reliability and Construct Validity in Multidimensional Poverty Measurement: An Illustration Using the Multidimensional Poverty Index for Latin America (MPI-LA). *The Journal of Development Studies*, *56*(9). https://doi.org/10.1080/00220388.2019.1663176

Ntsalaze, L., & Ikhide, S. (2018). Rethinking Dimensions: The South African Multidimensional Poverty Index. *Social Indicators Research*, *135*, 195-213. https://doi.org/10.1007/s11205-016-1473-4

Poggiese, M., & Ibañez Martín, M. M. (2024). Privaciones multidimensionales: El origen de la pobreza y la exclusión social. Un estudio para Argentina. *Visión de futuro*, *28*(1), 36-60. https://dx.doi.org/https://doi.org/10.36995/j.visiondefuturo.2023.28.01.002.es

Ravallion, M. (2011). On Multidimensional Indices of Poverty. *Journal of Economic Inequality*, *9*, 235-248. https://doi.org/10.1007/s10888-011-9173-4

Roelen, K. (2017). Monetary and multidimensional child poverty: A contradiction in terms? *Development and Change*, *48*(3), 502–533. https://doi.org/10.1111/dech.12306

Roelen, K. (2018). Poor children in rich households and vice versa: A blurred picture or hidden realities? *The European Journal of Development Research*, *30*(2), 320–341. https://doi.org/10.1057/s41287-017-0082-7

Roelen, K., Gassmann, F., & de Neubourg, C. (2009). The Importance of choice and definition for the measurement of child poverty: The case of Vietnam. *Child Indicators Research*, *2*(3), 245–263. https://doi.org/10.1007/s12187-008-9028-0

Roelen, K., Gassmann, F., & de Neubourg, C. (2012). False positives or hidden dimensions: What can monetary and multidimensional measurement tell us about child poverty in Vietnam? *International Journal of Social Welfare*, *21*(4), 393–407. https://doi.org/10.1111/j.1468-2397.2011.00836.x

Ruggeri Laderchi, C. (1997). Poverty and its many dimensions: The role of income as an indicator. *Oxford Development Studies*, *25*(3), 345-360. https://doi.org/10.1080/13600819708424139

Ruggeri, C., Saith, R., & Stewart, F. (2003). Does it matter that we do not agree on the definition of poverty? A comparison of four approaches. *Oxford Development Studies*, *31*(3), 243–274. https://doi.org/10.1080/1360081032000111698

Ruiz, M. A., Pardo, A., & San Martín, R. (2010). Modelos de Ecuaciones Estructurales. *Papeles del Psicólogo*, *31*(1), 34-45.

Salecker, L., Ahmadov, A. K. & Karimli, L. (2020). Contrasting Monetary and Multidimensional Poverty Measures in a Low-Income Sub-Saharan African Country. *Social Indicators Research*, *151*, 547-574. https://doi.org/10.1007/s11205-020-02382-z

Salvia, A., Bonfiglio, J. I. & Vera, J. (2017). La pobreza multidimensional en la argentina urbana 2010-2016. Un ejercicio de aplicación de los métodos OPHI y CONEVAL al caso argentino (Online). Observatorio de la Deuda Social Argentina, Barómetro de la Deuda Social Argentina, Serie del Bicentenario (2010-2016). https://repositorio.uca.edu.ar/handle/123456789/8206

Santos, M. E. (2014). El índice multidimensional y trampas de pobreza en el Cono Sur. *Revista Problemas del Desarrollo*, *178*(45), 89-112. https://doi.org/10.1016/S0301-7036(14)70877-6

Santos, M. E., Lugo, M. A., Lopez-Calva, L. F., Cruces, G., & Battiston, G. (2010). Refining the basic needs approach: A multidimensional analysis of poverty in Latin America. Research on Economic Inequality Vol. 18: Studies in Applied Welfare Analysis: Papers from the Third ECINEQ Meeting, pp. 1–29. Emerald. https://doi.org/10.1108/S1049-2585(2010)0000018004

Santos, M. E., & Villatoro, P. (2018). A Multidimensional Poverty Index for Latin America. *Review of Income and Wealth*, *64*(1), 52-82. https://doi.org/10.1111/roiw.12275

Santos, M. E., Villatoro, P., Mancero, X., & Gerstenfeld, P. (2015). *A multidimensional poverty index for Latin America*. OPHI Working Paper, 79. https://ophi.org.uk/publications/WP-79

Sen, A. (1984). *Rights and capabilities*. Basil Blackwell.

Sen, A. (1985). *Commodities and Capabilities*. Elsevier.

Sen, A. (1992). *Inequality reexamined*. Oxford University Press.

Sen, A. (2000). Social justice and the distribution of income. In A. B. Atkinson & F. Bourguignon (Eds.), *Handbook of Income Distribution* (Chapter 1, pp. 59-85). Elsevier.

Sione, C. A. (2024). La medición multidimensional de la pobreza en Argentina: propuesta metodológica. *Ciencia, Docencia Y Tecnología*, *35*(70), 1-43. https://doi.org/10.33255/3570/1642

Skrondal, A., & Rabe-Hesketh, S. (2004). Generalized Latent Variable Modeling. Multilevel, Longitudinal, and Structural Equation Models. Chapman & Hall/CRC.

United Nations Development Programme & Oxford Poverty and Human Development Initiative (2019). *How to Build a National Multidimensional Poverty Index (MPI): Using the MPI to inform the SDGs*. https://www.undp.org/publications/how-build-national-multidimensional-poverty-index

Wagle, U. (2009). Multidimensional Poverty Measurement: Concepts and Applications. Springer.

Walker, R (2015). *Multidimensional Poverty*. GSDRC Professional Development Reading Pack No. 22, University of Birmingham. https://gsdrc.org/wp-content/uploads/2015/10/Multidimensional-Poverty_RP.pdf

Wang, X., Feng, H., Xia, Q., & Alkire, S. (2016). *On the relationship between income poverty and multidimensional poverty in China*. Working Paper, 101, OPHI https://ophi.org.uk/publications/WP-101

Whelan, B. J. (1993a). Non-monetary Indicators of Poverty. In J. Berghman & B. Cantillon (Eds.), *The European face of social security: Essays in honour of Herman Deleeck* (pp. 24-42). Avebury.

Whelan, C. T. (1993b). The role of social support in mediating the psychological consequences of economic stress. *Sociology of Health and Illness*, *15*(1), 86-101. https://doi.org/10.1111/1467-9566.ep11343797

Zhang, Y., & Huai, J. (2023). A Case Study of Farmers' Behavioral Motivation Mechanisms to Crack the Fractal Multidimensional Relative Poverty Trap in Shaanxi, China. *Agriculture*, *13*(11), 20-43. https://doi.org/10.3390/agriculture13112043