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Pro-Metrics

ORIGINAL ARTICLE

Measuring multidimensional poverty in Mexico using bibliometric and structural equation analysis

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ABSTRACT

Objective. Multidimensional poverty in Mexico was measured through a bibliometric and structural equation analysis.

Design/Methodology/Approach. We used the technique developed by the National Council for the Evaluation of Social Development Policy (CONEVAL, in Spanish) in Mexico, based on information from the National Household Income and Expenditure Survey (ENIGH, in Spanish). The Smart PLS software also used the partial least squares (PLS) technique. Regarding the bibliometric part, a descriptive analysis was performed using the Scopus database and VOSviewer as a processing tool.

Results/Discussion. The results showed that basic housing services, access to food, quality, housing spaces, and income significantly impact multidimensional poverty. The PLS model showed adequate predictive superiority and goodness of fit. From the bibliometric point of view, there was clear interest on the part of the academic and scientific community in developing knowledge in this field.

Conclusions. The effectiveness of the PLS model for measuring multidimensional poverty in Mexico is demonstrated, and several determinants are highlighted. Future studies are recommended to improve social policies and poverty reduction strategies.

Originality/Value. The study provides a novel approach by using the PLS model to measure multidimensional poverty in Mexico. It applies a robust exploratory methodology that can be replicated in similar contexts and is supported by bibliometric contrast.

Keywords: multidimensional poverty; Mexico; bibliometrics; partial least squares; bibliometric analysis; social policies.

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1. INTRODUCTION

Talking about poverty implies emphasizing deprivations and vulnerabilities that go beyond the monetary sphere. However, many other aspects must now be considered, such as well-being and rights, as well as social, economic, and cultural rights. At the international level, the debate has been ignited on the need to develop multidimensional indicators of poverty so that, from there, policies can be implemented to reduce it (Florio & Labrunée, 2021).

Since the Human Development Report (HDR) was launched in 2010, multidimensional poverty has been the subject of criticism and heated discussions. This is because the report included dimensions such as possession of assets, fuel used for cooking, access to electricity and water, housing deprivation, and sanitation measures until reaching the current indicators, which are not so far from those initially handled (Dotter & Klasen, 2017).

Given that poverty is not easy to define, attempts have been made in recent years to clarify it. So much so that the World Bank described it as the inability of people to achieve a minimum standard of living. However, this is an incomplete definition since the term implies more extensive elements. Different researchers have examined how to define and measure poverty, starting with poverty lines, such as Citro and Michael (1995), Hagenaars (1987), Foster, Greer, and Thorbecke (1984), and Sen (1976). Concerning poverty lines, we cite Van Praag, Hagenaars, and Van Weeren (1982), as well as Atkinson (1974); while with equivalence scales, we mention the works of Coulter, Cowell and Jenkins (1992), Jenkins and Lambert (1993), Podder (1971) and Kakwani (1986). No less important are the authors who point to the existence of poverty measures, such as Sen (1976), Thon (1979), Chakravarty (1983), Foster, Greer and Thorbecke (1984), Alkire and Santos (2010) and Hutto *et al.* (2011).

To conceptualize poverty, it is necessary to define who the poor are. In this sense, Sen (1992) pointed out that, in the first place, a poverty threshold must be defined so they would be made up of those with consumption levels below those standards or those with income below that line. Ravallion (2003) contemplates that, mainly, the characteristics or context of individuals should be considered (Ortiz and Ríos, 2013).

The literature on the phenomenon of poverty is very extensive and varied. Still, finding elements that allow us to classify and differentiate how it is analyzed is possible. First, the approach to poverty is perceived objectively as a lack and, in turn, can be recognized as quantifiable. On the other hand, there is the subjective approach to poverty, which conceives it as a situation of restriction but which is measured through the perception of individuals (Feres and Mancero, 2020). Therefore, two variables are used to measure poverty: monetary and non-monetary. The former establishes thresholds that define who is intrinsically and extrinsically in an environment of poverty. On the other hand, non-monetary variables quantify or dictate the particularities that a household or individual must have to be considered poor or non-poor (Ortiz and Ríos, 2013).

For this purpose, deprivation or unsatisfied basic needs (UBN) indices are generally used. Some of the methodological limitations of the UBN method are inherent to multidimensional methods, such as the characterization of poor people based on a deprivation count. In addition, the method by which poverty is measured must be considered. The direct method involves the analysis of variables directly related to well-being and satisfaction of needs. These multidimensional variables can include primary elements of livelihood, skills, and social participation, among others. In contrast, the indirect method uses variables that reflect access to the precise aspects of well-being. In short, this method measures the income or consumption of households and individuals as a measure of well-being (Sánchez, 2013).

1.1. The Mexican context

It should be noted that the definition of poverty has been a topic of debate in Mexico since the 1970s. However, the most important and present effort has been made in the context of a discussion of the definition of social rights, which originated with the approval of the 2004 General Law for Social Development (Boltvinik, 2005). Said law defines social rights as “education, health, food, housing, enjoyment of a healthy environment, work and social security" (Portales, 2014). However, the evaluation of poverty in Mexico follows general guidelines and criteria established by the National Council for the Evaluation of Social Development Policy (CONEVAL, in Spanish). The measurement of poverty in Mexico has been carried out habitually from a unidimensional aspect in which income is handled as an approach to the population's economic well-being. Consequently, an origin or poverty line is usually conceptualized, which interprets the minimum income sufficient to obtain a basket of estimated essential goods.

The origin above contrasts with household income to establish which households are poor. According to the National Council for the Evaluation of Social Development Policy, this approach makes it possible to identify the population that needs to satisfy essential conditions as long as they can be acquired through the goods and services markets (CONEVAL, 2019). Thus, in the 1980s, the idea of multidimensional poverty began to emerge, which emphasized the need to consider various factors that contribute to poverty. This includes a lack of financial and material resources and deficiencies in education, security, and freedom. Although numerous theoretical approaches exist to identify poverty, there is greater consensus on its multidimensional nature. This consensus recognizes that everyone needs to make free, informed, and equal decisions about their options. This is because poverty cannot be reduced to a single characteristic or dimension of its essence, as Alkire and Foster (2007) and Kakwani and Silber (2008) show in their work.

The truth is that, in recent years, precipitous progress has been made in the different environments related to the evaluation of poverty in its multiple dimensions. The creation of multidimensional poverty indices that efficiently address the problems arising from the addition of dimensions in a single indicator has generated the creation of various indices and analytical techniques. Proposals based on axioms, which consist of creating a set of desirable properties for poverty indicators and developing those that satisfy them, are the most widely used. This group includes proposals such as those of Bourguignon and Chakravarty (2003) and Alkire and Foster (2007).

Consequently, for some years now, three levels of well-being have been defined in Mexico to help people with insufficient income: food, capability, and patrimonial poverty. Since 2008, poverty has been estimated using a multidimensional method that associates the social rights dimension —based on six fundamental rights: food, health, education, housing, essential services, and social security— as well as the income dimension —based on four welfare lines that are renewed monthly based on the cost of food and non-food commodities in rural and urban areas of the world—.

According to the above, the latest proposal and new perspective are the following: "A person is in a situation of multidimensional poverty when he/she cannot exercise at least one of his/her rights for social development and his/her income is scarce to meet his/her needs" (CONEVAL, 2019). In addition, nationally and internationally, there has been a proliferation of practical applications to measure multidimensional poverty. Latin American countries such as Chile, Uruguay, and Bolivia have shown that using multivariate statistical techniques to classify and group people in poverty and identify those government programs should target represents an effective tool to reduce poverty levels (Brodersohn, 1999).

In contrast to the current state of poverty in Mexico, which affects more than half of the population, poverty in Uruguay has decreased from 47 % in 1986 to 6.2 % in 2016, while in Bolivia it has decreased from 66 % in 2000 to 38 % in 2015. In Chile, where the multidimensional method is also used, poverty declined from 45 % in 1987 to 12 % in 2015 with the income method and from 28 % to 21 % with the multidimensional method between 2009 and 2005 (Aguilar, Caamal & Portillo, 2018).

Therefore, to quantify poverty, a distinction must be made between "absolute" and "relative" poverty, "direct" and "indirect" approaches, as well as "objective" and "subjective" perspectives. It is important to note that no single method of identification and aggregation is sufficient on its own, so their combination may be a more accurate option for poverty estimation (Sen, 1992). The Multidimensional Poverty Index (MPI) measures acute poverty, which indicates deficiencies in primary services and vital functions in dimensions such as education, health, and living conditions for the metropolis of 104 countries, involving several countries in Latin America and the Caribbean.

The dimensions of the above index were chosen based on criteria such as parsimony (the few dimensions simplify the comparison with the monetary measure of $1 per day used by the World Bank), consensus (education, health, and a high standard of living have a widely recognized value) and the inclusion of instrumental and intangible aspects of human development (Alkire *et al.,* 2010, 2015).

Regarding the COVID-19 pandemic and multidimensional poverty in Mexico and the world, the Economic Commission for Latin America (CEPAL, 2020) has published a study on the influence of COVID-19 on poverty in Latin America. Poverty in the region was a problem even before COVID-19. Between 2002 and 2010, there was a significant decrease, from 45.4% to 31.6%. But since 2011, it has remained stable at around 30% of the population.

Mexico was already the second poorest country in the region, behind only Honduras and Venezuela, if two factors were considered: general and extreme poverty. As a result of the COVID-19 pandemic, many countries began to face social pressures that could influence their poverty levels. This, in turn, led several countries to implement policies to mitigate these effects, such as social transfers; as a result, some countries were able to reduce the burden of poverty. The most important case was Brazil, which reduced poverty post-cob-19 by more than 7% due to its fiscal policy. It was followed by countries such as Chile and Peru, which had a 4% reduction in poverty.

It should be noted that the countries most affected by the change in trend were those that received the most minor support for their economies, such as Nicaragua, Honduras, and, especially, Mexico. In the latter, no new monetary aid was provided, nor was existing aid increased, nor were food and medicines distributed. Mexico has the lowest social spending in the region, representing only 9.3% of GDP. This contrasts with the cases of Chile, Brazil, and Uruguay, which have the highest GDP, with 17.1%, 17.6%, and 17.7%, respectively. In addition, Mexico has one of the lowest investments in COVID-19 products, equivalent to less than 0.5% of GDP (Garza, 2021).

To reinforce the vision of the elements covered by multidimensional poverty, a bibliometric analysis is included in this study to reveal patterns and trends in poverty research. This will enrich the focus of the study's theoretical framework and improve the proposed model by contrasting the elements from the scientific literature. In addition, it will optimize the accuracy and usefulness of the model for measuring multidimensional poverty in Mexico (Álvarez & López, 2022; Álvarez *et al.,* al 2023).

2. MATERIALS AND METHOD

The article's methodology begins with a bibliometric analysis to identify patterns and trends in research on multidimensional poverty. For this purpose, the Scopus database was used to extract data from the publications, while the VOSviewer tool was used to process and visualize the networks of the main topics. This bibliometric analysis provided a comprehensive overview of the predominant techniques, tools, and methodological approaches in the study of multidimensional poverty. It also provided insight into key elements to optimize the research model (López *et al.,* 2019).

Subsequently, an exploratory quantitative approach was applied using the partial least squares (PLS) model for structural equation analysis. For this purpose, data from the National Household Income and Expenditure Survey (ENIGH, 2020) were used. The study was conducted with the Smart PLS v.3.3.5 software to determine the validity and reliability of the constructs related to multidimensional poverty in Mexico. While bibliometrics served as a technique to confirm that all the elements were included and thus avoid that some of them were not being measured in the corresponding variables.

2.1. Procedures for bibliometric analysis

A search was performed in the Scopus database, using the terms "multidimensional povert*" or "multidimension povert*" in the title, abstract and keywords (TITLE-ABS-KEY) fields. The search was limited to article ("ar"), book chapter ("ch"), conference paper ("cp") and review ("re") documents. It was also restricted to publications in English (LANGUAGE, "English"). The search equation was as follows:

TITLE-ABS-KEY ("multidimensional povert*" OR "multidimension povert*") AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")).

The results of this search yielded 1424 relevant publications, which accumulated 21157 citations. The earliest identified publication dates back to 2002. The result set presented an index of 63, indicating that 63 publications have been cited at least 63 times. This reflected a significant influence on academic research on the subject. The indicators analyzed are shown in Figures 1 and 2.

2.2. Structural Equation Analysis Procedures

Based on the methodology of the National Council for the Evaluation of Social Development Policy (CONEVAL, 2014), an appropriate model for measuring multidimensional poverty was examined. A quantitative approach was employed at the explanatory research level, using secondary, cross-sectional data measured from August 21 to November 28, 2020 (Hernández, Fernández, and Baptista, 2014).

The General Law of Social Development (LGDS, in Spanish) establishes a set of criteria that the CONEVAL must follow to measure poverty. Every two years at the state level and every five years at the municipal level, using for this purpose the information generated by the National Institute of Statistics and Geography (INEGI, in Spanish) of Mexico (CONEVAL, 2014), the National Household Income and Expenditure Survey (ENIGH, in Spanish), whose objective was to provide a statistical overview of the behavior of household income and expenditures.

The ENIGH 2020 sample size was 105,483 dwellings, plus 1,363 found in the aforementioned sample, out of a total of approximately 35.7 million dwellings throughout Mexico. It was applied to household members over 18 years of age in urban localities with a population over 2500 people and rural localities with less than 2500 inhabitants (INEGI, 2020).

It should be noted that, among the databases generated by the ENIGH, the CONEVAL has the file *"pobreza_20.sav",* which is in SPSS format for downloading and consists of 79 variables with 315,619 records (CONEVAL, 2020). From this, a random sample of approximately 1 % was taken using the SPSS v. 24 program. This file consists of 79 variables and 315 619 records, and a random sample of roughly 1 % was taken. The final file consisted of 3063 records, which were analyzed with the statistical software SmartPLS version 3.3.5 (Ringle, Wende, and Becker, 2015), which is a much larger number than the minimum sample required (100 records) by a structural equation (Hair *et al.,* 2010; Roldán and Sánchez, 2012).

The partial least squares technique (PLS) is employed in theoretical and empirical research in the social sciences where robust theories are not available (Wold, 1979). Falk and Miller (1992) point out that PLS has advantages, such as conjectural relationships between constructs, and non-experimental research designs, such as surveys or secondary data, are used.

According to Henseler (2017), given the nature of the constructs, the relationships between them and the indicators are determined. Starting from the initial model shown in Table 1, in which the analysis is approached based on the indicators: *educational backwardness, access to social security, housing quality and spaces, access to basic housing services,* and *access to food,* based on the CONEVAL methodology (CONEVAL, 2014).

3. RESULTS

3.1. Bibliometric analysis

The results of the present study begin with a comprehensive bibliometric analysis that identifies the most relevant research patterns in multidimensional poverty research. Figure 1 shows the evolution of scientific production, as well as its impact, measured through publications and citations in the Scopus database from 2002 to 2024. Since 2002, production in this field has grown notably. Until 2009, publications were scarce, gradually increasing from 2010 onwards. However, from 2013 onwards, a more sustained increase in annual publications has been observed, reflecting greater academic interest in this subject. This growth accelerated from 2018, reaching its highest point in 2022, with more than 200 publications. In 2023, although there

List of items used in the first approach to the model	
Educational backwardness	
edu_back1	Indicator of educational backwardness
edu_back2	Non-attendance at school
edu_back3	Educational level
Access to health services	
health_s1	Indicator of deprivation due to lack of access to health services
health_s2	Direct access to health services
health_s3	Medical services provided by other households or self-employed persons
health_s4	Members who have access by other members
Access to social security	
soc_sec1	Indicator of deprivation due to lack of access to social security
soc_sec2	Direct access to social security for the head of household
soc_sec3	Direct access to social security
soc_sec4	Direct access to social security for the spouse of the head of household
soc_sec5	Direct access to social security for children of the head of household
soc_sec6	Economically active population
soc_sec7	Pensioned or retired population
soc_sec8	Senior Citizens Program
Housing quality and space	
hous_spa1	Indicator of deprivation due to lack of housing quality and space
hous_spa2	Indicator of housing material deprivation by housing floor material
hous_spa3	Indicator of housing material deprivation by walls of the home
hous_spa4	Indicator of housing material deprivation by roofing material
hous_spa5	Indicator of deprivation due to overcrowding in the home
Access to basic housing services	
hous_ser1	Indicator of deprivation of access to basic services in housing
hous_ser2	Indicator of lack of access to water
hous_ser3	Indicator of lack of sewage service
hous_ser4	Indicator of lack of electricity services
hous_ser5	Cooking fuel shortage indicator
Access to food	
food1	Indicator of deprivation of access to nutritious and quality food
food2	Households with population from 0 to 17 years old
food3	AI scale for households with no children under 18 years of age
food4	AI scale for households with children under 18 years of age
food5	Degree of Food Insecurity
food6	Access to food deprivation indicator
food7	Limitation of food consumption
food8	Diet consumed in households

List of items used in the first approach to the model	
Income	
income1	Total current income per capita
income2	Total current household income
income3	Household current monetary income
income4	Current labor monetary income
income5	Current monetary rental income
income6	Current monetary income from transfers
income7	Non-cash current income
income8	Non-cash current income payment in kind
income9	Non-cash current income gifts in kind
Multidimensional poverty (endogenous variable)	
poverty1	Population with at least one deprivation
poverty2	Population with three or more deprivations
poverty3	Index of Social Deprivation
poverty4	Non-poor and non-vulnerable population
poverty5	Poverty
poverty6	Extreme poverty
poverty7	Moderate poverty
poverty8	Vulnerable population by deprivation

Table 1. List of elements used in the first approximation to the model.
Source: Prepared by the authors based on the dataset *poverty_20.sav* (CONEVAL,2014).

is a slight decrease, the production remains high, with more than 175 publications. This indicates the continued relevance of the topic.

Regarding citations, the trend shows exponential growth, especially from 2013 onwards, in parallel with the increase in publications. This pattern suggests that published papers have increasingly influenced the academic community. The peak in citations occurs in 2023, with more than 4000, coinciding with the highest production year. In 2024, although citations decreased slightly, they are still significant, evidencing the sustained impact of the literature on the topic in recent years.

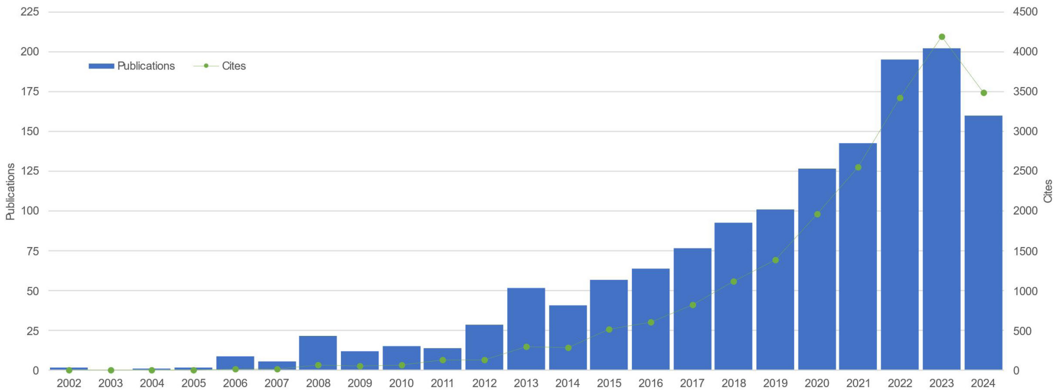

Figure 1. Scientific production and impact on multidimensional poverty.
Source: Prepared by the authors based on Scopus data.

Table 2 shows a detailed analysis of the most influential key players, organizations, countries, and areas of knowledge. Among the most prominent authors are *Alkire, S.,* with 31 publications, and *Santos, M. E.* and *Silber, J.,* with 14 publications each. Other relevant authors are *Betti, G., Callander, E. J., Schofield, D. J.* (13 publications), *Pinilla-Roncancio, M.* (11 publications), and *Trani, J. F.* (10 publications). These authors have contributed significantly to the theoretical and methodological development of the study of multidimensional poverty, with *Alkire* and *Santos* leading research in this area.

In terms of organizations, the most productive is the *University of Oxford* (United Kingdom), with 65 publications, followed by the *Universidad de Los Andes* (Colombia), with 21 publications, and the *World Bank* (United States), with 17 publications. Other influential institutions are *Georg-August-Universität Göttingen* (Germany), with 16 publications, and international organizations such as *UNICEF* and *Washington University in St. Louis* (United States), with 15 publications each. These organizations are essential in the generation of knowledge and the implementation of public policies to combat poverty.

In terms of productivity by country, China leads the ranking with 197 publications, closely followed by the United States with 196 and the United Kingdom with 195. India, with 154, and Italy, with 81, are also countries with high production in this area, indicating a global interest in studying multidimensional poverty and its relationship with different socioeconomic contexts.

The most prolific publications in this field are led by the journal *Social Indicators Research,* with 129 articles, followed by *World Development* (35), *Economic Studies in Inequality, Social Exclusion and Well-being* (30), *Child Indicators Research* (29) and *Plos One* (25). These sources focus on the multidimensional analysis of poverty from social, economic, and welfare perspectives.

Finally, the areas of knowledge most represented in research on multidimensional poverty are the social sciences, with 876 publications, followed by economics, econometrics, and finance, with 468; psychology, with 191; environmental sciences, with 177; and arts and humanities, with 171. The analysis in Table 1 reveals a global and interdisciplinary network of researchers, institutions, and publications that have driven progress in the study of multidimensional poverty, highlighting both theoretical approaches and practical applications in public policy and social development.

Description	(Publications) Description
Most productive authors	(31) Alkire, S. (14) Santos, M. E.; Silber, J. (13) Betti, G.; Callander, E. J.; Schofield, D. J. (11) Pinilla-Roncancio, M. (10) Trani, J. F.
More productive organizations	(65) University of Oxford (21) Universidad de Los Andes, Colombia (17) The World Bank, USA (16) Georg-August-Universität Göttingen (15) Bar-Ilan University; UNICEF; Washington University in St. Louis
Most productive countries	(197) China (196) United States (195) United Kingdom (154) India (81) Italy
More productive sources	(129) Social Indicators Research (35) World Development (30) Economic Studies in Inequality, Social Exclusion and Well Being (29) Child Indicators Research (25) Plos One
Main research areas	(876) Social Sciences (468) Economics, Econometrics and Finance (191) Psychology (177) Environmental Sciences (171) Arts and Humanities

Table 2. Principal authors, organizations, countries, and areas of knowledge in multidimensional poverty. Source: Prepared by the authors based on Scopus data.

The map of keywords in Figure 2, generated using VOSviewer software, shows the evolution of the primary research, development, and innovation topics in multidimensional poverty, according to data from the Scopus database (5289 topics). The map uses a color scale ranging from blue (2018) to yellow (2021) to indicate the years these terms have been most prominent in the literature.

The most prominent central term is *"poverty behavior,"* which connects densely with other key terms such as *"household survey," "socioeconomic status"* (and *"multidimensional poverty index")*. This suggests that much recent research has focused on analyzing *poverty behavior through household surveys,* highlighting the importance of socioeconomic *status* and using *multidimensional indicators for its measurement.* This suggests that much recent research has focused on analyzing poverty behavior through household surveys, highlighting the importance of socioeconomic status and using multidimensional indicators for its measurement. Significant connections are also observed with *income distribution, education, health,* and *child poverty*. This indicates a multifaceted approach to studying poverty, encompassing educational, health and distributional aspects. Research on p*overty alleviation* and *poverty measurement* also features prominently, suggesting a continuing interest in evaluating policies and strategies to reduce poverty.

Regarding temporal evolution, themes such as *"sustainable development"* and *"covid-19"* have gained prominence more recently, as reflected in the colors closer to yellow. This indicates an emerging focus on the impact of the COVID-19 pandemic on multidimensional poverty and its relationship to the Sustainable Development Goals. In addition, geographic terms such as *"China," "India," "Colombia,"* and *"South Africa"* stand out, evidence that these countries are critical contexts in recent studies on multidimensional poverty. The importance of demographic studies, such as those focusing on *"female"* and *"male",* is also highlighted, reflecting the interest in gender differences in the impact of the topic under study.

Overall, Figure 2 illustrates how studies on multidimensional poverty have evolved to include a broader and more diversified approach, integrating multiple socioeconomic and demographic dimensions and responding to recent global contexts such as the Covid-19 pandemic and efforts towards sustainable development.

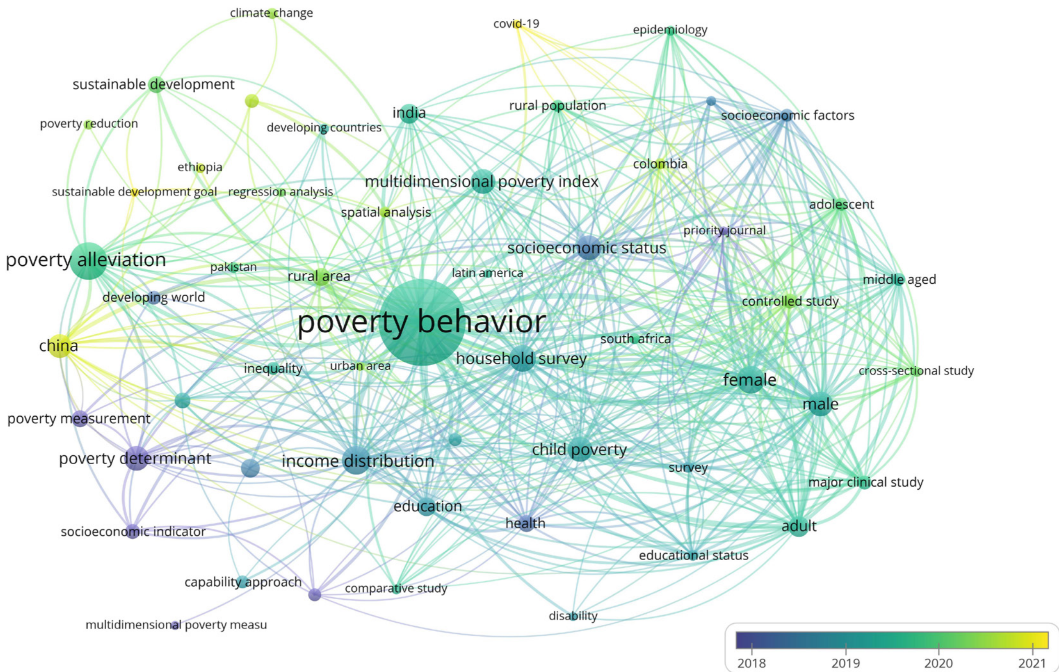

Figure 2. Evolution of the primary research, development, and innovation topics in multidimensional poverty. Source: Prepared by the authors based on Scopus data.

3.2. Structural equation analysis

Using the elements of the *poverty_20.sav* database (CONEVAL, 2014) shown in Table 1, the first model (nomogram), visualized in Figure 3, was obtained.

The first approach was based on the measure used by CONEVAL to measure poverty in a multidimensional manner, considering all the elements involved in the different constructs related to the respective dimensions of poverty. Then, the respective valuation analyses of a variance-based structural equation system were performed (Ringle, Wende & Becker, 2015). Compared to covariance-based models, PLS is better suited for predictive applications and theory development, i.e., exploratory analyses (Cepeda & Roldán, 2004). Jöreskog and Wold (1982) mention that PLS is more comfortable with causal-predictive analysis in complex situations for which insufficient theoretical information is available. The model is shown in Figure 4.

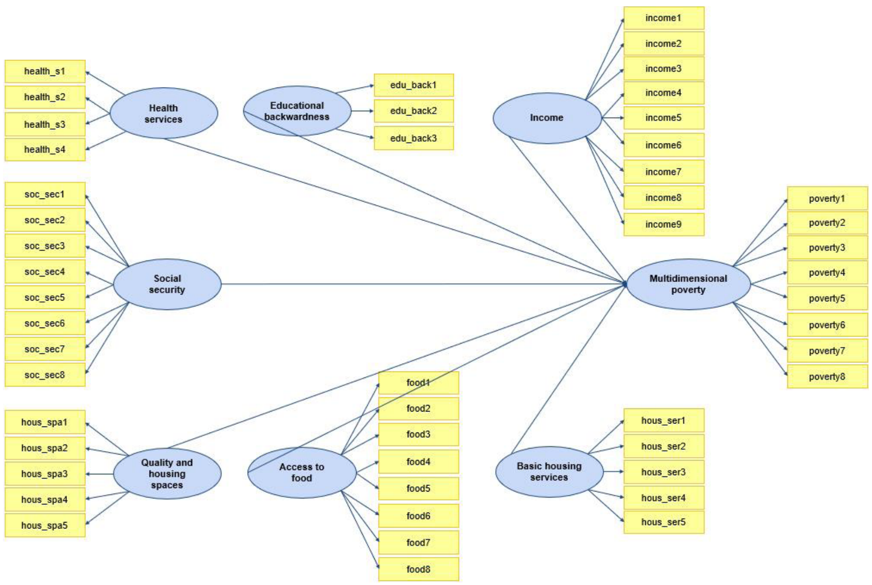

Figure 3. First approximation to the multidimensional poverty model by partial least squares. Source: Elaboration based on the statistical package SmartPLS version 3.2.2 (Ringle, Wende, and Becker, 2015).

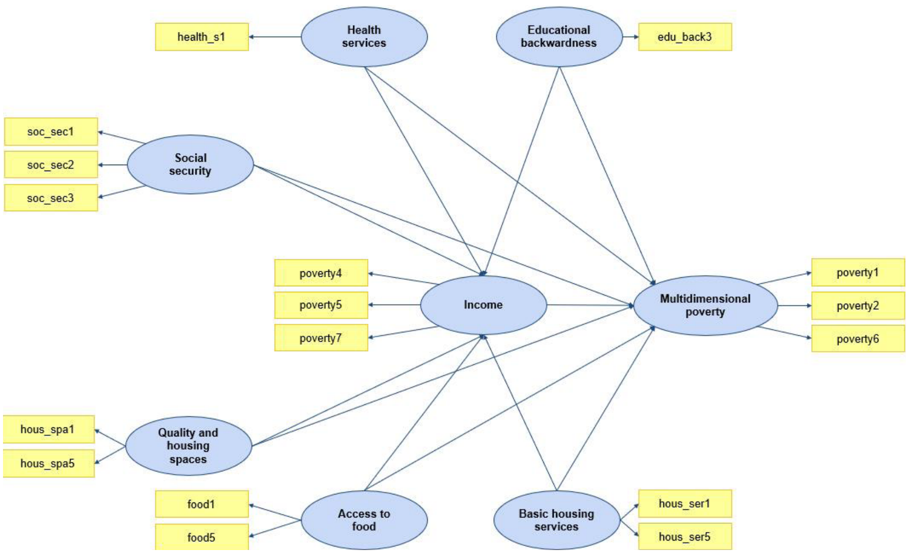

Figure 4. The final model of multidimensional poverty by partial least squares. Source: Elaboration based on the statistical package SmartPLS version 3.2.2 (Ringle, Wende, and Becker, 2015).

The Statistical Package for Social Sciences (SPSS) version 24 was used to evaluate the descriptive statistics. The results show that 49.7% of the sample are women and 50.3% are men; 27.7% have incomplete primary education, 18.2% have complete primary or incomplete upper secondary education, 24.7% have complete secondary or incomplete upper secondary education and 25.3% have complete upper secondary education or higher. The economically active population (EAP) accounts for 24.1 %, of which 46.6 % are employed and 2.1 % are unemployed; 5.8 % are retired. Regarding the evaluation of the proposed model (after evaluating several models), SmartPLS (Partial Least Squares (PLS) Regression Modeler) in its version 3.3.5 (Ringle, Wende & Becker, 2015) was used. The minimum sample size required by a structural equation is 100, so the current sample is 3063 (Hair *et al.,* 2010).

3.2.1. Evaluation of the measurement model

Therefore, when evaluating the measurement model (Hair *et al.,* 2007) in which the convergent validity - item loadings, average extracted variance (AVE) - and reliability - Cronbach's alpha and composite reliability (Chin, 2010) - of the initial model are examined, items whose external loading was not at least 0.60 were eliminated, whereby at least 50% of the variance of each indicator must be explained by the underlying construct (Sarstedt, Ringle & Hair, 2017). When the initial model was evaluated, it was modified according to the evaluated parameters and others, such as discriminant validity, remaining as shown in Table 3.

Construct/dimension/indicator	Convergent validity		Reliability	
	Charges	AVE	Composite reliability	Cronbach's alpha
Educational backwardness		1.00	1.00	1.00
edu_back3: educational level	1.00			
Access to health services		1.00	1.00	1.00
health_s1: indicator of deprivation of access to health services	1.00			
Access to social security		.689	.869	.776
soc_sec1: indicator of deprivation of access to health services	.908			
soc_sec2: direct access to social security for the head of household	.821			
soc_sec3: direct access to the social security system	.753			
Housing quality and space		.885	.939	.872
hous_spa1: housing quality and space deprivation indicator	.953			
hous_spa5: Indicator of deprivation due to overcrowding in housing.	.928			
Access to food		.925	.961	.918
food1: indicator of deprivation of access to nutritious and quality food	.960			
food7: Indicator of food access deprivation	.928			
food5: degree of Food Insecurity				
Access to basic housing services		.887	.940	.873
hous_ser1: indicator of lack of access to basic services in housing	.950			
hous_ser5: cooking fuel shortage indicator	.933			
Income		.699	.874	.795
poverty4: non-poor and non-vulnerable population	.804			
poverty5: poverty	.888			
poverty7: moderate poverty	.814			
Multidimensional poverty (endogenous variable)		.574	.800	.635
poverty1: population with at least one deprivation	.748			
poverty2: Population with three or more deprivations	.846			
poverty6: Extreme poverty	.668			

Table 3. Evaluation of the measurement model: reliability and convergent validity (n=3063).
Source: Own elaboration based on the statistical package SmartPLS version 3.2.2 (Ringle *et al.,* 2015).

Being unit item dimensions, "educational backwardness" and "access to health services" are not interpreted as perfect reliability and/or convergence (Zeithmal, Bery & Parasuraman, 1996). As can be seen in Table 3, there are significant differences with respect to the model proposed at the beginning, in which several indicators did not meet the factor loading of .7 (minimum .6) (Sarstedt, Ringle & Hair, 2017). Even some dimensions, such as income, presented high collinearity with the "multidimensional poverty" indicators, being more correlated in this dimension (Henseler, Ringle & Sarstedt, 2015).

According to Hair *et al.* (2007), discriminant validity was tested using the criterion of Fornell and Larker (1981), according to which each construct should explain the variance of its own indicators better than the variance of others. As can be seen in Table 4, the square root of the average variance extracted (AVE) that is located on the main diagonal has the highest correlations with respect to the other constructs, thus proving discriminant validity. The value of the constructs "educational backwardness" and "access to health services", being single-item indicators (Hair *et al.*, 2007, cited in Bañuelos *et al.*, 2021), always present this value as a result of this type of analysis.

	Educational backwardness	Access to health services	Access to social security	Housing quality and space	Access to food	Access to basic housing services	Income	Multidimensional poverty
Educational backwardness	1.00							
Access to health services	0.019	1.00						
Access to social security	0.219	0.455	0.830					
Housing quality and space	-0.112	-0.055	-0.120	0.941				
Access to food	0.079	-0.077	-0.147	0.161	0.792			
Access to basic housing services	-0.173	-0.065	-0.258	0.249	0.173	0.962		
Income	-0.275	-0.308	-0.601	0.193	0.346	0.287	0.836	
Multidimensional poverty	-0.286	-0.488	-0.623	0.371	0.466	0.535	0.616	0.758

Table 4. Evaluation of the measurement model: discriminant validity (n=3063).
Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle *et al.,* 2015).

	Educational backwardness	Access to health services	Access to social security	Housing quality and space	Access to food	Access to basic housing services	Income	Multidimensional poverty
Educational backwardness								
Access to health services	0.019							
Access to social security	0.268	0.493						
Housing quality and space	0.119	0.059	0.139					
Access to food	0.082	0.080	0.170	0.179				
Access to basic housing services	0.185	0.068	0.305	0.279	0.193			
Income	0.288	0.316	0.708	0.205	0.376	0.305		
Multidimensional poverty	0.346	0.582	0.812	0.494	0.594	0.714	0.815	

Table 5. Heterotrait-monotrait ratio (HTMT). Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle *et al.,* 2015).

Cross-loadings, together with the Fornell and Larker test (1981, cited in Bañuelos *et al.*, 2021), are a way of detecting discriminant validity problems, checking whether the items of a construct explain the variance of its own indicators better than that of other constructs. In the present case, the problem above was not encountered. In addition to the Fornell and Larcker criteria and cross-loadings, to detect discriminant validity problems, the heterotrait-monotrait ratio (HTMT) is used, which consists of verifying that the correlations between items of the same construct should be more significant than the correlations of items of different constructs (Henseler, Ringle, & Sarstedt, 2015). Table 5 verifies that the HTMT values are less than .85 (Henseler, Ringle & Sarstedt, 2015).

3.2.2. Evaluation of the structural model

According to Chin (2010), once it has been proven that the measurement model meets the specifications of the partial least squares technique, evidence must be provided to support the theoretical model. Among them are the predictive power with the values of the coefficient of determination R^2 and the significance of the path estimates.

For the structural model, Hair *et al.* (2007) suggest evaluating the following:

- Collinearity between constructs
- Significance and relevance of path coefficients
- Predictive relevance *(R^2, f^2, Q^2, q^2, PLSpredict)*
- Goodness of fit

In particular, PLS is a reasonably robust method for assessing collinearity (Cassel, Hackl & Wetlund, 1999). To do so, the variance inflation factor (VIF) is used. When evaluating the VIF, as shown in Table 6, its value is verified to be less than five, so no collinearity problem was found between Chin's (2010) constructs.

	Educational backwardness	Access to health services	Access to social security	Housing quality and space	Access to food	Access to basic housing services	Income	Multidimensional poverty
Educational backwardness							1.080	1.111
Access to health services							1.277	1.283
Access to social security							1.418	1.851
Housing quality and space							1.089	1.096
Access to food							1.059	1.162
Access to basic housing services							1.160	1.172
Income								1.852
Multidimensional poverty								

Table 6. Variance inflation factor (VIF). Source: Elaboration based on the statistical package SmartPLS version 3.2.2 (Ringle *et al.,* 2015).

3.2.3. Significance and relevance of path coefficients

High (absolute) values represent stronger relationships since they have direct effects when a construct is touched by a single arrow and indirect ones when it involves at least one other construct called intervening (Hair *et al.,* 2007).

As shown in Table 7, essential housing services are strongly related to multidimensional poverty (.307), access to food to multidimensional poverty (.272), and to income (.236), while access to social security is strongly inversely related to income (-.484) and to multidimensional poverty (.254).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics (| O/STDEV|)	P Values
Access to food -> Income	0.236	0.236	0.014	17.244	0.000
Access to food -> Multidimensional poverty	0.272	0.272	0.011	24.46	0.000
Access to social security -> Income	-0.484	-0.485	0.015	33.322	0.000
Access to social security -> Multidimensional poverty	-0.254	-0.254	0.01	24.443	0.000
Housing quality and space -> Income	0.059	0.06	0.014	4.185	0.000
Quality and space of housing -> Multidimensional poverty	0.168	0.168	0.013	13.123	0.000
Income -> Multidimensional poverty	0.138	0.138	0.011	12.495	0.000
Educational_ backwardness -> Income	-0.129	-0.129	0.015	8.782	0.000
Educational_ backwardness -> Multidimensional poverty	-0.094	-0.094	0.01	9.851	0.000
Health services -> Income	-0.058	-0.057	0.014	4.157	0.000
Health services -> Multidimensional poverty	-0.278	-0.279	0.012	23.765	0.000
Basic housing services -> Income	0.08	0.08	0.013	6.01	0.000
Basic housing services -> Multidimensional poverty	0.307	0.307	0.012	24.604	0.000

Table 7. Path coefficients. Source: Elaboration based on the statistical package SmartPLS version 3 (Ringle *et al.,* 2015).

Total effects, the sum of direct and indirect effects, indicate the strength of the effect on a target variable, in this case, the multidimensional poverty construct. Similarly, Table 8 shows that basic housing services (0.318) have the most substantial total effect on the multidimensional poverty target variable, followed by access to food (0.305), housing quality and spaces (0.176), and income (0.138). Access to social security has a solid but inverse effect (-0.321).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics (| O/STDEV|)	P Values
Access to food -> Income	0.236	0.236	0.014	17.244	0.000
Access to food -> Multidimensional poverty	0.305	0.305	0.011	28.845	0.000
Access to social security -> Income	-0.484	-0.485	0.015	33.322	0.000
Access to social security -> Multidimensional poverty	-0.321	-0.321	0.01	32.468	0.000
Housing quality and space -> Income	0.059	0.06	0.014	4.185	0.000
Quality and space of housing -> Multidimensional poverty	0.176	0.176	0.013	13.826	0.000
Income -> Multidimensional poverty	0.138	0.138	0.011	12.495	0.000
Educational_ lag -> Income	-0.129	-0.129	0.015	8.782	0.000
Educational_ backwardness -> Multidimensional poverty	-0.112	-0.112	0.01	11.472	0.000
Health services -> Income	-0.058	-0.057	0.014	4.157	0.000
Health services -> Multidimensional poverty	-0.286	-0.286	0.012	24.615	0.000
Basic housing services -> Income	0.08	0.08	0.013	6.01	0.000
Basic housing services -> Multidimensional poverty	0.318	0.318	0.012	25.743	0.000

Table 8. Total effects. Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle *et al.,* 2015).

The explanatory power of the within-sample prediction is given by the predictive significance, the coefficient of determination, and the effect size. R^2 and the effect size f^2. The coefficient of determination R^2 represents the variance in the endogenous constructs explained by all the exogenous constructs linked to it, with values between zero and one where higher levels indicate greater predictive accuracy (Hair *et al.,* 2007).

As shown in Table 9, the multidimensional poverty value has the highest coefficient of determination, .759, representing the amount of variance explained by the constructs linked to it, directly and indirectly. Income demonstrates, with its coefficient of .460, that it is a construct that directly affects multidimensional poverty and indirectly affects others.

	R square	**Adjusted R-squared**
Income	.460	.459
Multidimensional poverty	.759	.758

Table 9. Coefficient of determination R^2. Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle *et al.,* 2015).

The effect size f^2, according to Table 10, evaluates how strongly an exogenous construct contributes to explaining a specific endogenous construct in terms of R^2. Thus, concerning the effect size, it was found that the exogenous construct basic housing services strongly affects multidimensional poverty (f^2>.35), with a moderate effect on the same objective construct (see Figure 1). ($15 \geq f^2 < .35$) is access to food (.264) and access to health services (.249). Access to social security has a moderate effect on the income construct.

	Access to food	Access to social security	Housing quality and space	Income	Multidimensional poverty	Educational lag	Health services	Basic housing services
Access to food				0.098	0.264			
Access to social security				0.305	0.145			
Housing quality and space				0.006	0.106			
Income					0.043			
Multidimensional poverty								
Educational_ backwardness				0.029	0.033			
Health services				0.005	0.249			
Basic housing services				0.01	0.334			

Table 10. f^2 effect size. Source: Elaboration based on the statistical package SmartPLS version 3.2.2 (Ringle *et al.,* 2015).

After applying the blindfolding technique for predictive relevance (Hair *et al.,* 2007), assessing the predictive relevance of an *exogenous construct for* a given endogenous construct Q^2 (Hair *et al.,* 2007), assessing the predictive relevance of an exogenous construct for a given endogenous construct; an out-of-sample predictive measure is considered, as it remains almost intact in its calculation (Sarstedt *et al.,* 2017). Table 11 shows the construct income with moderate predictive power. ($15 \geq f^2 < .35$), while multidimensional poverty has a strong predictive power (Q^2>.35). which ratifies the chosen model.

	SSO	SSE	Q^2 (=1-SSE/SSO)
Access to food	6126	6126	
Access to social security	9189	9189	
Housing quality and space	6126	6126	
Income	9189	6531.539	0.289
Multidimensional poverty	9189	5348.371	0.418
Educational backwardness	3063	3063	
Health services	3063	3063	
Basic housing services	6126	6126	

Table 11. Predictive relevance Q^2. Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle, Wende, and Becker, 2015).

3.2.4. Predictive PLS

When running the predictive PLS algorithm that generates and evaluates predictions from PLS nomogram estimates (Shmueli *et al.,* 2016), all values observed in Table 12 are more significant than zero, indicating the model's superiority over other predictions. It presents strong predictive power for the items *no_pobv, deficiencies* and *deficiencies_3,* moderate for *poverty, poverty_e* and weak for *poverty_m*.

	RMSE	MAE	MAPE	Q^2_predict
poverty_m	0.449	0.38	infinite	0.112
poverty	0.403	0.335	infinite	0.337
no_pobv	0.321	0.256	infinite	0.405
deficiencies3	0.286	0.235	infinite	0.56
deficiencies	0.329	0.292	infinite	0.485
poverty_e	0.248	0.171	infinite	0.203

Table 12. PLS prediction. Source: Elaboration based on the statistical package SmartPLS version 3.3.5 (Ringle, Wende, and Becker, 2015).

3.2.5. Goodness-of-fit

Tenenhaus *et al.* (2005) mention that in goodness-of-fit, using PLS, it is impossible to separate valid from invalid models, as occurs with covariance-based models. However, according to Lohmöller (1989), the degree to which the residuals of the external model correlate can be measured using the root mean square residual covariance (RMStheta), which should be between values of ≤ 0.12 - 0.14 (Henseler & Sarstedt, 2013). For the present investigation, a value of RMStheta =.235 was obtained. This indicates that it is still perfect according to the model's goodness of fit, emphasizing that it is a measure for covariance-based structural equations. In the present case, predictive power is prioritized, and the present study is conducted at an exploratory level.

4. DISCUSSION

As noted in the literature review, there are numerous theoretical approaches to identifying poverty since there is more significant agreement on the multidimensional nature of this concept, which records elements that violate people's dignity, restrict their fundamental rights and freedoms, prevent them from satisfying their basic needs and fully integrating into society. Therefore, it cannot be reduced to a single characteristic or dimension of its essence.

Thus, by 2021, the Multidimensional Poverty Index had covered 109 countries, representing about 449 million people living in developing regions. This study considered multiple indicators, such as economic level, primary provider - hierarchized by age -, cultural preferences, and even the role played by gender in the responses that related research represents (Alkire *et al.*, 2021).

It should be noted that, in Europe, 20% of the population is permanently poor in terms of income and 20% in terms of material deprivation. Only 10% of the population is persistently poor regarding income and material deprivation. This reflection motivated the establishment of a multidimensional poverty measurement in Europe. For this reason, the United Nations Development Programme (UNDP, 2010) uses a multidimensional approach that does not include income. It uses equal weights for each dimension and very low thresholds, implying lower poverty levels than the World Bank.

In some countries, such as Argentina, there are two official methods to measure poverty: poverty by unsatisfied basic needs (UBN) and poverty based on a poverty line (PL). The calculation is made officially by the National Institute of Statistics and Census (INDEC) based on census data, updated every ten years. Unlike Colombia, which has two official and complementary indicators to measure poverty - monetary poverty and the multidimensional poverty index - there are no annual measures of multidimensional poverty or analysis of the relationship between the two poverty measures at the departmental level.

It should be noted that in Chile, since 2015, five dimensions have been used to assess multidimensional poverty in the National Socioeconomic Characterization Survey (CASEN, 2017). The five dimensions evaluated are the following: education (schooling (schooling, school attendance, and backwardness), health (malnutrition in children, affiliation to a health system, and access to health), work and social security (occupation, social security, and pensions), housing and environment (habitability, basic services, and environment), in addition to social networks and cohesion (social support and participation, equal treatment, and security). This variable was added in 2015; in previous versions, only four dimensions were assessed.

Similarly, in countries such as Peru, the multidimensional poverty index measures poverty beyond economic income by indicating deficiencies in the three dimensions of human development such as education, health, and quality of life. It reveals the number of people who are multidimensionally poor and the severity of their poverty. The use of low-level parameters is common in Latin American countries and international organizations, leading to people being labeled as “non-poor” despite being vulnerable.

In Mexico, poverty indicators account for income and six dimensions of social rights: educational backwardness, access to health, food, social security, quality of life, basic housing services, and social cohesion. The inclusion of indicators and dimensions is due mainly to data availability, as there is significant variation in data availability and in the questions that set limits to comparability between countries.

Consequently, the study of poverty and its solutions must be based on poverty fluctuation models based on longitudinal data that allow for the analysis of its dynamics and duration. Thus, PLS or partial least squares regression models aim to predict the dependent variables. This objective translates into an attempt to maximize the explained variance of these variables, so PLS may be more suitable for predictive purposes and is mainly aimed at predictive causal analysis in highly complex scenarios, but with little advanced theoretical knowledge.

5. CONCLUSIONS

The bibliometric analysis revealed remarkable growth and diversification in recent years in research on multidimensional poverty. The literature has evolved to encompass a more holistic approach, incorporating multiple socioeconomic dimensions, such as education, health, income distribution, and gender disparities.

Authors such as Alkire and Santos have led this methodological transformation, developing more robust and complex models that allow for a more comprehensive understanding of poverty, overcoming the limitations of unidimensional approaches focused exclusively on income. The convergence of studies from different areas of knowledge, reflected in the collaboration between high-impact institutions such as Oxford University and the World Bank, also highlights the interdisciplinary nature of this field of study.

Likewise, bibliometrics reveals that certain countries, such as China, the United States, the United Kingdom, India, and Italy, have been the nerve centers of academic production on multidimensional poverty. This indicates a growing interest and recognition of the relevance of this approach in diverse contexts. This geographical pattern suggests a transfer of knowledge and international academic exchange that have strengthened the quality and impact of research in the area.

The most productive sources, such as *Social Indicators Research* and *World Development,* confirm that the academic literature is increasingly oriented toward examining poverty from a multidimensional perspective. This perspective allows us to identify the multiple facets of deprivation and well-being in contemporary societies.

The bibliometric analysis evidences increased interest in emerging topics, such as the impact of the Covid-19 pandemic on poverty and the relationship between multidimensional poverty and the Sustainable Development Goals. These new approaches reflect a response from the academic community to current global challenges as they adapt traditional tools and methodologies to new contexts and issues. In this sense, bibliometrics has not only made it possible to map the development and evolution of research on multidimensional poverty but has also facilitated the identification of critical areas and knowledge gaps that require greater attention, thus promoting a more relevant and solution-oriented research agenda for poverty reduction in all its dimensions.

Following the objective of this research, the initial model was modified according to the parameters evaluated, and significant differences were observed for the model proposed at the beginning. Several indicators did not meet the factor loadings, and some dimensions presented high collinearity with multidimensional poverty.

When running the predictive PLS (Partial Least Squares Regression) algorithm, which generates and evaluates predictions from PLS nomogram estimates, all observed values are more significant than zero, indicating the model's superiority over other predictions. Goodness-of-fit, using PLS, does not allow separating valid from invalid models. The root mean square residual covariance (RMStheta) was used, which, in the context of the present investigation, showed that it is refineable according to the model's goodness of fit. This reiterates that it is a measure for covariance-based structural equations. In the present case, predictive power is prioritized, and the present study is conducted at an exploratory level.

Multidimensional poverty showed a strong relationship with basic housing services (with f^2>.35) access to food, housing quality and space, and income). Multidimensional poverty revealed a higher coefficient of determination of .759, while income presented a coefficient of .460. This had a direct impact on the construct mentioned above.

Finally, the multidimensional poverty field must consider the social aspect, which is nurtured by the interactions between people and countries. All actors must assume their social responsibility, dimensions that converge to create an ecosystem that promotes positive change in society and the environment. In this ecosystem, community and environmental values must be communicated to society, audiences must be sensitized, and citizens must be mobilized to build a dynamic field that addresses the most pressing challenges of our times (Félix *et al.,* 2020).

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Conflict of Interest

The authors declare that they have no conflicts of interest.

Contribution Statement

Conceptualization, data curation, validation, research, resources: Victor Hugo Bañuelos García, Flor de María García Martínez, Blanca Isabel Llamas Félix.

Formal analysis, software: Victor Hugo Bañuelos García.

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Writing - original draft, writing - review & editing: Blanca Isabel Llamas Félix.

Data Consent Statement

The data generated during this study has been included in the article.

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