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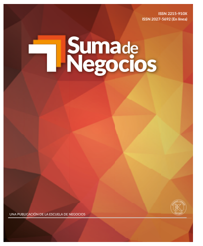

Research paper

Synthetic index for the evaluation of territorial poverty in the municipalities of Querétaro, Mexico

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ABSTRACT

Introduction/Objectives: Poverty is a multidimensional phenomenon that affects various aspects of well-being across territories. This study aims to develop a Synthetic Municipal Poverty Index (SMPI) for the state of Querétaro, with the objective of assessing socioeconomic disparities among municipalities and prioritizing areas for public policy intervention.

Methodology: A quantitative approach with a deductive, non-experimental design was employed. Socioeconomic data from 16 municipalities in Querétaro were collected from official sources such as INEGI and CONEVAL. The SMPI was constructed using Principal Component Analysis (PCA), a technique applied to determine the weights of selected indicators. Index validation was carried out through hierarchical clustering and the XGBoost machine learning model, ensuring the robustness and accuracy of the index.

Results: The findings reveal significant disparities in poverty levels across the analyzed municipalities. Income and food-related sub-indices emerged as the main determinants of poverty. Validation using the XGBoost model demonstrated high predictive performance of the SMPI, reinforcing its value as an analytical tool.

Conclusions: The SMPI serves as a reliable instrument for measuring multidimensional poverty at the municipal level. Its application supports the identification of priority areas and contributes to the design of more targeted and effective public policies. This index provides a solid framework for evidence-based decision-making and the development of comprehensive strategies to reduce poverty at the territorial level.

Palabras clave:
Pobreza, índice sintético,
Querétaro,
análisis de componentes principales,
clustering,
aprendizaje supervisado.

Índice sintético para la evaluación de la pobreza territorial en los municipios de Querétaro, México

RESUMEN

Introducción/Objetivo: La pobreza es un fenómeno multidimensional que impacta diversos aspectos del bienestar en los territorios. Este estudio tiene como propósito desarrollar un Índice Sintético de Pobreza Municipal (ISPM) para el estado de Querétaro, con el fin de evaluar las desigualdades socioeconómicas entre municipios y priorizar áreas de intervención en materia de política pública.

Metodología: Se adoptó un enfoque cuantitativo, con un diseño deductivo y no experimental. Se recopilaron datos socioeconómicos de 16 municipios del estado de Querétaro, provenientes de fuentes oficiales como el INEGI y el CONEVAL. La construcción del ISPM se realizó mediante Análisis de Componentes Principales (ACP), técnica utilizada para asignar ponderaciones a los indicadores seleccionados. La validación del índice se llevó a cabo mediante análisis de conglomerados jerárquicos (clustering) y el modelo de aprendizaje automático XGBoost, lo que permitió asegurar su robustez y precisión.

Resultados: Los resultados revelan marcadas disparidades en los niveles de pobreza entre los municipios analizados. Los subíndices relacionados con ingresos y alimentación emergieron como los principales determinantes de la pobreza. La validación con el modelo XGBoost mostró una alta capacidad predictiva del ISPM, lo cual respalda su utilidad como herramienta analítica.

Conclusiones: El ISPM constituye un instrumento confiable para medir la pobreza multidimensional a escala municipal. Su aplicación facilita la identificación de áreas prioritarias y contribuye al diseño de políticas públicas más focalizadas y efectivas. Este índice ofrece un marco sólido para la toma de decisiones basadas en evidencia y para la formulación de estrategias integrales orientadas a la reducción de la pobreza en el territorio.

Introduction

Poverty evaluation has been a fundamental aspect of global development efforts. The COVID-19 pandemic exacerbated this problem and pushed more than 97 million people into poverty (Gerszon et al., 2021). This sudden increase impacted the objective of eradicating poverty worldwide.

The pandemic-induced crisis affected Latin America in different ways, which can be attributed to preexisting structural inequalities. Mexico experienced a significant drop in its Gross Domestic Product and an increase in working poverty. In the state of Querétaro, poverty levels at the municipal level rose or fell in different areas of the municipality, depending on their socioeconomic characteristics.

Poverty assessment has become a key aspect of development initiatives, particularly in regions characterized by ongoing socioeconomic disparities, which were exacerbated by unexpected occurrences like the COVID-19 pandemic (Ribeiro et al., 2024). This research is prompted by the pressing need to create accurate and comprehensive instruments capable of recognizing, examining, and mitigating these disparities within the municipalities of Querétaro state. The current global health crisis has exacerbated pre-existing inequalities and highlighted the inadequacies of conventional metrics for assessing the spatial ramifications of complex events. This situation emphasizes the need for a novel poverty assessment method to guide the development of more efficient governmental strategies.

In view of this situation, tools are required that can accurately measure poverty levels at the municipal level and improve decision-making processes. This study proposes the creation of a Synthetic Municipal Poverty Index (SMPI) for Querétaro, with the goal of establishing a reliable metric that considers multiple poverty-related factors and facilitates the effective evaluation of government strategies.

This research is very important as it investigates the levels of poverty in Querétaro from a multidimensional perspective, specifically examining the socioeconomic disparities that were exacerbated by the COVID-19 pandemic. The methodology extends beyond the evaluation of the financial setbacks resulting from job loss, business closure, and economic downturn, highlighting the need to evaluate the varying impacts of these disparities in different municipalities. Identifying territorial gaps is crucial for developing inclusive public strategies that support equitable and sustainable recovery. This analysis is in line with the Sustainable Development Goals (SDGs), specifically SDG 1 (poverty reduction) and SDG 10 (inequality reduction), underscoring the significance of reliable indicators such as the SMPI in informing effective policy-making.

In order to effectively address the challenges at hand, it is essential to establish a strong theoretical foundation for the proposed SMPI. This framework will examine the evolution of poverty measurement, its multifaceted characteristics, and its relationship with territorial inequality, laying the groundwork for the methodological advancements presented in this research.

Theoretical context

Poverty is a complex concept that has been investigated from various points of view. Townsend (1979) defines poverty as the inability of certain people to meet social standards due to limited available resources. Sen (2000) emphasizes that poverty includes not only the lack of financial resources, but also the absence of the essential capacities necessary for a dignified life. This highlights the recognition that economic measures, although important, are insufficient to completely capture the nature of poverty (Thorbecke, 2013).

Poverty measurement has evolved significantly over the years. Early studies focused mainly on the insufficiency of monetary resources (Lipton & Ravallion, 1995). With the expansion of the concept, authors such as Fields (2001) and Spicker (2009) argued that poverty should also be analyzed through indicators of health, education, and access to services, which has led to the development of more comprehensive methodologies, such as unmet basic needs and multidimensional indices (Alkire & Foster, 2007; Boltvinik & Damián, 2020).

In Latin America, poverty has been characterized as structural, affecting rural and urban populations differently (Strabidis et al., 2019; Ziccardi, 2019). In Mexico, the creation of the National Council for the Evaluation of Social Development Policy (CONEVAL) in 2006 represented progress in establishing a methodology to measure multidimensional poverty (CONEVAL, 2022). The methodology includes indicators related to income, access to education, health, and housing, enabling an assessment of the country's socioeconomic situation (Saraví, 2004; Sevilla, 2019).

Recent literature proposes using synthetic indices as robust tools to assess poverty and territorial inequality. Principal component analysis (PCA) is used to combine multiple indicators into a single measure, facilitating comparisons and decision-making in various fields (Alonso, 2004; Schumann & Moura, 2015). This technique reliably reduces the number of variables in a data set and creates compound indicators that accurately represent the overall socioeconomic well-being of a population (Hotelling, 1933; Molina, 2022).

The use of composite indices has become common practice internationally. Research such as that of Burbano et al. (2022), who developed a Synthetic Quality of Life Index for Colombia, and Sobczak et al. (2021), who analyzed the implementation of SDG 1 in the Visegrad Group countries, are examples of how these tools can be applied to assess poverty in specific contexts and to develop effective policies.

Tikadar and Swami (2024) utilized synthetic indices to assess residential energy poverty in India through a multidimensional analysis, aiming to capture the range of energy accessibility and associated disparities. This method has been commonly employed to address global issues such as energy poverty and water scarcity. A recent study utilized the Water Poverty Index in conjunction with fuzzy-MCDM techniques to analyze water scarcity in vulnerable regions. The study identified critical areas and recommended sustainable management strategies. These international examples demonstrate the effectiveness of synthetic indices in addressing complex issues using a multidimensional and geospatial approach.

The SMPI uses multiple indicators to analyze socioeconomic disparities at the municipal level in Querétaro. The integration of advanced statistical methodologies, such as PCA, enhances the representativeness and utility of the index for decision-making purposes, similar to previous studies.

In conclusion, measuring poverty must consider its multidimensional nature and its interrelationship with territorial inequality (Boltvinik & Damián, 2020; Sen et al., 2020). The application of synthetic indicators in this study permits an overall assessment that goes beyond conventional monetary measures and provides a very valid basis for predicting public policy formulation in the effort to improve living standards (De la Fuente, 2014; Dorin et al., 2018).

Methodology

Data

This research was carried out using data from all the municipalities in the state of Querétaro, from 2020 to 2022. The dataset used in this study was sourced from reputable institutions, such as INEGI and CONEVAL. It includes a wide range of indicators related to quality of life, education, health, housing, and income. To ensure accuracy and consistency, only public and official databases were used, guaranteeing the reliability of the information.

The municipalities included in the study were selected based on data availability and quality. Two municipalities were excluded due to incomplete information for the specified period. The selection process aimed to ensure that the sample accurately represented the various socioeconomic dynamics in the region. The structure and collection procedures of the indicators remained consistent over time, promoting high comparability.

Type, scope, and design

This study employed a quantitative, non-experimental methodology, incorporating descriptive and correlational techniques to analyze the socioeconomic dynamics of Querétaro. By observing variables without intervention, this approach enabled a comprehensive investigation of poverty in the region. The analysis centered on developing an SMPI that integrates multiple indicators into a single measure to evaluate poverty levels across municipalities.

The study employed PCA to identify and reduce variables, selecting the most representative dimensions for analysis. This method allowed for a comprehensive evaluation of poverty levels in various municipalities.

Procedure

The procedure was formulated through a series of distinct and identifiable phases:

1. **Indicator selection:** Socioeconomic indicators associated with poverty, including healthcare access, education, housing, and income, were determined through a review of existing literature (Álvarez et al., 2021; Boltvinik & Damián, 2020; Jolliffe & Cadima, 2016; Mitra & Das, 2018).

2. **Variable reduction using PCA:** PCA was utilized to minimize redundancy and identify underlying patterns within the dataset. This approach facilitated a more precise depiction of the socioeconomic attributes of the municipalities. Previous applications of PCA in Latin America have demonstrated its effectiveness in synthesizing multidimensional data for poverty evaluation. For instance, Burbano et al. (2022) used PCA to develop a Synthetic Quality of Life Index in Colombia, identifying key socioeconomic disparities across regions. Similarly, Sobczak et al. (2021) applied composite indices to evaluate poverty in the Visegrad Group, showcasing the robustness of these methods in diverse contexts. Building on these examples, this study applied PCA to the municipalities of Querétaro, adapting it to the region's specific socioeconomic dynamics.
3. **Construction of the SMPI:** The weights assigned to components derived from the PCA were used to create the SMPI, which combines various dimensions of poverty into a unified metric.
4. **Index validation:** The validation process involved the utilization of hierarchical cluster analysis (HCA) to categorize municipalities with comparable attributes, and the eXtreme Gradient Boosting (XGBoost) supervised learning algorithm to assess the predictive capability of the index. XGBoost was chosen for its capacity to manage intricate relationships between variables, thereby ensuring rigorous validation (Jarupunphol et al., 2024; Sahin, 2025).

Data analysis

The analysis of the data was conducted in two main phases:

1. **Principal Component Analysis:** PCA was utilized to reduce the initial set of variables into components that accounted for most of the variance. The Kaiser-Meyer-Olkin (KMO) index and Bartlett's test were conducted to validate the appropriateness of the PCA methodology.
2. **SMPI validation:** The validation process utilized HCA to identify clusters of municipalities and XGBoost to assess the predictive capabilities of the index. HCA revealed patterns of territorial disparities, while XGBoost confirmed the consistency and reliability of the SMPI.

Results

This section presents the results of the PCA and the building of the SMPI for the municipalities in the state of Querétaro, and the verification of the index using advanced statistical economy.

Principal component analysis

After adjusting the set of variables, eliminating those with low representativeness and insufficient communalities, a PCA was carried out. The objective was to retain as few components as possible, without compromising the explanatory capacity of the model.

Figure 1 displays an elbow plot, indicating that the first 13 components account for 80% of the total variance in the dataset. This level of cumulative variance is commonly accepted as appropriate in socioeconomic and administrative studies, as it enables the researcher to capture the most significant dimensions of the phenomenon being analyzed while reducing model complexity without significant information loss.

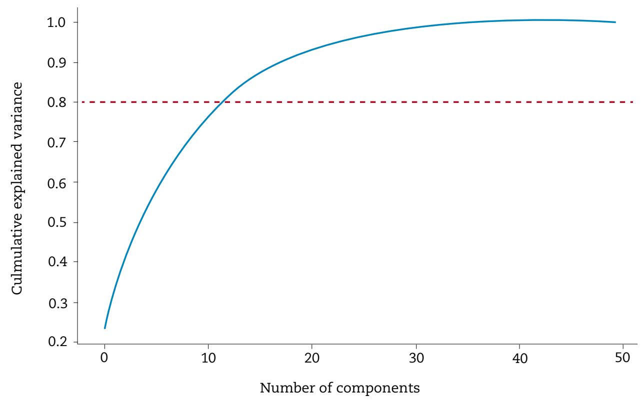


Figure 1. Elbow plot for component retention

Note. The first 13 components that explain 80% of the variance are retained.
Source: own elaboration.

Adequacy tests: Kaiser-Meyer-Olkin and Bartlett sphericity

To evaluate the suitability of the data set and its correlation structure, sample adequacy and Bartlett's sphericity tests were performed. The KMO resulted in a value of 0.70, indicating an acceptable level of adequacy for conducting a PCA. This implies that the partial correlations between variables are adequately representative.

The Bartlett sphericity test yielded a statistically significant p-value of 0.00 at the 1%, 5%, and 10% significance levels, with a Chi-square value of 5,462,043.56.

Total explained variance

Table 1 shows the cumulative percentage of variance explained by the first 13 components obtained from PCA with varimax rotation. Together, these components account for 80.73% of the total variance, suggesting a satisfactory representation of the socioeconomic phenomenon.

Table 1. Total variance explained by component

Component	Individual Explained Variance	Cumulative Variance
Component 1	14.38%	14.38%
Component 2	9.53%	23.90%
Component 3	7.84%	31.74%
Component 4	5.21%	36.96%
Component 5	7.81%	44.77%

(Continued)

Component	Individual Explained Variance	Cumulative Variance
Component 6	7.64%	52.41%
Component 7	4.56%	56.97%
Component 8	3.61%	60.58%
Component 9	3.77%	64.35%
Component 10	4.13%	68.48%
Component 11	5.11%	73.59%
Component 12	4.03%	77.62%
Component 13	3.11%	80.73%

Note. The first 13 components were retained to ensure adequate explanation of total variance.
Source: Prepared by authors from the results obtained using Python.

Commonality of the variables

The variables ic_rezedu and par exhibited the lowest communalities in the analysis, with values of 0.4113 and 0.3898, respectively. Despite their lower communalities, these variables were included in the model due to their theoretical significance.

Key variables with high commonalities (> 0.9):

- *icv_techos* (0.9799)
- *ic_sbv* (0.9316)
- *ic_ali_nc* (0.9096)

Sub-indexes of the SMPI

The SMPI was created by defining five main sub-indices: Education, Health, Housing, Income, and Food. Each sub-index was calculated by combining several key indicators with weights determined through PCA. The equations for the sub-indices are presented below, along with an explanation of the importance and effect of the weights assigned to each.

Education Sub-index (S_ Education)

$$S_{Education} = 0.2878 \times ic\_rezedu + 0.3758 \times anac\_e + 0.3364 \times inas\_esc \quad (1)$$

The Education sub-index reflects the extent of educational deprivation and consists of three indicators: educational lag (*ic_rezedu*), year of birth (*anac_e*), and school non-attendance (*inas_esc*). The highest weight is assigned to the year of birth (0.3758), indicating that the demographic composition and age distribution of the population are closely linked to educational disparities in municipalities.

Health Sub-index (S_ Health)

$$S_{Health} = 0.1753 \times ic\_asalud + 0.1681 \times ic\_segsoc + 0.2340 \times sa\_dir + 0.2293 \times ss\_dir + 0.1933 \times s\_salud \quad (2)$$

The sub-index under consideration quantifies deprivation in the realm of health services and social security. Key indicators include direct access to health services (sa_dir) and social security (ss_dir), assigned weights of 0.2340 and 0.2293, respectively. These values underscore the significance of sufficient access to medical services and social security coverage in mitigating deprivation in the health domain.

Housing Sub-index (S_ Housing)

$$S_{Housing} = 0.2135 \times ic\_cv + 0.2120 \times icv\_hac + 0.2215 \times ic\_sbv + 0.1889 \times isb\_agua + 0.1641 \times isb\_combus \quad (3)$$

Within the housing dimension, indicators related to housing quality (*ic_cv*), overcrowding (*icv_hac*), and access to basic services (*ic_sbv*) are assessed. Access to basic services (0.2215) and housing quality (0.2135) were given the highest weights, suggesting that these factors have the greatest impact on individuals' quality of life and housing security.

Income Sub-index (S_ Income)

$$S_{Income} = 0.0942 \times plp_e + 0.0562 \times plp + 0.0620 \times pobreza + 0.0805 \times pobreza_e + 0.0796 \times pobreza_m + 0.0738 \times ictpc + 0.0834 \times ict \quad (4)$$

The Income sub-index includes indicators related to the financial capabilities of households, such as the percentage of individuals with incomes below the poverty line and total current income (ICT). The indicator with the highest weight is extreme poverty (0.0805), highlighting the importance of extreme poverty conditions in evaluating the economic situation of municipalities.

Food Sub-index (S_ Food)

$$S_{Food} = 0.1304 \times ic\_ali\_nc + 0.1473 \times tot\_iamen + 0.1497 \times ins\_ali + 0.1635 \times ic\_ali + 0.2044 \times lca \quad (5)$$

This sub-index focuses on food security and includes indicators such as food deficiency (*ic_ali_nc*), food insecurity scale (*tot_iamen*), and food consumption limitation (*lca*). The indicator with the highest weight is food consumption limitation (0.2044), highlighting the significance of ensuring access to an adequate and nutritious diet to alleviate deprivation in this area.

The combined sub-indices provide a thorough evaluation of different dimensions of poverty in the municipalities of the state of Querétaro. The weighting of the indicators considers its importance within each dimension and its priority in the formulation of poverty reduction policies. The creation of the SMPI by combining various sub-indices allows for a comprehensive and multidimensional assessment of well-being levels in each municipality. This method helps identify specific areas requiring immediate intervention.

The sub-indices were calculated using data from INEGI and CONEVAL, with a focus on maintaining methodological rigor and reliability. These datasets offer a holistic representation of various socioeconomic indicators such as education, health, housing, income, and food security, which are crucial for developing the SMPI.

Synthetic municipal poverty index

The SMPI was created by aggregating the weighted values of five sub-indices (Education, Health, Housing, Income, and Food). These sub-indices represent important aspects of socioeconomic welfare and enable a comprehensive assessment of poverty across municipalities in the state of Querétaro. The formula for building the SMPI is shown below:

$$SMPI = 0.0713 \times S\_Education + 0.1682 \times S\_Health + 0.1491 \times S\_Housing + 0.4174 \times S\_Income + 0.1940 \times S\_Food \quad (6)$$

The weighted coefficients for each sub-index were determined through PCA, utilizing the variance explained by each sub-index in the poverty dimension. The purpose of constructing this index is to consolidate the level of socioeconomic deprivation within each municipality into a single numerical value, allowing for easier comparison and analysis of poverty conditions over time and across different geographical areas.

Income sub-index: The income sub-index, with a weight of 0.4174, holds the highest significance within the SMPI). This suggests that the financial resources available to households, specifically disposable income, significantly influence the overall poverty levels in the municipalities. These results emphasize the need to enact policies aimed at enhancing economic prospects and mitigating income insecurity.

Food sub-index: The food sub-index has a weight of 0.1940, making it the component with the second highest influence. This finding is aligned with the importance of food security for the general well-being of a population. Inadequate access to nutritious and high-quality food is the main obstacle to achieving a decent standard of living, underlining the critical importance of addressing this dimension.

Health sub-index: The health sub-index has a weight of 0.1682, which suggests its importance as a determinant of poverty. Access to health and social security services plays a critical role in maintaining household quality of life, particularly when facing economic and health crises.

Housing sub-index: The housing sub-index weight of 0.1491 underlines the importance of housing conditions in determining poverty. Housing must be sufficiently decent, complete with all personal comforts, and free from overcrowding, in order to create a life environment that is safe and healthy for the families.

Education sub-index: The education sub-index is assigned a weight of 0.0713 in the composition of the SMPI, making it the component with the lowest weight. Nevertheless, education is considered a crucial dimension as it plays a significant role in enhancing job prospects and social mobility over an extended period.

The SMPI is a composite measure that integrates various dimensions of poverty to offer a holistic assessment of the standard of living in the municipalities of Querétaro. The SMPI is a normalized index ranging from 0 to 1, with higher values indicating greater levels of poverty. This procedure enables the identification of municipalities exhibiting elevated levels of deprivation, facilitating the implementation of tailored public policies to effectively address the specific needs of each locality.

The findings of the SMPI indicate statistically significant disparities in poverty levels among municipalities, as evidenced by variations in the index values reflecting discrepancies in income, access to basic services, housing conditions, education, and food security. The prominence of the income sub-index underscores how the households' economic status critically influences the population's overall quality of life.

Compared to the previous studies, the results of this index will allow for a more precise intervention approach and efficient prioritization of resources for municipalities with higher levels of deprivation. This is a multidimensional approach, serving as a robust tool for decision-making in the hands of local and state authorities, enabling them to design strategies for improving poverty reduction and socioeconomic well-being in the state.

Robustness and validation of SMPI *weighting scheme*

A two-step methodology was implemented to assess the reliability of the SMPI. Initially, a Monte Carlo simulation was utilized to analyze the fluctuation of the index when subjected to random modifications in the weights assigned to individual sub-indices. This approach assessed the sensitivity of the SMPI to potential changes in the assigned weights, providing insight into its stability when subjected to perturbation. A cross-validation technique was also utilized to enhance the validation of the index. The data was divided into distinct subsets (folds) and the SMPI was recalculated for each subset to assess the consistency and reliability of the weighting scheme across different data partitions. These methodologies provide a thorough assessment of the SMPI's robustness and reliability under varying conditions

Monte Carlo simulation

The Monte Carlo simulation comprised 10,000 iterations in which random perturbations were introduced to the base weights of the sub-indices: Education, Health, Housing, Income, and Food. These perturbations were drawn from a normal distribution with a standard deviation of 10%. The resulting weights were then normalized to maintain a sum of one, in accordance with the original SMPI methodology.

The results of the simulation indicate that the mean SMPI value was 0.1459, calculated across all iterations, with a standard deviation of 0.0364, suggesting moderate variability. The minimum and maximum SMPI values observed were 0.1008 and 0.4712, respectively, illustrating the potential range of outcomes resulting from changes in weighting. This variability is expected, as the weights directly influence SMPI values (see Table 2).

Table 2. Statistical summary of SMPI (Monte Carlo simulation)

Statistic	Value
Count	10,000
Mean	0.1459
Standard Deviation	0.0364
Minimum	0.1008
25th Percentile	0.1200
Median	0.1373
75th Percentile	0.1602
Maximum	0.4712

Source: Prepared by authors from the results obtained using Python.

The findings confirm the resilience of the ISPM in maintaining stability when subjected to controlled variations in sub-index weights. This underscores its credibility as a comprehensive tool for assessing multidimensional poverty and making well-informed policy decisions.

Cross-validation of SMPI weighting scheme

In order to assess the reliability of the SMPI weighting scheme, a five-fold cross-validation approach was utilized. The dataset was divided into five equal subsets, with one subset used as the test set and the remaining four subsets used as the training set. For each fold, the weights assigned to the sub-indices—Education, Health, Housing, Income, and Food—were recalculated using the training data, and the SMPI was recomputed for the test set.

The findings displayed in Table 3 indicate a consistent weighting pattern across the folds. The mean normalized weights for each fold show little variation, suggesting the stability of the weighting system. Furthermore, the average SMPI values computed for the test sets exhibit low standard deviations, supporting the reliability of the index across various data partitions.

Table 3. Statistical Summary of SMPI (Cross-Validation)

Fold	Education	Health	Housing	Income	Food	Mean SMPI	SMPIStd. Dev.
1	0.4875	0.2074	0.1348	0.0796	0.0906	0.3696	0.0221
2	0.4896	0.2099	0.1166	0.0866	0.0972	0.3640	0.0158
3	0.4863	0.2028	0.1319	0.0836	0.0954	0.3568	0.0132
4	0.4839	0.2044	0.1231	0.0921	0.0965	0.3562	0.0250
5	0.4740	0.1967	0.1437	0.0901	0.0956	0.3518	0.0202

Source: Prepared by authors from the results obtained using Python.

Consistency in SMPI values across folds is evident in Figure 2, which displays mean SMPI values and the corresponding standard deviations for each fold. The narrow error bars suggest stability in SMPI calculations, supporting the robustness of the weighting scheme.

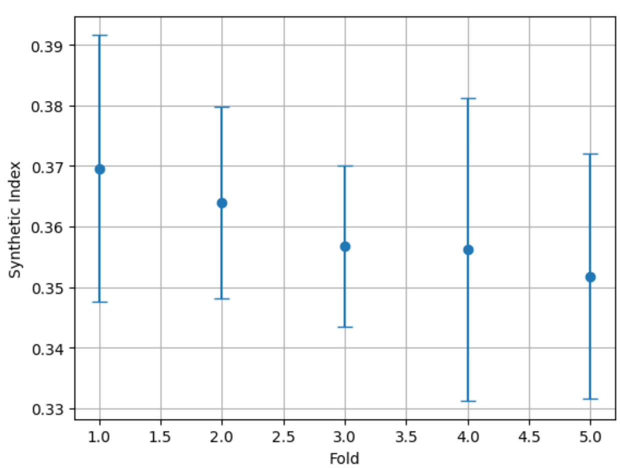


Figure 2. SMPIaverage and standard deviation (cross-validation)

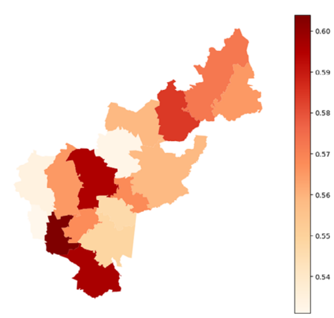
Note. The figure shows the average SMPI values across five folds, with error bars representing the standard deviation for each fold. The stability of the results highlights the robustness of the SMPI weighting scheme.
Source: own elaboration.

The cross-validation procedure demonstrated the consistency of the SMPI weighting scheme across diverse data subsets. This validation highlights the stability of the index in maintaining uniform weighting distributions and calculations, even in the presence of different data arrangements. These results support the efficacy of the SMPI as a dependable multidimensional tool for evaluating poverty levels in various municipalities.

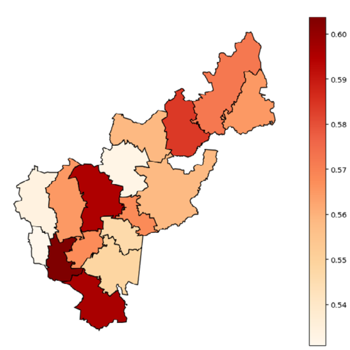
SMPI results for 2020 and 2022

The values for 2020, ranging between 0.5311 and 0.6039 for the Education sub-index, show great inequity between different municipios of Querétaro with regard to access to and quality of education. The municipality of Huimilpan presented the highest value (0.6039), which indicates greater deprivation in access to educational services and high school dropout rates. This finding suggests the need for specific interventions to improve educational infrastructure and expand access to basic education.

In 2022, the results followed a similar pattern, with Huimilpan and Amealco de Bonfil standing out with the highest sub-index values (0.6038 and 0.5963, respectively). This pattern, sustained over time, shows that educational inequality in these municipalities has not been mitigated, which highlights the importance of designing public policies aimed at strengthening the education system in the most vulnerable regions (See Figure 3).



a) Education sub-index 2020



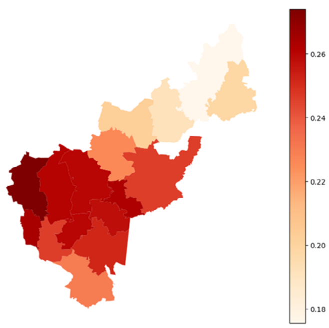
b) Education sub-index 2022

Figure 3. Education Sub-Index by Municipality in Querétaro (2020 and 2022)

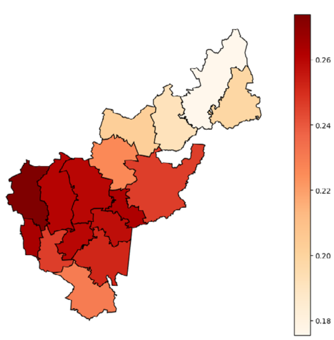
Note. The sub-index values represent the level of educational deprivation in each municipality. Darker colors indicate higher deprivation levels. Data are normalized and range from 0 to 1, with higher values reflecting greater challenges in educational access and quality.
Source: own elaboration.

In 2020, the Health sub-index revealed that the municipalities of Jalpan de Serra and Pinal de Amoles registered the lowest values of deprivation (0.1756 and 0.1921, respectively), which suggests that the majority of their inhabitants have better access to medical services and social security. Less deprivation in these areas may be linked to the implementation of public health programs that prioritize care in rural communities.

Continued low levels of deprivation are observed in 2022, particularly in Landa de Matamoros and Pinal de Amoles, which have similar values (0.1985 and 0.1920, respectively). However, the municipality of Querétaro presented a higher value (0.2739), which may indicate is a lack of equitable access to health services, despite the availability of hospital infrastructure, possibly influenced by economic or resource distribution barriers (See Figure 4).



a) Health Sub-Index 2020



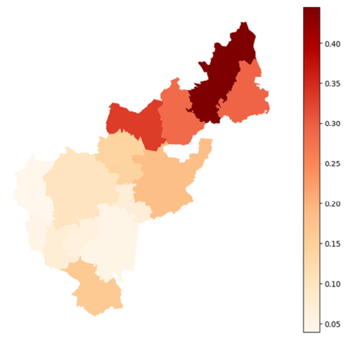
b) Health Sub-Index 2022

Figure 4. Health sub-index by municipality in Querétaro (2020 and 2022)

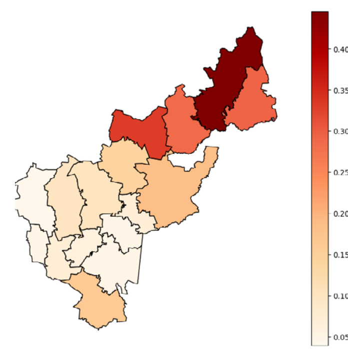
Note. The sub-index values indicate the degree of deprivation in access to healthcare and social security services. Darker colors represent higher deprivation levels. Data are normalized and range from 0 to 1, emphasizing areas requiring targeted health interventions.
Source: own elaboration.

Regarding the housing sub-index, the results for 2020 reveal that the municipalities with the most pronounced deficiencies in housing quality and access to basic services were: Jalpan de Serra, with 0.4449, and Peñamiller, with 0.3312. This level of deprivation correlates to the lack of access to drinking water, electricity, and adequate sanitation services. These conditions not only affect the quality of the inhabitants' lives but also impact their health.

In 2020, the most significant housing deprivations were found in Jalpan de Serra, which suggests that the interventions implemented to improve the housing infrastructure continue to be insufficient. This underlines the urgent need for adequate housing policies to increase access to essential basic services in this municipality (See Figure 5).



a) Housing Sub-Index 2020



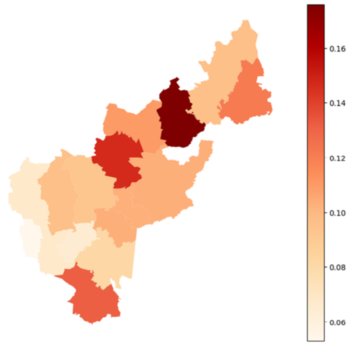
b) Housing Sub-Index 2022

Figure 5. Housing sub-index by municipalities in Querétaro (2020 and 2022)

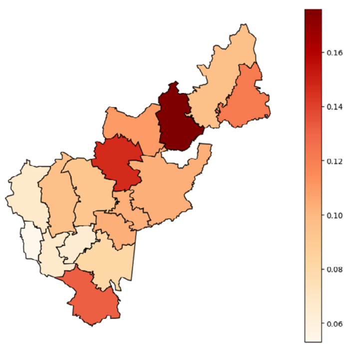
Note. The sub-index values reflect the quality of housing and access to basic services, such as potable water and sanitation. Darker colors signify higher levels of deprivation. Data are normalized and range from 0 to 1, highlighting critical housing deficiencies.
Source: own elaboration.

According to the analysis conducted by the Income sub-index, during 2020, both Pinal de Amoles and Tolimán registered high monetary poverty levels, with values above 0.14. This indicates that a large portion of the population lives below the minimum welfare line, revealing the households' reduced economic capacity to meet their basic needs. This situation is largely attributed to the scarcity of job opportunities that offer adequate income.

In 2022, the municipalities of Jalpan de Serra and Cadereyta de Montes maintained high levels of deprivation (about 0.16), reflecting the persistence of unequal access to adequate income. On the other hand, municipalities such as Corregidora and Pedro Escobedo presented sub-indices under 0.07, indicating a better economic situation. These results highlight the need to promote economic development programs that boost employment and improve income distribution, especially in the most vulnerable areas (see Figure 6).



a) Income Sub-Index 2020



b) Income Sub-Index 2022

Figure 6. Income sub-index by municipalities in Querétaro (2020 and 2022)

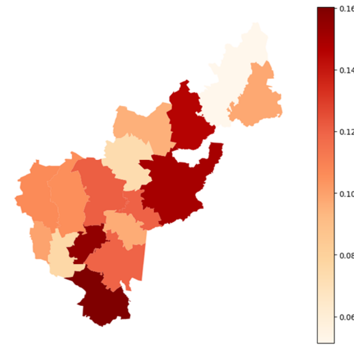
Note. The sub-index values measure the financial capacity of households, focusing on income levels relative to poverty thresholds. Darker colors denote higher monetary deprivation. Data are normalized and range from 0 to 1, underscoring areas with severe income challenges.
Source: own elaboration.

In the Food sub-index, in 2020, the municipality of Amealco de Bonfil presented the highest level of deprivation (0.1603), denoting significant limitations in access to adequate and sufficient food. This situation could be related to inadequate access to quality food, high prices, and insufficient economic resources.

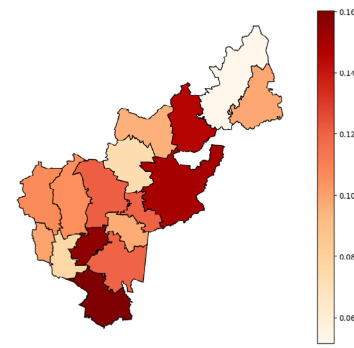
In 2022, the municipalities of Corregidora and Huimilpan displayed the lowest values, which means that they had the best food security conditions compared to other municipalities in the state. This underlines the need to coordinate the food security strategy, prioritizing rural areas, where deprivation is most notorious (see Figure 7).

The SMPI integrates all the sub-indices provided above, presenting an overview of the poverty levels within the Queretaro municipalities. For 2020, municipalities with the lowest poverty levels included Corregidora, Huimilpan, and Querétaro, with values below 0.18. These results signify better conditions of access to services, income, and quality of life in these counties.

In 2022, Pinal de Amoles and Jalpan de Serra presented the highest levels of poverty, with 0.277 and 0.268, respectively. These results are consistent with the sub-indices showing high education, income, and food deprivation. This would suggest the need for policies that will comprehensively tackle the different factors that affect poverty in these municipalities.



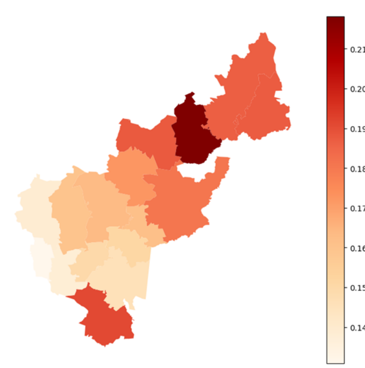
a) Food Sub-Index 2020



b) Food Sub-Index 2022

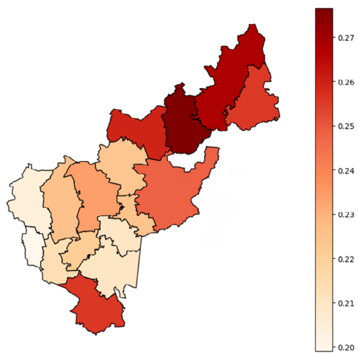
Figure 7. Food sub-index by municipality in Querétaro (2020 and 2022)

Note. The sub-index values assess food security and nutritional access across municipalities. Darker colors indicate higher levels of food insecurity. Data are normalized and range from 0 to 1, identifying areas with critical dietary needs.
Source: own elaboration.



a) SMPI 2020

(Continued)



b) SMPI2022

Figure 8. Synthetic municipal poverty index by municipality in Querétaro (2020 and 2022)

Note. The SMPI values integrate all sub-indices to provide a comprehensive measure of poverty levels. Darker colors represent higher poverty levels. Data are normalized and range from 0 to 1, offering a holistic view of socioeconomic deprivation across municipalities.
Source: own elaboration.

Validation of the SMPI

The ISPM was validated by implementing two complementary approaches: hierarchical clustering analysis and the application of the XGBoost supervised learning model. These methods allow an evaluation of the consistency and predictive capacity of the index.

Hierarchical clustering

The hierarchical analysis, based on the Euclidian distance metric, allowed the identification of grouping patterns between municipalities. Figure 9 shows the resulting dendrogram, with three main groups. The hierarchical clustering results revealed three distinct groups of municipalities. Municipalities with lower poverty levels, such as Querétaro and Corregidora, formed one cluster, reflecting better socioeconomic conditions. Conversely, the group comprising municipalities like Pinal de Amoles and Amealco de Bonfil indicate severe deprivation and the need for targeted interventions.

The hierarchical conglomerate technique has been used by authors such as Everitt et al. (2011) and Kaufman & Rousseeuw (1990) to identify homogeneous groups in a dataset. This research permitted the validation of the behavior of the synthetic index with respect to aspects of poverty and levels of deprivation within the municipalities of Querétaro by means of this technique.

Model XGBoost

The XGBoost supervised learning model was used to complement the analysis and evaluate the predictive capacity of the SMPI. This technique is known for its robustness and accuracy in classification tasks (Chen & Guestrin, 2016). The model achieved 100% accuracy in the classification of municipalities, indicating that the selected characteristics (sub-indices of Education, Health, Housing, Income and Food) are highly predictive of the municipal poverty index.

The XGBoost supervised learning model was utilized to validate the SMPI due to its robustness and high predictive accuracy in handling complex relationships among variables. XGBoost effectively integrates multiple decision trees to optimize performance and reduce prediction errors. Its applicability to multidimensional datasets ensures thorough validation, affirming the significance of the chosen sub-index in forecasting municipal poverty levels.

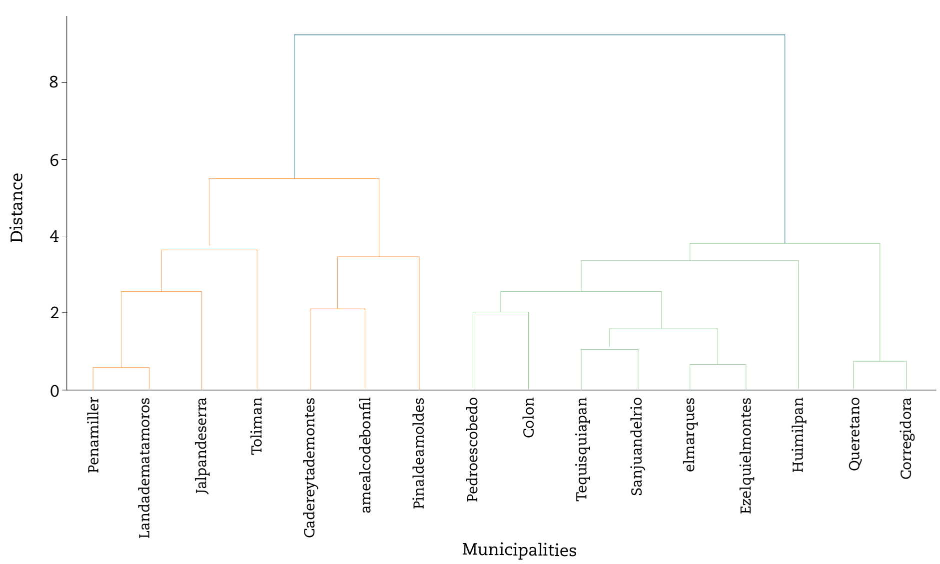


Figure 9. Dendrogram of hierarchical clustering for municipalities in Querétaro

Note. The dendrogram illustrates the grouping of municipalities based on socioeconomic deprivation levels. Three main clusters are identified: one consisting of municipalities with the highest poverty levels (e.g., Peñamiller, Tolimán), another with moderate levels of deprivation, and a third cluster representing municipalities with better socioeconomic conditions (e.g., Querétaro, Corregidora). The vertical axis represents the distance or dissimilarity between clusters, while the horizontal axis lists the municipalities.
Source: own elaboration.

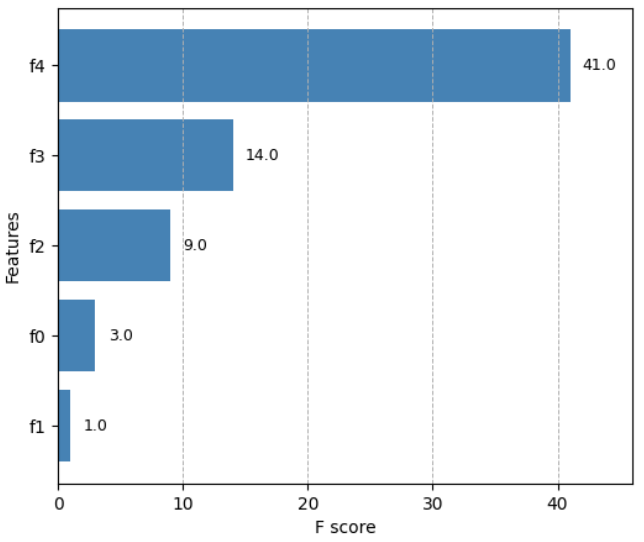


Figure 10. Importance of features in the XGBoost model

Note. The bar chart illustrates the relative importance of features of the XGBoost model for predicting SMPI. The Food sub-index (f4) is the most significant predictor, followed by the Income sub-index (f3) and the Health sub-index (f2). The F-score represents the frequency with which a feature is used in decision trees, highlighting its predictive weight.

Source: own elaboration.

The relative importance of the sub-indices showed that the Food sub-index is the most determinant factor for predicting the SMPI, followed by the Income sub-index. This relevance is consistent with previous studies that highlight the direct relationship between food security and poverty levels (Alkire & Foster, 2011; FAO, 2015). Figure 8 highlights the importance of these factors, which is consistent with existing literature on the multidimensional impact of poverty (Sen, 1981).

The results of the SMPI validation align with previous research on food security and poverty, specifically Alkire and Foster (2011) and FAO (2015), which emphasize the correlation between nutritional access and socioeconomic welfare. These findings illustrate the effectiveness of the SMPI in measuring the multifaceted aspects of poverty and its geographical variations.

The validation of the SMPI by hierarchical clustering and the XGBoost model confirms the robustness of the index as an effective tool to evaluate poverty conditions in the municipalities of the state of Querétaro. The Food and Income sub-indices proved to be the main predictors of the overall index, underlining the need for political interventions aimed at improving these dimensions in the most affected municipalities (Boltvinik & Damián, 2020). These validations reinforce the usefulness of the SMPI in designing and evaluating public policies that promote the effective reduction of socioeconomic disparities, thus contributing to the SDGs.

The XGBoost model, known for its resilience, operates under the assumption of linear separability within its decision trees, potentially oversimplifying intricate socioeconomic relationships. Likewise, SMPI offers a thorough multidimensional evaluation, yet its dependence on existing data sources may overlook dynamic components of poverty, such as mental health and digital connectivity, that hold significance in modern analyses.

Based on the results of the study, it is recommended that policy interventions focus on prioritizing food security programs and income distribution initiatives in the most disadvantaged municipalities. Enhancing access to nutritious food and implementing targeted economic development strategies are essential in addressing the underlying factors that contribute to poverty in Querétaro.

The focus of the SMPI on Food and Income sub-indices is consistent with SDG 1: No Poverty and SDG 10: Reduced Inequalities. These results highlight the significance of utilizing multidimensional poverty indices to track advancement towards these global aims.

Discussion

The findings of the SMPI offer a holistic perspective on poverty levels within the municipalities of Querétaro, aiding in pinpointing the regions with heightened vulnerability. This multidimensional approach is essential for comprehending the intricacies of poverty and its correlation with geographical factors. The results of this study demonstrate notable discrepancies in the socioeconomic factors examined, with a particular emphasis on income and food security, which emerged as the primary determinants of poverty in the analyzed municipalities.

Comparison with recent literature

Recent research has demonstrated the need to conduct a thorough multidimensional poverty analysis in order to effectively pinpoint key areas for intervention. Santos and Villatoro (2018) contend that utilizing multidimensional approaches enables a more nuanced comprehension of the interconnected nature of various socioeconomic disadvantages, which aligns with the methodology employed in this study. This methodology is particularly pertinent within the Latin American region, where systemic disparities heighten levels of poverty (Sánchez-Ancochea, 2021).

The significant emphasis placed on the Income sub-index within the SMPI indicates that economic stability continues to be a key factor affecting households in Querétaro. This finding aligns with the conclusions drawn by Ji et al. (2024) in their research on urban and rural poverty in China. The authors emphasize the importance of poverty reduction policies that enhance employment prospects and augment disposable income, a model that could be implemented in the state of Querétaro.

The Food sub-index has been identified as a significant determinant of poverty levels. Wani et al. (2023) have highlighted the increasing food insecurity concerns in middle-income countries, exacerbated by the post-pandemic crisis and rising food prices. This study in rural municipalities of Querétaro aligns with these findings.

Description of the SMPI creation process

The SMPI was constructed by identifying variables based on their theoretical relevance and statistical reliability, utilizing PCA to determine the weights for the most pertinent indicators. These selected variables were subsequently grouped into five distinct sub-indices: Education, Health, Housing, Income, and Food. The index was validated through hierarchical clustering and the XGBoost supervised learning model, confirming the predictive reliability of the SMPI. These validation techniques were employed to ensure the robustness and applicability of the index for measuring poverty at the municipal level.

This methodology is consistent with approaches observed in similar studies, such as Grajales-Marín et al., (2025), who applied spatial and socioeconomic data analysis to examine territorial inequalities and their impact on illicit crop cultivation in Nariño, Colombia. Their findings underscore the value of integrating statistical and spatial methods to evaluate complex social issues, further reinforcing the robustness of the SMPI framework.

Advantages of the SMPI over traditional methods

The SMPI offers significant advantages over traditional poverty measurement methods, such as monetary income thresholds or unmet basic needs approaches. Traditional methods often fail to capture the multidimensional and interconnected nature of poverty, particularly in the context of municipalities with diverse socioeconomic structures. In contrast, the SMPI integrates multiple dimensions—education, health, housing, income, and food security—using PCA to obtain a comprehensive index.

Moreover, the validation of the SMPI using advanced techniques like XGBoost improves its robustness and predictive capability. Unlike static measures, the ISPM allows for dynamic, multidimensional assessments that are essential for pinpointing specific areas requiring intervention. These benefits are consistent with current research supporting the use of multidimensional indices to offer practical insights for policymaking (Gawusu, 2024).

Structural and systemic causes of disparities

The pronounced differences between rural and urban areas can be attributed to underlying structural and systemic inequities. Rural regions frequently experience limited access to essential services, insufficient infrastructure, and limited economic prospects (Nickson, 2024; Safi, 2024). The presence of structural limitations in certain regions, particularly those where agriculture is the main economic activity, contributes to the perpetuation of cycles of poverty (Dios Palomares et al., 2015). In Querétaro, rural areas like Peñamiller and Tolimán exhibit elevated levels of deprivation, underscoring the necessity for policy interventions aimed at addressing systemic inequities.

Impact of digital connectivity on poverty

The importance of digital connectivity in promoting socioeconomic inclusion is now recognized. In rural areas, the absence of digital infrastructure contributes to disparities in education, information access, and economic engagement, further perpetuating existing inequalities (Ishmuradova et al., 2024). Digital technologies and connectivity play a significant role in poverty alleviation across various sectors. Information and communication technologies have been shown to have positive effects on healthcare, economic development, and education, with improved infrastructure and access amplifying their impact (Sharma et al., 2024). Subsequent versions of the SMPI should consider digital connectivity as a metric to assess its impact on poverty rates.

Geographic factors and poverty

Geographic isolation and inadequate infrastructure are key factors that contribute to poverty in Querétaro. Municipalities located in remote regions, such as Jalpan de Serra and Landa de Matamoros, exhibit higher levels of deprivation as a result of limited transportation, healthcare, and market access. This finding is consistent with research highlighting the correlation between geographic isolation and poverty, especially in areas with mountainous topography that hinders economic opportunities and access to services (Wang & Wang, 2024).

Policy implications

The SMPI findings identify key areas that require policy intervention. One effective example of targeted intervention is Brazil's "Zero Hunger" initiative, which has resulted in a substantial decrease in malnutrition and poverty rates (de Waal, 2025; Zafar et al., 2025; Chinnala, 2024). Potential interventions could be designed for rural municipalities in Querétaro to target the Food and Income sub-indices, identified as significant poverty determinants. Furthermore, infrastructure investments and economic development programs should prioritize improvement of connectivity and access to essential services in rural areas.

International case studies have shown that the SMPI can effectively guide localized interventions. Tikadar and Swami (2024) illustrated the utility of a multidimensional analysis in examining energy poverty in India, revealing disparities in energy access and informing the formulation of context-specific policies. Pham et al. (2024) conducted a water scarcity analysis utilizing the Water Poverty Index in conjunction with fuzzy-MCDM techniques to pinpoint critical regions and recommend sustainable water management strategies. This research demonstrates the effectiveness of composite indices in addressing complex challenges in at-risk areas, offering practical policy recommendations.

In Querétaro, the SMPI has the potential to identify priority municipalities for targeted interventions in the areas of education, income, and food security. This strategy could facilitate the development of tailored programs for addressing each dimension of poverty, utilizing the detailed data provided by the index to enhance the effectiveness of public policy initiatives.

Food insecurity and poverty

Food insecurity plays a crucial role in determining poverty levels, as indicated by the substantial impact of the SMPI. Rising food costs and limited availability of nutritious food disproportionately impact rural households, leading to the continuation of cycles of deprivation .This discovery is consistent with the research conducted by Li and Zhang (2025), which emphasizes the need to use integrated methodologies to enhance food security in middle-income populations. Resolving food insecurity in Querétaro requires a comprehensive strategy that incorporates agricultural assistance, market entry, and nutritional instruction.

Limitations of the study

One significant constraint of this study is the limited availability of data at the municipal level, leading to the exclusion of two municipalities due to incomplete information for the specified time frame. The lack of data may impede the SMPI's comprehensive assessment of all municipalities in Querétaro. It is recommended that future studies expand data collection to include additional indicators, such as digital connectivity and environmental factors, as proposed by Zuniga-Gonzalez (2023).

The study's cross-sectional design restricts the examination of temporal changes. Data was collected in 2020 and 2022, however, a longitudinal study would offer a more comprehensive understanding of the impacts of public policies and economic fluctuations over time. Furthermore, the absence of dynamic poverty factors, including mental health and climate vulnerability, underscores the need for future research to take a more holistic approach.

Recommendations for future research

Future studies should build on this research by using more extensive datasets that encompass emerging aspects of poverty. These should encompass indicators related to digital inclusion, environmental resilience, and mental health, which are increasingly recognized as crucial elements in poverty assessment {Formatting Citation}. Furthermore, longitudinal studies are necessary to track the long-term impact of interventions and economic shifts on poverty dynamics in Querétaro.

Conclusions

The analysis of territorial poverty in the state of Querétaro, based on the application of the SMPI, revealed disparities between municipalities, thus confirming the multidimensional nature of the phenomenon of poverty. The utilization of PCA facilitated the identification of the key dimensions that underlie poverty in the region, including education, access to health, housing quality, income, and food. This multivariate approach, complemented by validation techniques, such as hierarchical clustering and the XGBoost supervised learning model, yielded a robust tool for evaluating and tracking socioeconomic conditions at the municipal level.

The findings indicate that significant disparities exist in rural and peripheral municipalities, including Landa de Matamoros, Tolimán, and Jalpan de Serra, characterized by elevated levels of deprivation across all dimensions of the SMPI. On the contrary, more urbanized municipalities, such as Querétaro and Corregidora, exhibit more positive trends, indicative of improved socioeconomic status and reduced prevalence of multidimensional poverty. Nonetheless, persistent structural obstacles hinder the equitable provision of essential services.

This research identified the Income and Food sub-indices as significant indicators of poverty in the municipalities of Querétaro, highlighting the importance of purchasing power and food security in determining well-being. The validation of the results using the XGBoost model showed the strong predictive ability of the sub-indices, highlighting the significance of public policies aimed at enhancing access to economic and food resources.

Financing

This work did not receive funding from any institution or organization.

Conflict of Interest

The authors declare that there is no conflict of interest in relation to this study.

Authors' Contributions

Dafne Quetzalli Valdez Gallegos: conceptualization, data conservation, formal analysis, research, methodology, project management, writing - original draft, visualization; Roberto Yoan Castillo Dieguez: conceptualization, supervision, validation, resources, writing - review and editing.

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