Id: 1811631

Participatory Educational Research (PER)
Vol.13(3), pp. 93-118, May 2026
Available online at http://www.perjournal.com
ISSN: 2148-6123
http://dx.doi.org/10.17275/per.26.36.13.3

Exploring Urban Factors Influencing Academic Achievement: An International Comparative Study

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Article history
Received:
27.10.2025

Received in revised form:
02.01.2026

Accepted:
19.01.2026

Key words:
Urbanization; PISA; academic achievement; overurbanization; urban primacy

This study investigates the impact of urbanization on the Programme for International Student Assessment (PISA) academic performance and conducts comparisons among different countries. Rather than focusing only on school-based variables, it examines whether broader urban and well-being conditions help explain cross-national differences in student achievement. Various dimensions of urbanization, including economic, social, and educational outcomes, are examined. This quantitative study employs a correlational design. Utilizing methodologies such as stepwise regression analysis, hierarchical cluster analysis, and discriminant function analysis, this research sheds light on the complex relationship between urbanization and education, providing valuable insights for future research endeavors. Using OECD Better Life Index data, the study identifies the most salient predictors, groups countries according to shared patterns, and distinguishes between relatively higher- and lower-performing contexts. The study covers 37 Organization for Economic Co-operation and Development (OECD) countries. The study empirically demonstrates that indicators such as rooms per person, homicide rate, years in education, long-term unemployment, and life satisfaction significantly correlate with PISA academic performance. These results also reveal distinct country clusters associated with different combinations of urban advantages and disadvantages. The findings suggest that urbanization should be understood not simply as population concentration, but as a multidimensional process shaped by housing quality, safety, educational participation, labour market conditions, and subjective well-being..

Introduction

In the context of the internationally competitive environment of PISA examinations, numerous scientific studies are conducted to understand the factors underlying academic achievement and to enhance PISA academic achievement levels in countries accordingly. The

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primary challenge encountered in these studies is the limited scope of indicators and independent variables related to evaluating PISA exam results within educational settings. Therefore, this current research aims to provide a different perspective on assessments that are constrained by indicators such as students' socioeconomic characteristics, physical conditions of schools, leadership abilities of school administrators, and competence levels of teachers. To achieve this goal, instead of focusing on schools, the research has shifted its focus to the levels of urbanization in the regions where schools are situated, aiming to comprehend the differences in PISA achievements among OECD countries.

Beyond school-based explanations, a growing body of literature has emphasized that countries' general development and human development levels are closely associated with student achievement outcomes measured by international large-scale assessments such as PISA. In this respect, the Human Development Index (HDI), developed by the United Nations Development Programme (UNDP), has become one of the most widely used composite indicators for capturing multidimensional development by integrating health, education, and income dimensions (UNDP, Human Development Reports). Unlike single economic indicators such as GDP per capita, HDI provides a broader framework for understanding how structural and social development contexts may shape educational outcomes.

Important studies have been conducted to understand the factors behind PISA achievement. Yang and Lee (2022) have found that the enhancement of students' performance in mathematics, reading, and science is not correlated with supplementary material resources (such as the number of computers per student in a school) and human resources (including the percentage of teachers with a master's degree). In another study, Daniele (2021) focused solely on the 2012 and 2018 PISA mathematics scores and regions in Italy, Spain, Australia, Belgium, and Canada. According to the research findings, there exists a significant and negative relationship between relative poverty rates and PISA mathematics scores. This relationship is independent of students' socioeconomic and cultural backgrounds and some school-related factors. Relative poverty rates are negatively correlated with GDP per capita; however, the impact of poverty on average mathematics scores is also independent of regional development levels. Increasing income inequality and socioeconomic disparities are also being investigated regionally and globally (Byun & Kim, 2010; Chmielewski, 2019; Lam & Zhou, 2022). A common finding of these studies is that academically disadvantaged groups exhibit significantly lower academic achievement levels compared to advantaged groups. Among these studies, the work conducted by Rowley et al. (2020) holds a distinct place. Prioritizing high-income countries, this study reveals that socioeconomic disparities are associated with academic achievement across all countries, but the extent of these differences varies from country to country. In other words, when academic achievement is examined based on socioeconomic status in countries with similar income levels, it is found that the academic achievement gap is not consistent.

Parallel to this line of research, several cross-national studies have explicitly examined the relationship between PISA outcomes and countries' human development levels. Korkmaz and Şahin (2013), using PISA 2009 data, demonstrate a significant association between students' academic performance and countries' general and human development levels, suggesting that educational achievement cannot be fully understood independently of broader development indicators. Similarly, Avcu (2021) argues that although PISA outcomes are not the sole or central determinant of human development, they remain closely intertwined with human development dimensions and structural inequalities across countries. These findings highlight the importance of interpreting PISA results within a broader development framework rather than as isolated indicators of school effectiveness.

Literature in this field has led us to seek a different perspective in identifying the factors influencing PISA academic achievement. Relying solely on school-based indicators to understand the differences between countries is insufficient for understanding the factors influencing PISA achievement. In this research, the first strategy we developed to address this issue is to delve more deeply into the indicators used in previous studies. For example, indicators previously considered only as income in the literature are now examined in more detail with sub-dimensions such as household net adjusted disposable income and household net wealth. Similarly, socioeconomic indicators such as housing are explored through sub-dimensions like dwellings without basic facilities, housing expenditure, and rooms per person, while indicators related to income levels under the title of jobs include sub-dimensions such as labor market insecurity, employment rate, long-term unemployment rate, and personal earnings.

Secondly, the inadequacy of school-based data in explaining PISA academic achievement has directed our attention to factors outside the school environment. In other words, we developed the assumption that the factors influencing academic achievement may not be directly related to schools but rather shaped by the characteristics of the regions in which schools are located. To explore this, we examined a wide range of variables under the headings of environment, civic engagement, health, life satisfaction, safety, and work-life balance. These variables encompass a broad spectrum, ranging from homicide rates to time devoted to leisure and personal care; from air pollution to feeling safe walking alone at night.

Recent cross-country studies based on PISA 2018 further support this perspective by demonstrating that inequality-related indicators—such as income distribution, social stratification, and access to basic living conditions—play a crucial role in explaining differences in student performance across countries. Evidence shows that disparities in PISA achievement are strongly linked to broader inequality patterns rather than solely to education system characteristics, reinforcing the argument that student outcomes reflect the wider social and developmental environments in which education systems are embedded (Inequality and Students' PISA 2018 Performance: A Cross-Country Study). Moreover, more recent analyses confirm that the relationship between PISA outcomes and HDI remains robust over time, although its strength varies across countries and development contexts (Acido & Caballes, 2024).

It is plausible to assert that the indicators we are working on overlap under two distinct topic headings in the literature. Firstly, the indicators mentioned above are considered well-being indicators under the Better Life Index (BLI) in the OECD's 'How's Life - Well-being' database. However, we have identified that these indicators have also been addressed in different studies within the urbanization literature (Andersson et al., 2009; Haryanto et al., 2021; Marcuse & van Kempen, 2002; Saunders, 2003). In other words, we have adopted the assumption that the well-being level of a particular region may be, to some extent, synonymous with the level of urbanization. At this point, the challenge we faced was to integrate well-being indicators with urbanization indicators and demonstrate the potential use of well-being indicators for understanding the level of urbanization. Therefore, we constructed the theoretical framework of the research based on this assumption. In the final stage, we developed the following research questions to understand which factors related to urbanization explain PISA academic achievement:

- What urbanization indicators are significant predictors of PISA academic achievement?
- What urbanization indicators are significant predictors in the clustering of countries based on their PISA academic achievement?
- What urbanization indicators are significant predictors of countries' placement in upper and lower groups based on their PISA academic skills?

Well-being, Urbanization, and Education

Urbanization, commonly defined by the increase in urban population, entails a complex interplay of various factors, necessitating a nuanced understanding beyond mere population growth. Its pace and magnitude compel nations to address housing, infrastructure, and service provision (Zhu et al., 2021). As Martine (2008) has expressed, urbanization can signify increased human resources and development for specific cities, while as Davis (2020) has indicated, urbanization can mean slum formation for third-world countries. However, what is inevitable, whether good or bad, is that urbanization increases the population of certain cities, and consequently, infrastructure and services in these areas must be provided in line with the rate of population growth. Accordingly, it is reasonable to assume that in cities and countries with the potential to provide necessary infrastructure and services in line with the pace of urbanization, the level of well-being would also be high.

The indicators mentioned above are closely related to variables in the OECD Better Life Index (BLI) data set, such as dwellings without basic facilities, housing expenditure, and rooms per person. Furthermore, there is evidence of a mutual interaction between educational quality and housing prices. In other words, acknowledging that areas with high housing prices tend to have high educational quality represents one dimension of these research findings. However, educational quality also plays a role in driving up housing prices. In other words, as families competing for access to quality education are willing to pay higher prices to reside in areas near prestigious schools, the housing prices surrounding these schools also increase (Davidoff & Leigh, 2008).

This situation directs us to a different area in the BLI. Under the income and jobs category in the BLI, indicators related to well-being are presented as household net adjusted income, household net wealth, labor market insecurity, employment rate, long-term unemployment rate, and personal earnings data. Indeed, the distribution of variables in the income and jobs category can significantly influence the production of urban space. Socioeconomic disparities in urban areas, evidenced by housing prices, often lead to the segregation of affluent and economically disadvantaged populations into distinct neighborhoods, impacting access to quality education and reflecting income discrepancies. Similarly, another factor contributing to urban segregation is homeownership. Homeowners tend to exhibit higher levels of civic engagement (another indicator in the BLI) compared to renters, thus positively impacting community cohesion (Rotolo et al., 2010). However, the presence of quality educational institutions in a neighborhood or district both increases housing prices and shortens the time it takes for houses to be sold (Zahirovic-Herbert & Turnbull, 2008). Therefore, a negative relationship between the presence of quality schools in an area and civic engagement can be expected.

Likewise, the increase in urban population, depending on geographical features, may lead to an increase in population density in cities. With the growing population and population density, energy consumption, greenhouse gas emissions, and carbon emissions also increase in urban areas. For developing countries, it is essential to promote the urbanization process by increasing energy efficiency, optimizing the final energy consumption structure, and reducing carbon intensity. This includes elements such as information dissemination, technological advancement, industrial renewal, centralized use of low-carbon energy, and the scale effect brought by urbanization (Wang et al., 2021). Failure to meet these requirements may result in a decrease in the quality of life and life satisfaction in urban areas, as well as an increase in health problems.

Urban Space Division and Its Impact on Educational Outcomes

Urbanization is inevitable for all countries, though the way it is managed differs. Balanced urbanization across provinces and districts, while maintaining social diversity, may be an ideal goal. However, differences in quality and quantity of urban development between cities and regions within and across countries can arise. Kasarda and Crenshaw (1991) introduce concepts such as *overurbanization* and *urban primacy*, where cities grow excessively but fail to meet the service needs of their populations, or where one city dominates development within a country.

Urban sociology links the division of space with indicators like safety and life satisfaction. Countries with well-planned urbanization tend to exhibit balanced life satisfaction, while those with sharp regional disparities show uneven quality of life. Where rapid urban growth exceeds the capacity for service provision, such as healthcare or education, lower academic performance often follows. This aligns with urban primacy, a concept Erder (2023) connects to colonial histories, where key cities were developed to exploit resources, leaving deep disparities that persist today.

In this context, the PISA exam, which uses a diverse sample of schools, reflects overall academic performance. If performance disparities are large, PISA may present skewed results. More successful schools in lower-ranking countries may outperform those in higher-ranking nations. Tze et al. (2022) highlight that solidarity-based cultures improve academic outcomes, further indicating that urbanization issues like overurbanization and primacy can lead to uneven educational quality across regions.

This study aims to explore urbanization indicators influencing PISA performance, focusing on identifying variables for future research rather than offering definitive conclusions. By examining various urban factors, the research integrates multiple variables previously studied in isolation, creating a comprehensive framework.

Method

This study employed a quantitative correlational research design, utilizing stepwise regression, hierarchical cluster, and discriminant function analyses to examine the relationships between urban indicators and academic achievement across OECD countries.

A quantitative correlational research design refers to an analytical approach that aims to identify and examine the direction and strength of statistical relationships between variables without manipulating them or implying causal inference (Creswell, 2014; Cohen et al., 2018). This design is particularly appropriate for cross-national comparative studies where the objective is to explore systematic associations among macro-level indicators rather than to test experimental effects.

In the context of this study, the quantitative correlational design was adopted to investigate how a broad set of urbanization-related indicators—derived from socioeconomic, housing, labor market, environmental, and well-being domains—are statistically associated with countries' average PISA academic achievement levels. First, stepwise regression analysis was employed to identify the most significant predictors of PISA performance among a large pool of urban indicators. Second, hierarchical cluster analysis was used to classify OECD countries into homogeneous groups based on similarities in both academic achievement and urbanization characteristics. Finally, discriminant function analysis was conducted to determine which urban indicators most effectively distinguish between countries located in higher and lower PISA achievement groups.

This multi-stage analytical strategy allows for a comprehensive examination of the relationships between urbanization and academic achievement from complementary statistical perspectives, while remaining consistent with the non-causal and exploratory nature of a quantitative correlational research design.

Data Set

The OECD Better Life Index serves as a comprehensive dataset developed by the Organisation for Economic Co-operation and Development (OECD) to assess the quality of life across countries. This dataset encompasses a wide range of critical indicators that cover various aspects influencing the quality of life. These components include but are not limited to life satisfaction, financial well-being, educational attainment, health status, environmental quality, social connections, living conditions, and work-life balance. Each indicator provides insights into different dimensions of well-being and allows for a holistic evaluation of living standards. Importantly, these indicators also reflect aspects related to urbanization and the built environment, such as access to education, health services, transportation, housing quality, and community infrastructure. Thus, the OECD Better Life Index (BLI) not only offers insights into individual well-being but also provides valuable information on urban development and the quality of life in urban areas. Table 1 demonstrates the categories and subdimensions in the data set.

Table 1. Better Life Index categories and subdimensions

Category	Subdimensions	Category	Subdimension	Category	Subdimension
Housing	Dwellings without basic facilities (percentage)	**Income**	Household net adjusted disposabile income (US Dollars)	**Jobs**	Labour market insecurity (percentage)
	Housing expenditure (Percentage)		Household net wealth (US Dollars)		Employment Rate (percentage)
	Rooms per person (Ratio)				Long term unemployment rate (percentage)
					Personal earnings (US Dollars)
Category	**Subdimensions**	**Category**	**Subdimension**	**Category**	**Subdimension**

Community	Quality of support network (percentage)	**Education**	Educational attainment (percentage)	**Environment**	Air pollution (Micrograms per cubic meter)
			Student skills (Average Score)		Water quality (percentage)
			Years in education (Years)		
Category	**Subdimensions**	**Category**	**Subdimension**	**Category**	**Subdimension**
Civic engagement	Stakeholder engagement for developing regulations (average score)	**Health**	Life expectancy (years)	**Life satisfaction**	Life satisfaction (percentage)
	Voter turnout (percentage)		Self reported Health (percentage)		
Category	**Subdimensions**	**Category**	**Subdimension**		
Safety	Feeling safe walking alone at night (percentage)	**Work-life balance**	Employees working very long hours (percentage)		
	Homicide rate (ratio)		Time devoted to leisure and care (hours)		

In Table 1, the data presented under "Student skills" represents students' average scores in reading, mathematics, and science as assessed by the OECD's Programme for International Student Assessment (PISA). In this study, "student skills" has been considered as the dependent variable, while the variables in the subdimensions have been utilized as independent variables.

The OECD Better Life Index was selected as the primary data source because it is grounded in a well-established conceptual framework that defines well-being as a multidimensional construct encompassing material conditions and quality-of-life outcomes (OECD, 2020; OECD, 2023). Unlike single economic indicators, the BLI framework explicitly links housing conditions, labor market structures, safety, education, and subjective well-being to broader social and economic development processes, many of which are closely associated with urbanization dynamics.

Within this framework, specific indicators—namely rooms per person, years in education, long-term unemployment rate, homicide rate, and life satisfaction—were deliberately selected because they represent core structural and experiential dimensions of social and economic conditions that are repeatedly emphasized in both the OECD well-being framework and the urbanization literature. Rooms per person was included as a proxy for housing quality and residential density, reflecting overcrowding and living space conditions commonly used to assess urban housing inequalities. Years in education was chosen to capture cumulative human capital formation at the country level, representing long-term educational investment rather than short-term school performance.

Similarly, the long-term unemployment rate was included to reflect labor market exclusion and economic insecurity, which are known to have persistent effects on household stability, social cohesion, and intergenerational educational outcomes. The homicide rate was selected as an objective indicator of public safety and social stability, capturing structural aspects of urban safety that extend beyond individual perceptions. Finally, life satisfaction was incorporated as a subjective well-being indicator that reflects individuals' overall evaluation of their living conditions, integrating economic, social, and environmental experiences into a single evaluative measure.

All indicators were obtained from the OECD Better Life Index database, which is publicly available and periodically updated to reflect the most recent and comparable cross-national data. The data used in this study correspond to the latest available releases at the time of data collection, thereby capturing a contemporary snapshot of social, economic, and urban conditions across OECD countries (OECD Better Life Index, https://www.oecdbetterlifeindex.org). Explicitly specifying the OECD framework and data source ensures transparency and addresses potential concerns regarding temporal variability in indicator definitions and measurement.

Data Analysis

In the study, the analyses were divided into three parts. In the first stage, the OECD Better Life Index dataset was examined using stepwise regression. Stepwise regression, as described in the study, is a method utilized for constructing regression models where the selection of predictor variables is automated (Draper & Smith, 1998). Specifically, a forward selection approach was favored. This technique begins with no variables in the model and evaluates the inclusion of each independent variable based on a model fit criterion. Consequently, variables are added to the model if their inclusion significantly enhances the model fit; this process commences with those yielding the most statistically significant improvement and continues until further variables fail to substantially enhance the model fit. For the stepwise regression analysis to yield accurate results, certain assumptions must be checked before conducting the analysis. Accordingly, the dependent and independent variables should be at least on an interval scale and continuous, the variances of the independent variables should be non-zero, there should be no high correlation among the independent variables, and there should be no autocorrelation, meaning that the errors between the measured and model-predicted values should be independent of each other (Field, 2005).

In the OECD Better Life Index dataset, all variables are presented as percentages, average scores, years, hours, and US Dollars. In the research, a data preprocessing process was first conducted to check the assumptions. Variables with high correlation were examined, and those showing high correlation with multiple variables were removed from the analysis and observed through tolerance and variance inflation factor (VIF) coefficients for multicollinearity. Finally, autocorrelation was checked using the Durbin-Watson test. In assumption checks, tolerance values greater than .20 and VIF values less than 10 were considered acceptable, while the Durbin Watson test result between 1 and 3 was deemed to meet the assumptions. In addition, outlier detection among the examined countries was conducted using Mahalanobis Distance (Cook & Weisberg, 1982; Craney & Surles, 2002; Kim, 1996).

Having confirmed that the assumptions were met, stepwise regression analysis was conducted in two stages. Firstly, a missing data analysis was performed, revealing that the missing data were not randomly distributed. Consequently, in the initial stage, the analysis was conducted only on the data from 16 countries, after excluding the missing values. However, given that this study aimed to explore all possible relationships between urbanization and PISA academic achievement, missing data from the remaining 22 countries were imputed using regression analysis to ensure their inclusion in the research (Raghunathan et al., 2001). Multiple models were developed, and common values identified across different models were examined. Cross-validation was conducted to determine which model exhibited better predictive performance and fit. In this process, train and test sets were created for each model, and their prediction performances were compared using root mean square error (RMSE), R squared value, and mean absolute error. For model fits, Akaike information criterion (AIC) and Bayesian information criterion (BIC) were utilized (Jeelani et al., 2022).

In the subsequent stage of the research, the hierarchical cluster analysis method was employed to examine the distribution of statistically significant variables obtained through stepwise regression across countries. Hierarchical cluster analysis involves identifying clusters within a dataset, where each cluster can be further divided into subclusters at different levels or form a supercluster (Hennig et al., 2015). Ward's method presents an alternative paradigm for undertaking cluster analysis. Fundamentally, it conceptualizes cluster analysis through the lens of variance analysis, diverging from reliance on distance metrics or association measures. This approach employs an agglomerative clustering algorithm, initiating from the leaves and progressing metaphorically toward the trunk. It discerns clusters of leaves coalescing into branches, subsequently amalgamating into limbs, and ultimately converging into the trunk. Commencing with n clusters, each comprising a singular observation, Ward's method iterates until all observations coalesce into a unified cluster (Dias & Galdino, 2021). The purpose of conducting cluster analysis with statistically significant variables is to assess their validation at the country level. Although R^2 values can indicate the percentage of variance explained by the dependent variable in the obtained models, this ratio is limited to the variables included in the research scope. Therefore, to assess the accuracy of the models, countries were hierarchically clustered, and the reliability of the models was determined by examining the average PISA scores of the clusters. Additionally, identifying which countries are advantaged or disadvantaged in terms of urban indicators associated with PISA could be useful during the stage of developing recommendations.

In the final stage of the research, to enhance the generalizability and reliability of the study results, the dataset was further analyzed using the discriminant function analysis method. Considering the aim of reaching the maximum possible number of urban variables associated with PISA outcomes and accessing the maximum number of indicators for future research, it was deemed beneficial to employ a different analytical technique. Therefore, the dataset was scrutinized to identify indicators suitable for the study based on the results of the Box M test. In discriminant function analysis, a discriminant function, also referred to as a canonical root, is a latent variable created through a linear combination of independent variables, to maximize the distinction between the means of the dependent variable. This procedure resembles multiple regression, albeit with discriminant coefficients adjusted to enhance the separation between the means of the dependent variable groups. As for the Box's M test, it examines whether there are differences in covariance matrices across groups (Garson, 2012). In this study, the arithmetic mean of countries' PISA scores was calculated, and thus the dataset was divided into two groups: countries scoring below and above the arithmetic mean. The statistical significance of the variables added to the model was evaluated based on eigenvalues and Wilk's Lambda test results, and the effect sizes were examined according to the obtained function.

For enhanced clarity and wider accessibility of the findings and results from the study, the outcomes of assumption checks conducted before statistical analyses were compiled into a separate electronic file and not presented in this study[1].

Results

Urban Predictors of PISA Skills

In this study, stepwise regression analysis was initially conducted with missing data omitted, and in the first step, data from 16 countries were examined. The countries whose data were examined in the first step are Austria, Belgium, Canada, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, the United Kingdom (UK), and the United States of America (USA). The stepwise regression analysis conducted with BLI data revealed that only two indicators were significant for these 16 countries. Table 2 shows the analysis results.

Table 2. Stepwise regression analysis (Missing values omitted)

	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
(Constant)	401,30	43,782		9,166	,000		
Long-term unemployment rate	-5,92	1,005	-,864	- 5,890	,000	,949	1,054
Years in education	6,10	2,477	,361	2,463	,029	,949	1,054

Model = R^2 =, 694 (p<,0000)

As seen in Table 2, there is a negative relationship between the long-term unemployment rate and PISA academic skills. When compared to Years in Education, it is likely that the long-term unemployment rate has a stronger effect. To further examine the relationship between these three variables, the following visualization has been created.

[1] To access the analysis results regarding assumption checks, please scan the QR code.

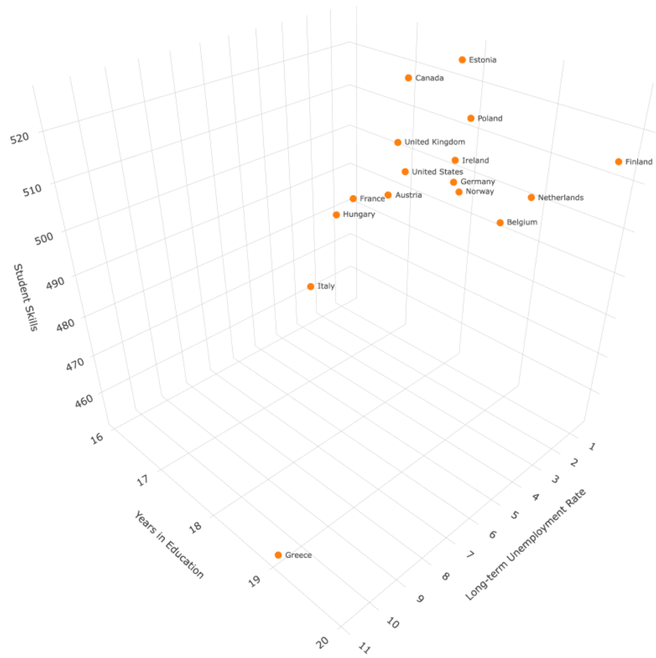

Figure 1. 3D plot of significant predictors

As seen in Figure 1, countries like Greece and Italy likely have high long-term unemployment rates compared to other countries. Still, the significance of these variables may be attributed to the high value of the Years in Education variable as well. Additionally, the fact that all countries with high PISA scores have low long-term unemployment rates can also be interpreted as an important factor. However, it is still necessary to examine other factors. Therefore, in the next stage of the research, five different models were developed by imputing missing values through regression, and the data of all countries except Spain, where PISA results were not available, were analyzed. The models obtained are presented in Table 3.

Table 3. Stepwise regression analysis (missing values imputed by regression)

	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
MODEL 1							
(Constant)	470,689	10,588		44,455	,000		
Homicide rate	-3,38	,686	-,673	-4,924	,000	,224	4,469
Long-term unemployment rate	-8,46	1,367	-,521	-6,185	,000	,588	1,700
Employees working very long hours	-1,07	,343	-,293	-3,125	,004	,476	2,099
Rooms per person	20,99	5,069	,314	4,140	,000	,726	1,378
Dwellings without basic facilities	1,33	,568	,264	2,342	,026	,330	3,031

Labour market insecurity	1,61	,748	,175	2,161	,039	,634	1,576
Adjusted R^2 = ,849							
MODEL2							
(Constant)	493,384	25,364		19,452	,000		
Educational attainment	,648	,212	,332	3,054	,005	,510	1,961
Homicide rate	-3, 470	,554	-,678	-6,259	,000	,513	1,948
Long-term unemployment rate	-7,394	1,998	-,343	-3,701	,001	,699	1,431
Housing expenditure	-1,826	,813	-,194	-2,247	,032	,803	1,245
Adjusted R^2 = ,783							
MODEL 3							
Constant	365,798	38,381		9,531	,000		
Educational attainment	,660	,222	,338	2,968	,006	,503	1,987
Homicide rate	-2,277	,617	-,444	-3,693	,001	,452	2,213
Long-term unemployment rate	-6,438	2,457	-,257	-2,621	,013	,680	1,471
Years in education	4,811	1,848	,252	2,604	,014	,697	1,434
Adjusted R^2 = ,765							
MODEL 4							
Constant	316,407	29,112		10,869	,000		
Educational Attainment	,732	,179	,376	4,083	,000	,555	1,801
Rooms per person	26,503	5,689	,410	4,659	,000	,606	1,649
Self-reported health	-,451	,205	-,206	-2,205	,035	,541	1,849
Feeling safe walking alone at night	,987	,200	,448	4,929	,000	,570	1,756
Years in education	5,873	1,584	,282	3,707	,001	,815	1,227
Life satisfaction	-11,615	5,111	-,264	-2,273	,030	,348	2,873
Adjusted R2 = ,831							
MODEL 5							
Constant	484,340	10,511		46,077	,000		
Homicide rate	-4,858	,439	-,966	-11,060	,000	,652	1,533
Long-term unemployment	-8,736	1,846	-,370	-4,733	,000	,814	1,229
Household net adjusted disposable income	,001	,000	,285	3,792	,001	,883	1,133
Household net wealth	-2,17	,000	-,333	-3,774	,001	,637	1,569
Stakeholder engagement for developing regulations	8,489	3,635	,172	2,335	,026	-914	1,094
Adjusted R^2 = ,821							

As seen in Table 3, the model with the highest adjusted R-square value is Model 1 (R^2 = ,849). This model explains approximately 85% of the total variance. In this model, the variables homicide rate, long-term unemployment rate, employees working very long hours, rooms per person, dwellings without basic facilities, and labour market insecurity have been statistically identified as significantly associated with PISA academic achievement. Among the five models developed, the most frequently recurring indicators are homicide rate, long-term unemployment rate, and educational attainment variables. These variables are followed by rooms per person and years in education variables. While the homicide rate and long-term unemployment rate variables have been identified as significant in four out of the five developed models, the educational attainment variable has been observed in three models.

The next step involved comparing the models using cross-validation to make a selection and achieve more accurate results. For each model, train and test sets were randomly created using the set.seed command, and the predictive power of the models was measured. To make comparisons, the Root Mean Square Error (RMSE), R Squared (R2) value, Mean Absolute Error (MAE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) values of the models were determined. The table below presents the cross-validation results.

Table 4. Cross Validation Results

	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5
RMSE	12.83543	19.96578	17.83024	6.76879	9.39333
R2	0.8881299	0.8613712	0.8057563	0.8516049	0.8467809
MAE	10.99409	15.75702	13.86725	5.55162	7.85372
AIC	217.116	216.8599	226.1362	255.267	254.0326
BIC	227.4827	224.635	233.9112	266.7389	264.0705

As seen from Table 4, the model with the lowest RMSE and MAE values is Model4, while Model1 has the lowest AIC and BIC values, indicating the best fit. Therefore, it was decided to evaluate the results obtained from both models. Figure 2 and Figure 3 visualize the results obtained in Model 1 and Model 2, respectively.

Figure 2 highlights that some countries stand out from others in terms of the selected variables. For instance, the homicide rate is found to be much higher in Mexico, Colombia, and Costa Rica compared to other OECD countries. In Chile, Spain, and Italy, the long-term unemployment rate is observed to be higher than in other countries. Moreover, in Mexico, Türkiye, Colombia, and Costa Rica, the variable "employees working very long hours" is higher compared to other countries. These three variables have negative correlations with PISA academic performance.

Regarding the variable "rooms per person," which has a positive correlation with PISA academic skills, Canada, the United States, Australia, and New Zealand are positively distinguished from the group, while in Latvia, Israel, Costa Rica, Mexico, Slovak Republic, Poland, Türkiye, and Colombia, the number of rooms per person is lower compared to other countries. The low percentages of dwellings without basic facilities in Israel and New Zealand also demonstrate why this variable has a positive correlation with PISA academic skills. Additionally, the fact that the percentage of dwellings without basic facilities is close to zero in almost all countries except Mexico, Colombia, Lithuania, Latvia, and Chile contributes to the positive correlation between this variable and PISA academic skills. Finally, the low percentages of labor market insecurity in many countries, except for examples like Türkiye and Spain, make the statistical relationship between this variable and PISA academic skills understandable.

Figure 2. Model 1 data visualization

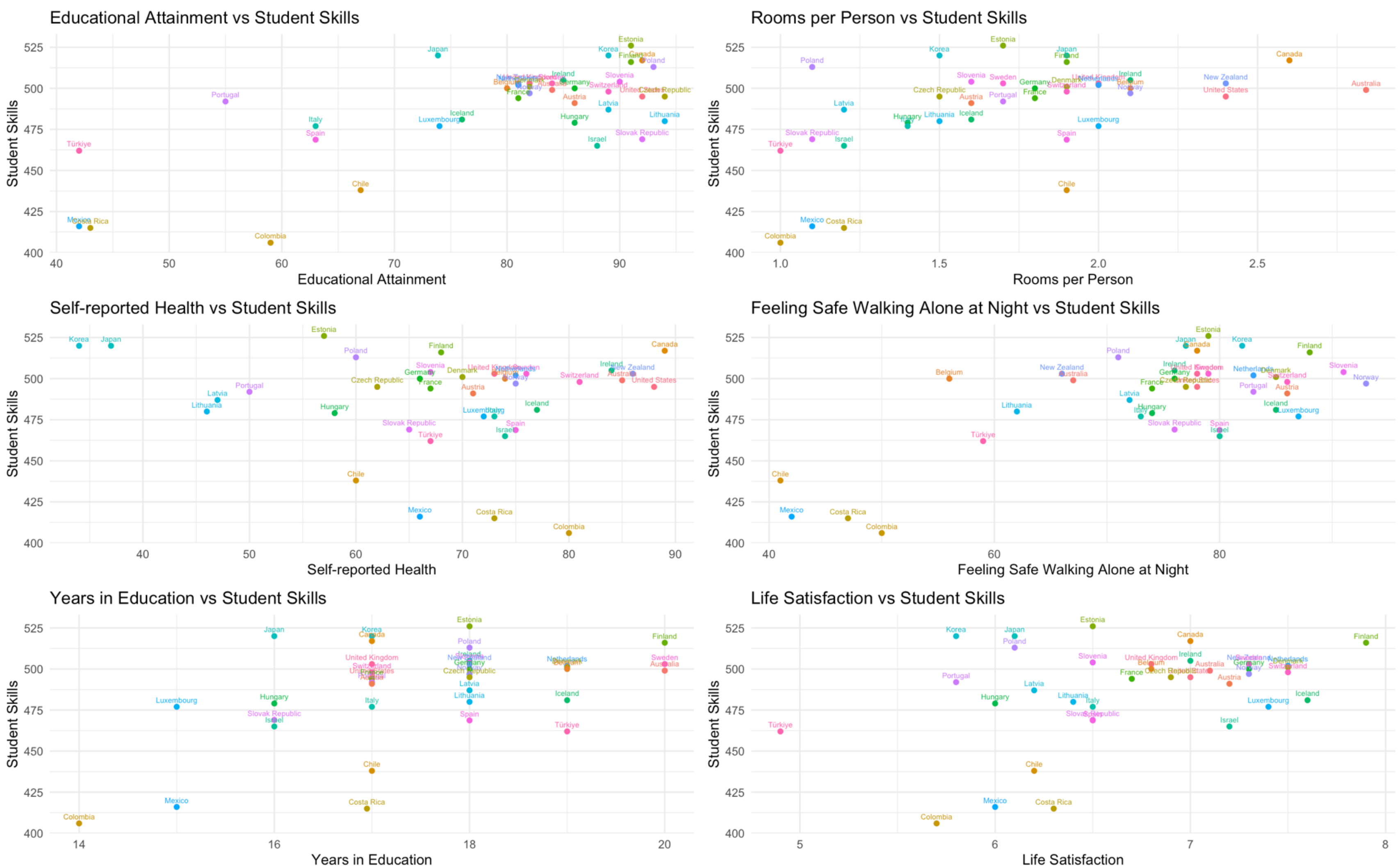

Figure 3. Model 4 data visualization

According to the data generated by Model 4, which has higher predictive performance, Figure 3 illustrates the distributions of the variables educational attainment, rooms per person, self-reported health, feeling safe walking alone at night, years in education, and life satisfaction along with student skills across countries. Based on the educational attainment variable, Türkiye, Mexico, Costa Rica, Portugal, Colombia, Italy, Spain, and Chile stand out from other OECD countries. It is observed that in these countries where educational participation is low, the average scores of PISA academic skills are also lower compared to other countries. Educational attainment reflects the educational status of the adult population aged 25 to 64 holding at least an upper secondary degree over the population of the same age, as defined by the OECD-ISCED classification. On the other hand, years in education represents the average duration of education in which a 5-year-old child can expect to enroll during his/her lifetime until the age of 39. It is calculated under the current enrollment conditions by adding the net enrollment rates for each single year of age from the age of five onwards. In other words, while educational attainment indicates the educational level of the adult population, years in education reveals how much of the maximum education duration the population has attended. In this regard, it is observed that the years in education variable is lower in Colombia, Luxembourg, and Mexico. In Japan, Hungary, Slovak Republic, and Israel, the years in education variable is relatively lower compared to other OECD countries. Conversely, in Finland, Sweden, and Australia, years in education is higher compared to other countries. Both years in education and educational attainment variables have a positive correlation with PISA academic skills. When evaluated in terms of effect size, the likelihood of predicting PISA academic skills scores based on the years in education variable is greater than that based on educational attainment. This implies that there is a stronger relationship between these two variables.

While not as influential as other variables, it is plausible to suggest that the variables of self-reported health and feeling safe walking alone at night are also associated with PISA academic skills. Self-reported health refers to the percentage of the population aged 15 years old and over who report “good” or better health. The positive correlation between this variable and PISA academic skills is a surprising finding. Especially noteworthy is the fact that the lowest values for this variable are found in Korea and Japan, followed by Lithuania, Latvia, and Portugal, which warrants further investigation. Additionally, the fact that self-reported health values are below 80% for all countries, except Ireland, Switzerland, Canada, the United States, New Zealand, and Australia is also a significant finding.

Another noteworthy variable is life satisfaction, which has a high negative coefficient value and is indicative of two distinct groups among countries. Life satisfaction considers people's evaluation of their life as a whole, measured on a scale from 0 to 10 using the Cantril Ladder (also known as the "Self-Anchoring Striving Scale"). The average life satisfaction values for Türkiye, Colombia, Portugal, Korea, Mexico, and Hungary are 6 or below. In Japan, Poland, Latvia, Chile, and Costa Rica, these values are very close to 6.

Unveiling Country Clustering: Insights into PISA Academic Performance through Hierarchical Cluster Analysis

Utilizing significant predictors from the two regression models obtained in the previous section, two cluster analyses were conducted. Figures 4 and 5 respectively present the results of cluster analyses conducted using the variables obtained from Model 1 and Model 2.

In the first hierarchical cluster analysis conducted using the variables obtained from Model 1, clusters with more interwoven subgroups are observed. Instead of clear polarization among OECD countries, the analysis results indicate the formation of subclusters comprising countries with similar characteristics. It is plausible to mention the existence of seven subclusters:

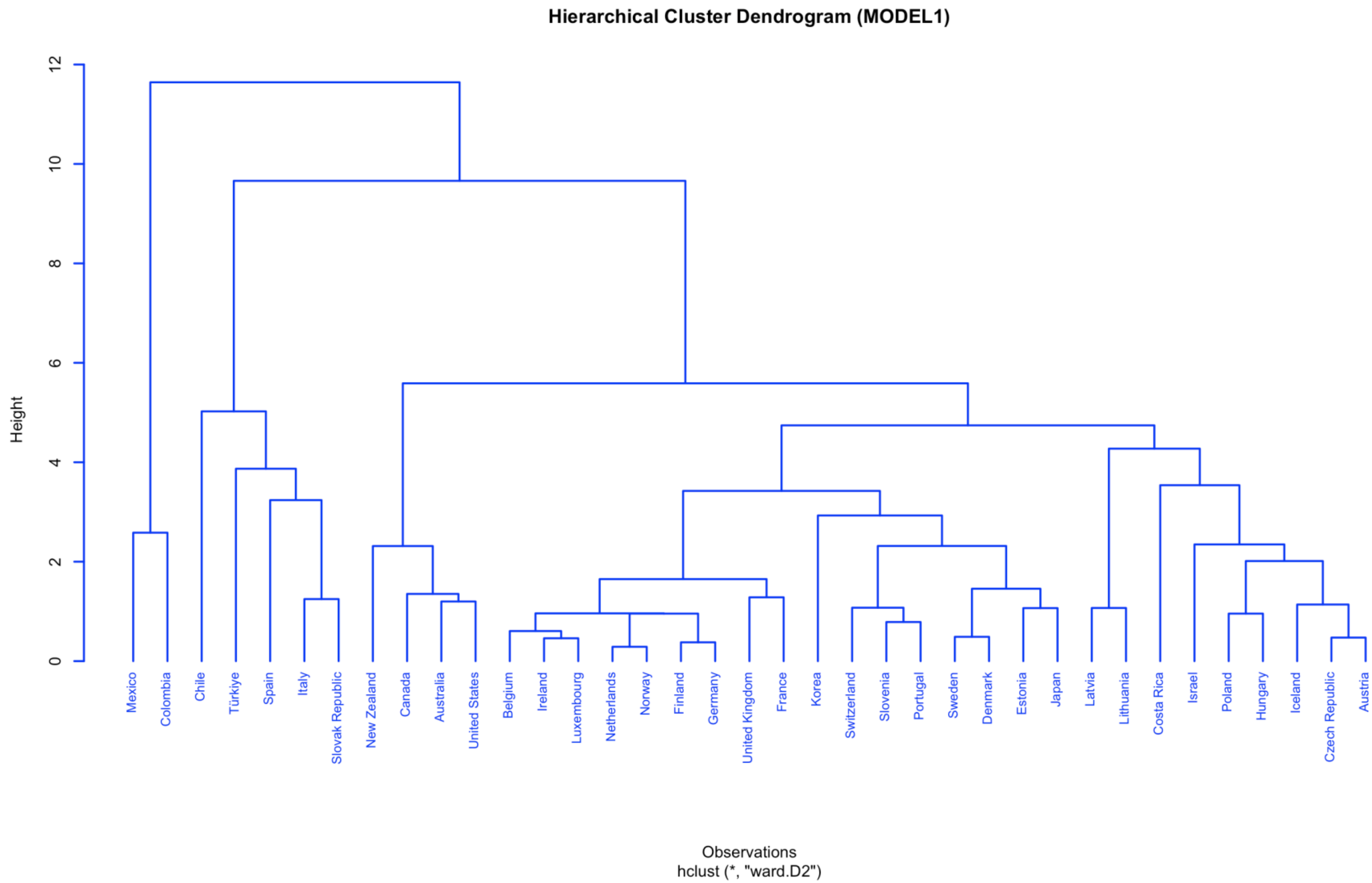

Figure 4. Hierarchical Cluster Analysis of Model1

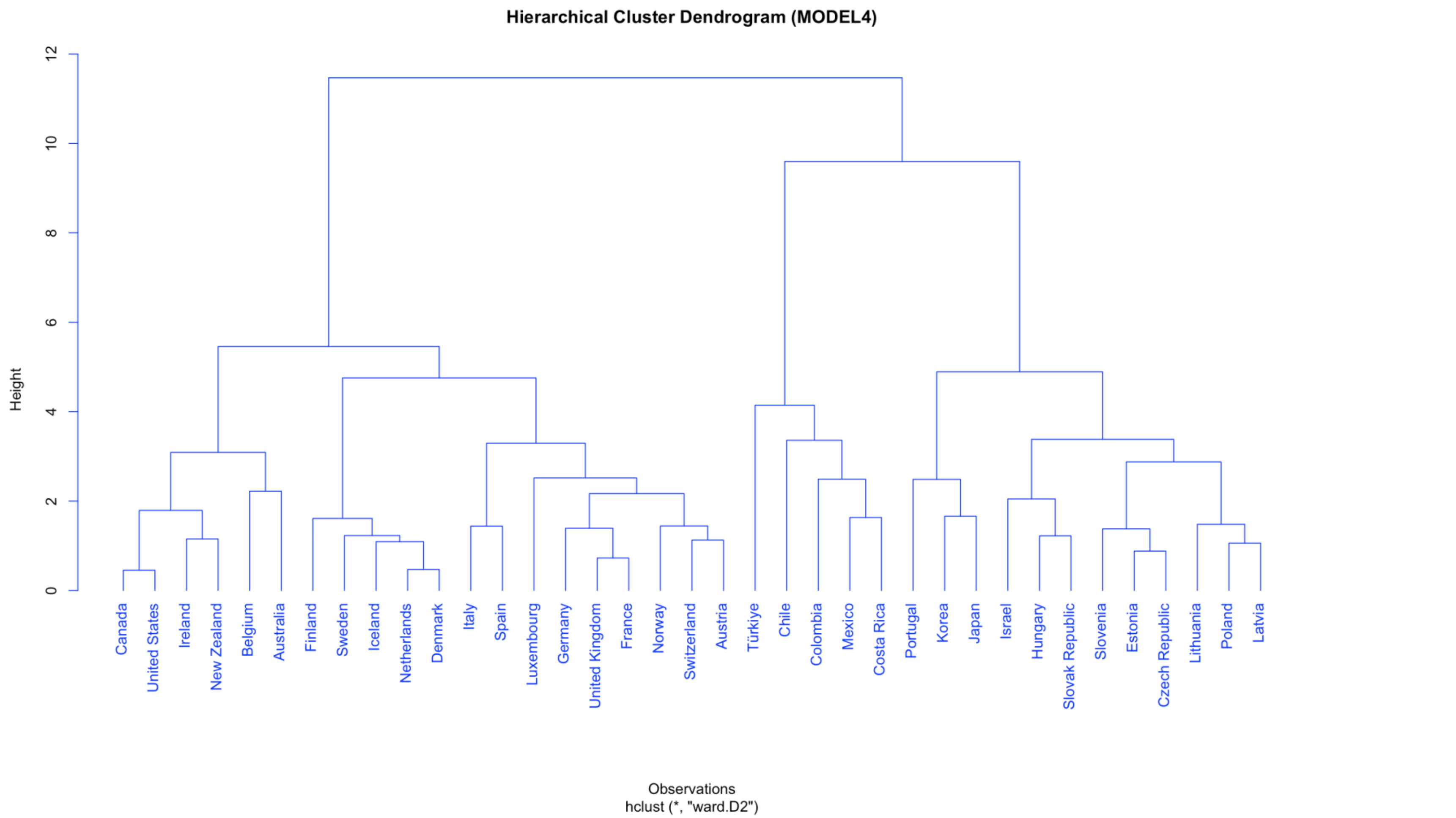

Figure 5. Hierarchical Cluster Analysis of Model4

(1) Mexico – Colombia (Average PISA Skills score = 411)
(2) Chile - Türkiye - Spain - Italy - Slovak Republic (Average PISA Skills score = 446,31)
(3) Costa Rica - Israel - Poland - Hungary - Iceland - Czech Republic – Austria (477)
(4) Latvia – Lithuania (483,5)
(5) Belgium - Ireland - Luxembourg - Netherlands - Norway - Finland - Germany - United Kingdom – France (Average PISA Skills score = 499, 34)
(6) New Zealand - Canada - Australia - United States (Average PISA Skills score = 503)
(7) Korea - Switzerland - Slovenia - Portugal - Sweden - Denmark - Estonia – Japan (Average PISA Skills score = 503)

When examining the average PISA academic proficiency scores of the subclusters, it is evident that the clusters are distinctly separated from each other. As the PISA average scores are arranged from lowest to highest, it is noteworthy that the score differences between clusters decrease as we move up. The first group consisting of Mexico and Colombia, and the second group consisting of Chile, Türkiye, Spain, Italy, and the Slovak Republic, have significantly lower scores compared to the remaining countries.

In the second model, despite having more subgroups, OECD countries present a bipolar image. The subgroups are as follows:

(1) Portugal - Korea – Japan (Average PISA Skills score = 510,67)
(2) Slovenia - Estonia - Czech Republic (Average PISA Skills score = 508,34)
(3) Canada - United States (Average PISA Skills score = 506)
(4) Ireland - New Zealand (Average PISA Skills score = 504)
(5) Finland - Sweden - Iceland – Denmark (Average PISA Skills score = 500,25)
(6) Belgium – Australia (Average PISA Skills score = 499,5)
(7) Norway - Switzerland – Austria (Average PISA Skills score = 495,34)
(8) Luxembourg - Germany - United Kingdom – France (Average PISA Skills score = 493,5)
(9) Lithuania - Poland – Latvia (Average PISA Skills score = 493,34)
(10) Italy – Spain (Average PISA Skills score = 472,86)
(11) Israel - Hungary - Slovak Republic (Average PISA Skills score = 471)
(12) Türkiye - Chile - Colombia - Mexico - Costa Rica (Average PISA Skills score = 418,75)

In the second analysis, it is observed that the number of subgroups increased and the sizes of the clusters decreased, resulting in a reduction in the average score differences between the subgroups. However, the average score of the group consisting of Türkiye, Chile, Colombia, Mexico, and Costa Rica is significantly lower compared to other groups.

Revealing Distinctive Patterns: Analyzing Factors of Variation

As the third part of the studies on BLI, a discriminant analysis with the variables 'water quality', 'rooms per person', 'educational attainment', 'air pollution', 'quality of support network', 'years in education', 'household net wealth', 'personal earnings', and 'life expectancy at birth'. The variables were chosen by analyzing the data set to discover significant variables that had the potential to classify countries depending on students' PISA skills. To carry out the analysis, the countries were separated into two groups one of which had scores over the average students' skills (over 487, 39) scores, and the other had scores below average (below 487,39). When the numbers of countries in the groups were controlled, it was found that 13 countries' PISA students' skills were below (Latvia, Iceland, Lithuania, Hungary, Luxemburg, Italy, Slovak Republic, Israel, Türkiye, Chile, Mexico, Costa Rica, and Colombia), and 23 countries' (Estonia, Korea, Japan, Canada, Finland, Poland, Ireland, Slovenia, New Zealand, Sweden, United Kingdom, Netherlands, Denmark, Belgium, Germany, Australia, Switzerland, Norway, United States, Czech Republic, France, Portugal, and Austria) scores were above average (Spain was not included as the PISA 2018 score was missing in the data set). As the number of countries in each group is higher than the number of variables, the sample sizes are accepted as enough to conduct a discriminant analysis. Significant variables' canonical discriminant functions and functions at group centroids are given in Table 5.

Table 5. BLI discriminant analysis canonical discriminant function coefficients

	Function 1
Rooms per person	3,084
Quality of support network	-,037
Educational Attainment	,032
Years in education	,428
Air pollution	,104
Water quality	,155
Life expectancy at birth	,019
Personal earnings	,000
(Constant)	-22,794
Functions at group centroids	
1 (Below average)	-1,645
2 (Above average)	,891

Table 5 demonstrates that in grouping countries as below average and above average as regards students' PISA skills, the most significant variable is rooms per person, and the second most significant variable is years in education. Though other variables are also significant in grouping cases, it is possible to conclude that rooms per person should be regarded as the most important determiner of student achievement. Furthermore, the variables of air pollution and water pollution quality address the fact that success in education is not completely dependent on individual socio-economic factors. These environmental factors indicate that the development levels of countries are also determiners of educational outcomes. These variables point to a link between urbanization and educational achievement. The classification results of the model are given in Table 6.

Table 6. BLI Discriminant analysis classification results

		cutoff	Predicted Group Membership		Total
			1,00	2,00	
Original	**Count**	1,00	11	2	13
		2,00	2	22	24
		Ungrouped cases	1	0	1
	%	1,00	84,6	15,4	100,0
		2,00	8,3	91,7	100,0
		Ungrouped cases	100,0	,0	100,0

a 89,2% of original grouped cases correctly classified.

In Table 6, the ungrouped case represents Spain, whose students' PISA skills score is missing in the data set. The model has an 89.2% prediction rate for grouping countries as above-average or below-average based on students' PISA skills.

Discussion and conclusion

This research investigates the relationship between urbanization and PISA academic skills from a different perspective, conducting a comparison among 37 OECD countries. The study explores which urban factors serve as statistically significant predictors of PISA academic achievement and examines countries grouped according to the obtained variables.

The assumption put forward in the study is that understanding urbanization solely through population data is insufficient. As suggested by Martine (2008), urbanization carries different meanings in different countries. While, for some countries, urbanization implies the planned development and growth of urban areas, for others, it signifies the inability of education, health, and infrastructure services to keep pace with rapid population growth in urban spaces. Therefore, while urbanization reflects economic growth and development for developed countries (Zhu et al., 2021), in different countries, it leads to adverse developments such as the formation of blighted areas (Marcuse & van Kempen, 2002), increased crime rates, decreased quality of support networks and human health (Davis, 2020), inadequate provision of education services, insufficient employment opportunities, production of poor-quality housing for accommodating the growing population, and a decrease in the number of rooms per dwelling or the cohabitation of multiple families within the same household (Buğra, 2018; Erder, 2023; Kasarda & Crenshaw, 1991; Keyder, 2018; Pandey, 1977; Pérouse, 2016).

In this study, the predictors of PISA academic achievement were identified as rooms per person, years in education, long-term unemployment rate, homicide rate, and life satisfaction across different types of analyses. In other words, an increase in the number of rooms per person and years in education in a country is expected to lead to an increase in PISA academic achievement. Conversely, long-term unemployment rate, homicide rate, and life satisfaction have a negative relationship with PISA academic skills. Therefore, an increase in long-term unemployment is expected to result in a decrease in PISA academic achievement. Similarly, an increase in the homicide rate in a country would likely lead to a decrease in PISA academic performance. Life satisfaction may be associated with population density in urban areas. Zhu et al.(2021) note that energy consumption is high in cities with high levels of urbanization. Additionally, Wang et al. (2021) suggest that without necessary measures and technological and industrial renewal, energy consumption-related carbon emissions in cities may increase. Thus, urbanization may potentially reduce the quality of life and life satisfaction in cities under certain circumstances. However, parallel to technological and industrial advancements, educational opportunities in these cities may also improve. Indeed, according to the European Commission, Joint Research Centre (2023), the life satisfaction average of Korea, with an urbanization rate of 98.83% in 2020, and Japan, with an urbanization rate of 95.95%, is lower compared to countries like Finland, Denmark, Switzerland, the Netherlands, and Iceland. Moreover, a panel data analysis conducted by Kaptan et al. (2023) suggests that low employment rates, household income levels with high NEET, gender wage gap, and perceived health deprivation can result in high PISA math scores.

In conclusion, it can be stated that the relationship between urbanization and educational outcomes varies depending on how urbanization occurs in a country. For example, in 2020, according to the data from the European Commission Joint Research Centre (2023), the proportions of the total population living in cities in countries with the lowest average PISA academic skills in 2018, such as Colombia, Costa Rica, Mexico, Chile, Türkiye, and Israel, were 87.82%, 78%, 83.22%, 87.52%, 90.23%, and 99.53%, respectively. On the other hand, in 2020, Estonia, which had the highest average PISA academic skills in 2018, had an urbanization rate of 67.20% according to the same dataset. This rate was 79.34% for Canada, 66.52% for Finland, and 63.40% for Poland, which were other countries with high average PISA academic skills in 2018. These data confirm that urbanization does not always result in positive outcomes in terms of economy, quality of life, and education. Therefore, it is possible to conclude that depending on the quality of urbanization, it also leads to changes in school compositions and affects the quality of education.

Limitations

One of the primary limitations of this study is its cross-sectional nature and reliance solely on data from the year 2018. However, the perspective on urbanization was evaluated in conjunction with better life indicators. Given the assumption that evaluating the concept of urbanization solely based on the proportion of urban population to the total population would be insufficient, it is possible to include other indicators of urbanization in addition to better life indicators. Another limitation of the study is associated with the analytical methods used. Despite being supported by methods such as hierarchical cluster analysis, discriminant analysis, and analysis of prediction and fit through the creation of train and test sets to ensure the reliability of the results obtained from the exploratory nature of the study, it is recommended to complement the findings with different methods such as multilevel regression analysis, panel data analysis, and structural equation modeling. The amount of missing data and the small number of observations in the dataset used for the study can also be considered as limitations.

An additional limitation of this study relates to the historical context of the data. Both the PISA student achievement scores and the OECD Better Life Index indicators used in the analysis correspond to the year 2018 and therefore reflect pre–COVID-19 social, economic, and urban conditions. Since the COVID-19 pandemic has led to substantial transformations in labor markets, housing conditions, well-being, and educational processes across OECD countries, the findings of this study should be interpreted as representative of pre-pandemic structural relationships. As such, the results may not fully capture the post-pandemic dynamics of urbanization and educational inequality. Future research could extend this framework by incorporating post-2020 data to examine whether the observed relationships have changed under altered social and economic conditions.

Future delimiters

This research aims to identify potential predictors of PISA academic performance and to open up new research areas for future studies. Therefore, it is recommended to conduct a more in-depth analysis of variables such as life satisfaction, homicide rate, long-term unemployment rate, and years in education obtained within the scope of the study. This could involve reducing the number of variables and/or utilizing qualitative research methods. It is observed that certain indicators are higher or lower in some countries compared to others. Therefore, in addition to studies comparing countries, it is also recommended to conduct studies that focus on selected specific indicators in certain countries. Furthermore, to test the robustness of the findings, longitudinal studies such as panel data analysis are suggested.

Declarations

Funding: *This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.*

Ethics Statements: *The study was reviewed and approved by the Ethics Committee of Yıldız Technical University, Social Sciences Institute, on 01.12.2022 (Approval No: 2022.12).*

Conflict of Interest: *The authors declare that they have no competing interests related to this research. Furthermore, this study did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.*

Informed Consent: *The study is based on publicly available open-access secondary data sources (OECD Better Life Index and PISA datasets). Therefore, no individual-level participation was required, and informed consent was not applicable.*

Data availability: *The datasets analyzed during the current study are publicly available in the OECD Better Life Index and PISA databases. Data can be accessed at: https://www.oecd.org/statistics/better-life-indicators.htm and https://www.oecd.org/pisa/.*

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