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Special Issue

Education as a factor of regional, economic, and social development: The Data Envelopment Analysis approach

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With this last issue of 2023, it is time to summarise the ERIES Journal's achievements. We are more than pleased that ERIES Journal has strengthened its position in Scimago Journal & Country (SJR) ranking. The journal was again ranked in Q3 in the Education category with the SJR score of 0.251 (+23%). Furthermore, we are very happy that all of the journal metrics maintained a growing tendency: +53% of total citations, +32.4% of external cites per document, and +16.1% of citations per document, among others. Similarly, we are very pleased that our page on LinkedIn attracted a bigger audience in the scientific field as the number of followers grew by 25.5%, terminating with 369 followers.

I would also like to announce that at the end of the year, doc. Ing. Igor Krejčí, PhD will step down from the executive editor position after 10 years. The whole editorial board team and I would like to express our gratitude to Igor for his endless effort in enhancing the ERIES Journal quality. During the first years, the main objective was to improve the journal's position within the international scientific community with the main goal to be indexed in Scopus database. When the first objective was reached, the next objective was to improve journal's metrics to sustain its development. As I mentioned before, all the metrics have been constantly growing and the journal's position has strengthened.

The new executive editor team member will be Ing. Jiří Fejfar, PhD, who has been involved in ERIES Journal operations for more than 5 years. I am more than sure that the journal will continue its development and will be recognized as a Q2 journal within few upcoming years.

We hope that all our readers will find this last issue of the year 2023 interesting. We also hope that ERIES Journal will contribute to the field of efficiency and responsibility in education and science as it has contributed during last years. With the end of the year 2023, we would like to thank all the authors who have submitted their manuscripts to ERIES Journal, to all reviewers who carefully reviewed all these manuscripts and provided helpful recommendations to improve articles quality, as well as to all members of the Editorial board who contributed to ERIES Journal bigger visibility. Their ongoing work is a huge responsibility for the Executive Editors to keep improving the journal's quality.

We wish you a Merry Christmas and a Happy New Year 2024.

Sincerely

Martin Flégl
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In an era where the global economy faces the spectre of recession and budgetary constraints, the role of education in fostering regional, economic, and social development becomes increasingly pivotal. This special issue of the Journal on Efficiency and Responsibility in Education and Science, entitled "Education as a factor of regional, economic, and social development: The Data Envelopment Analysis approach" delves into this critical theme, exploring the multifaceted impact of education through the lens of Data Envelopment Analysis (DEA).

The call for papers for this special issue highlighted the urgent need for objective methodologies to assess the influence of educational investments on development processes. In a world where economic growth alone is insufficient to drive substantial progress, education emerges as a dynamic tool for development. However, the long-term nature of educational investments necessitates robust, objective tools for evaluating their impact. This is where DEA, a method developed by Charnes, Cooper, and Rhodes in 1978 (Charnes et al., 1978), becomes invaluable.

DEA's application in various sectors, as evidenced by studies like those of Aparicio et al. (2020) in comparing gaps in education systems, Flegl et al. (2022) in the Mexican food industry, and Delahoz-Dominguez et al. (2022) in a professional football league, showcases its versatility. In education, DEA has primarily been used to evaluate university production efficiency. However, its potential to illuminate education's broader impact on regional, economic, and social development remains largely untapped.

This special issue aims to bridge this gap. It brings together pioneering research that employs advanced DEA models, such as two-stage models, fuzzy models, and the Malmquist index decomposition, to offer a nuanced understanding of education's role in development. The contributions in this issue extend beyond traditional one-stage DEA models, providing a richer, more comprehensive picture of education's developmental impact.

The articles in this issue cover a wide range of topics and methodologies. From examining the productivity of public universities concerning economic resources to comparative studies on educational gaps in European countries, the research presented here is diverse and insightful. These studies contribute to academic discourse and offer practical insights for policymakers and educators grappling with budgetary constraints and the need to efficiently allocate educational resources.

As the guest editor of this special issue, I am excited to present this collection of research. It is a testament to the power of DEA as a tool for understanding and enhancing the role of education in development. I am grateful to the authors for their valuable contributions, the reviewers for their rigorous evaluations, and the editorial team for their support throughout this journey.

In conclusion, this special issue is a beacon of knowledge for those seeking to understand and leverage education as a critical driver of regional, economic, and social development. I hope these insights will inspire further research and inform policy decisions, ultimately contributing to a more educated, equitable, and prosperous world.

The first article, "Graduate Employability as a Key to the Efficiency of Tertiary Education" by Veronika Blašková and Michaela Staňková presents a quantitative assessment of the efficiency of tertiary education in individual EU countries incorporating graduates' employability into the analysis. The authors used the SBM non-oriented super-efficiency Data Envelopment Analysis model covering a period from 2014 to 2020. The results revealed that only six countries (Bulgaria, Croatia, France, Ireland, Luxembourg, and Malta) were identified as efficient (or super-efficient) throughout the whole period under review. Countries such as Ireland and France emerge as top performers because of their ability to produce large numbers of graduates given their resources. On the other hand, Malta and Luxembourg have also performed very well in the efficiency assessment, but they produce far fewer graduates in terms of resources. Their efficiency is thanks to the system set up as their graduates are highly employable in the labor market.

The second article "A State-Level Analysis of Mexican Education and Its Impact on Regional, Economic, and Social Development: Two-Stage Network DEA Approach" by Martin Flegl, Sonia Valeria Avilés-Sacoto, David Güemes-Castorena and Estefania Caridad Avilés-Sacoto studies academic efficiency at the primary and secondary levels and its impact on the human development dimensions at the state level in Mexico. The authors proposed a network Data Envelopment Analysis (NDEA) model with two stages: The first stage investigates the educational process efficiency, while the second stage evaluates its impact in the form of the human development index. The results uncovered that the best-evaluated states in education reported lower Teacher/Student and School/Student ratios compared to the less efficient states. Further, the best-evaluated states in education have better regional, economic, and social development, although it was not reflected in the efficiency results.

In the third article "Ranking of European Universities by DEA-Based Sustainability Indicator", Markéta Matulová presented a novel approach to university rankings that considers a university's contribution to sustainable development. The conventional approach typically involves normalizing sub-indicators and applying subjective weights for aggregation, raising concerns about the rankings' reliability. In response to this issue, the author proposed an alternative method based on Data Envelopment Analysis (DEA) methodology that utilizes flexible weights Using data from the UI-GreenMetric World University Ranking, the author initially employed a general Benefit of the Doubt DEA model and subsequently enhanced its discrimination power by incorporating the super-efficiency approach. The results found positive correlations between university rankings and the fulfillment of sustainable development goals in their respective countries.

The fourth article "Assessing the Relative Impact of Colombian Higher Education Institutions Using Fuzzy Data Envelopment Analysis (Fuzzy-DEA) in State Evaluations" by Rohemi Zuluaga, Alicia Camelo-Guarín and Enrique De La Hoz presents an empirical methodology for estimating universities' relative impact on students as a sustainability factor in higher education. For this purpose, the authors used a Fuzzy Data Envelopment Analysis approach. The analysis consists of 92 universities evaluated regarding the results of the standardised evaluations of high school (Saber 11 - inputs) and university (Saber PRO – outputs) of the Industrial Engineering program in Colombia. The analysis observed that there is a representation of both public and private efficient universities, with a slightly higher percentage of private universities. However, no clear trend indicates that one type of institution (public or private) is more efficient than the other in terms of the evaluated academic programmes.

In the fifth article "Education Performance of Czech Public Higher Education Institutions Using Data Envelopment and Panel Regression Analysis", Jana Hančlová and Lucie Chytilová assessed education efficiency at public universities in the Czech Republic in 2020-2021 using an extended Data Envelopment Analysis model with undesirable outputs, non-proportional and non-radial measures of distance from the efficient frontier. Using the Feasible generalised least squares method, the authors estimated the influence of selected economic, social, regional, and institutional factors on education efficiency by a panel regression model. The results revealed that the average education efficiency worsened in the evaluated period, mainly due to an insufficient reduction in the number of unemployed graduates. Therefore, public universities cooperating with employers in the labor market should pay attention to this issue and improve this situation through deeper cooperation.

The last article "Measuring the Efficiency of Turkish Research Universities via Two-Stage Network DEA with Shared Inputs Model" by Hamza Dogan adopted a two-stage Network Data Envelopment Analysis (NDEA) with shared inputs model to assess teaching and research efficiencies of 23 Turkish research universities. The author used data from the Higher Education Information Management System and University Ranking by Academic Performance Research Center, which measures their academic performance by the quality and quantity of their scholarly publications. The research indicates that only 25% of the research universities demonstrated efficiency on all dimensions and that their overall efficiency scores were affected by the prioritization of teaching or research activities. In addition, the level of regional socio-economic development does not affect the efficiency of research universities.

Sincerely

Enrique de la Hoz, PhD
Guest Editor
Universidad del Magdalena, Colombia

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CONTENT

Full research paper

GRADUATE EMPLOYABILITY AS A KEY TO THE EFFICIENCY OF TERTIARY EDUCATION

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ABSTRACT

In the 21st century there is a lot of attention on sustainability (whether social or environmental). However, unfortunately, the economic perspective has been largely neglected in the field of education. This article deals with a quantitative assessment of the efficiency of tertiary education in individual EU countries, which allows to include the economic aspect of the evaluation. Furthermore, we are expanding the commonly established evaluation system based on the number of graduates to include another area, namely the graduate's employability on the labor market. We believe that for a correct evaluation of individual education systems it is necessary to include the relevance and quality of acquired knowledge and skills. Although the efficiency assessment is carried out for the whole EU, the results are presented according to identified groups of countries that have similar education systems. Countries such as Ireland and France emerge as top performers because of their ability to produce large numbers of graduates given their resources. Malta and Luxembourg have also performed very well in the efficiency assessment, although they produce far fewer graduates in terms of resources, but thanks to the system set up, graduates in these countries are highly employable in the labor market.

KEYWORDS

Efficiency, EU countries, labor market, Malmquist index, tertiary education

HOW TO CITE

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Highlights

- *Six countries (Bulgaria, Croatia, France, Ireland, Luxembourg, and Malta) were identified in our analyses as efficient throughout the period under review.*
- *Germany and Spain have the lowest tertiary education efficiency in the EU.*
- *It is not appropriate to analyze the efficiency of education only based on the number of graduates, but also on their ability to find a job.*

INTRODUCTION

The phenomenon of the ongoing fourth industrial revolution fundamentally affects the nature of the functioning of industry, trade, and many other parts of the economies of developed countries. In this regard, the need to recruit workers with a high-quality education corresponding to the needs and demands of technological development is increasing. Gleason (2018) deals with the issue of increasing qualifications as a condition for the implementation of Industry 4.0 in practice. He mentions that work needs to be done to create a digitally literate and technologically competitive society and, above all, with the help of experts who will be university-educated. Similar conclusions were reached by Jung (2020), who emphasizes that knowledge is the main driving force of economic growth in all world economies and, at the same time, becomes a new comparative advantage. In this way, Jung (2020) argues that the strengths that create the right environment for a knowledge economy are a skilled workforce with higher education and higher spending on research and development. Therefore, university-educated people and their applicability to the labor market come to the forefront of research.

The education sector (from primary to tertiary) has a very specific position. The efficiency of the education process itself also affects the effectiveness (and productivity) of other sectors in which graduates are later employed. If we were to support systems that produce low-quality labor, we would also negatively affect other sectors of the economy. In this regard comes another entity that closely monitors the education sector: national governments. The government must address the negative consequences of a poorly functioning education system in areas such as unemployment or insufficient GDP. Therefore, government reforms in areas such as unemployment should go hand in hand with reforms in education. However, this can only be done with an adequate evaluation of the efficiency of individual educational processes. The government is not just an entity that blindly receives the final products of the educational process but directly influences the educational system through its own actions. Firstly, we can mention the legislative framework (in terms of compulsory schooling, tuition fees, teachers' salary levels, etc.) and the expenditure on education. The amount of government expenditure will likely impact the quality of the educational process and, consequently, the quality of the students themselves. The results of efficiency assessments in the field of education are relevant not only for governments themselves but ultimately for everyone (companies and individuals), as the consequences of education are reflected in the overall economy of countries. Even taking into account the fact that the citizens of a given country generate government expenditure, it is necessary to assess the efficiency of its use.

It is possible to find studies that cover the evaluation of the educational process. Many analyses have been conducted at the individual school/university level. From the area of efficiency analysis, it is possible to name, for example, the analysis of Chilean (Cossani et al., 2022), Yemeni (AlMunifi and Aleryani, 2021), Vietnamese (Le et al., 2021), or Czech schools (Mikušová, 2017). These studies concentrate on secondary education and, moreover, on a single geographical area in which they are governed by the same legal regulations. If we want to look at the issue from a broader perspective, it would be necessary to make an international comparison.

Studies such as Mašková and Blašková (2021) or Stumbriene et al. (2022) focus on comparisons between EU countries based on aggregate data. Although individual EU countries are united by common efforts and regulations, due to a certain sovereignty, there are noticeable differences in individual countries in terms of the educational process. Regarding the focus on tertiary education, it can be stated that the greatest differences can be seen in the funding system. For example, in Germany or Austria, it is common for students to finance their studies for the most part themselves. Conversely, in Czechia or Slovakia, even prestigious universities have their studies fully covered by the state.

However, considerable efforts are being made for EU countries to minimize differences between graduates in terms of the outcomes of the education process across countries. A certain uniformity would then make it possible to dismantle the often complex and time-consuming processes of nostrification.

Major changes also connected with the so-called Europe 2020 strategy (European Commission, 2020b). Within the framework of this strategy, the task of the EU countries was that at least 40% of people aged 30–34 had a tertiary education. Furthermore, it sought to ensure the top level and quality of education and reduce the number of early school leavers below 10%. Thanks to these goals, there was an increase in the number of universities. Still, at the same time, it was a period when the number of potential tertiary education students decreased due to demographic changes. Thanks to this discrepancy, the need to evaluate the efficiency of the educational process has intensified.

Jelić and Kedžo (2018) addressed the efficiency of tertiary education from both a quantitative and a qualitative perspective. The authors examined EU countries in four periods between 2004 and 2015. Standard analyses based only on the number of students showed that some of the most developed countries in the sample, such as Austria and the Netherlands, were not efficient. In contrast, some less developed countries, such as Hungary, Estonia, and Bulgaria, were fully efficient in some periods. Due to these results, Jelić and Kedžo (2018) highlighted the need to correct the efficiency score to take into account the quality of educational processes sufficiently.

Similarly, studies can be found from various corners of the world evaluating efficiency at an aggregate level. However, these studies typically focus only on the number of students produced without evaluating their quality; see, for example, Kim et al. (2016), Andersson and Sund (2022), or Ma and Li (2021). In contrast to these studies, the analysis presented in this article includes the employability of graduates in the labor market. For this reason, the classic approach based on the number of graduates and the number of teachers is extended with information from the labor market. Our results should provide answers to the question of how efficient the tertiary education process is in each country regarding the graduates' labor market employability.

The main objective of the article is to evaluate the efficiency of individual EU countries in the field of tertiary education with regard to graduates' employability in the labor market. The period from 2014 to 2020 was chosen for the analyses considering EU regulations (especially the Europe 2020 strategy). However, it is not just a matter of compiling a ranking for individual EU countries but of complex analyses that will enable an assessment of how specifics in the education systems of individual countries affect the efficiency of tertiary education. As education systems are not identical in all EU Member States, our efficiency analysis allows us to assess which system is most suitable for students in terms of future employment. So, the analysis answers the following questions:

- What is the level of efficiency of tertiary education in EU countries?
- Is there a different efficiency level with respect to a different education system?
- Does the efficiency of individual countries change over time, or is its level relatively stable?

Differences in education systems in EU countries

The EU aims to support countries in their efforts to provide the best possible education. Although we have legislative documents (Treaty on the Functioning of the European Union, articles 165 and 166), the EU provides only a very general framework. As a result, individual countries are free to shape their own education system. It can be assumed that differences in individual systems will determine the different levels of efficiency of a given system.

Probably the biggest differences between countries can be seen in how education is financed and the education system. Although all countries have compulsory schooling, the length of schooling is not always the same. Most countries have compulsory schooling until the age of 15. For example, in Ireland, the Netherlands, and Luxembourg, compulsory schooling starts at the age of 4, while in countries such as Denmark, Finland, and Sweden, it starts at age 7. Compulsory school attendance is tuition-free, and its financing is covered by municipal and state budgets. Countries such as Austria also provide free transport and school supplies for children.

The Belgian-French community allows its students to replace classical teaching with e-learning, which is then verified by a final exam. About 1.5% of children complete primary and secondary education in this way (Eurydice, 2023). The German education system is very different in that it "forces" students to choose their future path at a relatively early age. As early as 4th grade, students have to decide whether to study general education or a school with specific qualifications. After completing compulsory schooling, they move on to upper secondary education. Secondary education can be vocational or general. Vocational secondary education in Germany (but also in other countries such as Austria) is in the form of a dual apprenticeship system. After completing general upper secondary education, students can complete tertiary education. The tertiary sector encompasses institutions of higher education and other establishments that offer study courses qualifying for entry into a profession to students who have completed the upper secondary level and obtained a higher education entrance qualification. Even Czechia (Germany's neighbor) emphasizes the early choice of a student's vocational field. In Czechia, 70% of students have already chosen their field of study/occupation at the secondary level. By comparison, the EU average is just 48%.

In the case of the focus on tertiary education, the main differences can be seen in funding. For example, in countries such as Denmark, Greece, Cyprus, Malta, Finland, and Sweden, full-time students on first-cycle programs pay no tuition fees. Introducing tuition fees is a challenging political and economic undertaking for the country, see for example, Zámková and Blašková (2013). In countries such as Bulgaria, Ireland, Spain, France, Italy, and the Belgian-French community, fees are charged to students. However, some students may be exempt from paying them. Typically, the fee is collected from about half of the students (the frequency is higher in France).

The payment of fees in first-cycle higher education was addressed by Eurydice (2020). The distribution of European countries according to the amount of fees is shown in the reproduced Figure 1. Norway and part of the UK typically have the highest fees, but these are fees at private schools. However, both of these countries are an EU Member State, so they are outside the scope of our study.

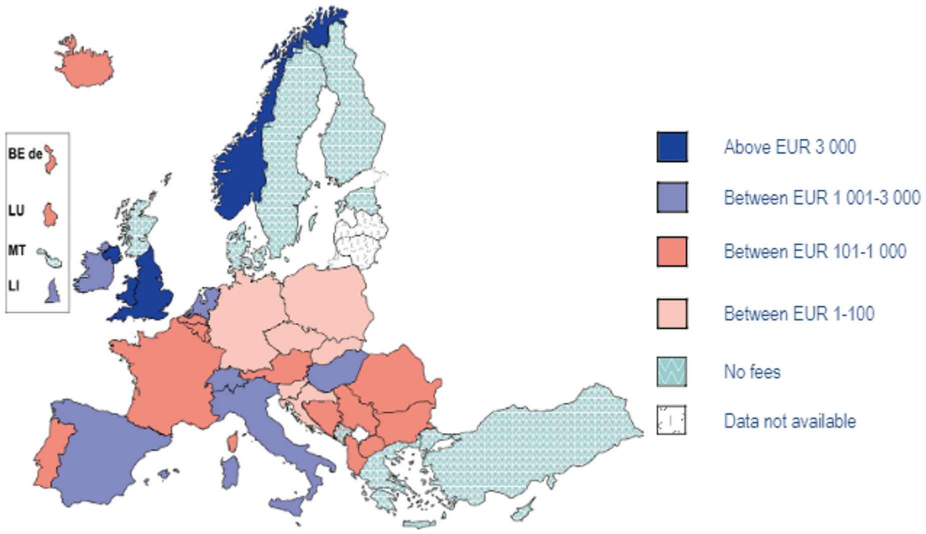

Figure 1: Typical annual tuition fees (first-cycle higher education) in the 2020/2021 academic year in European countries (source: Eurydice, 2020)

According to data from Eurydice (2020), in Poland, for example, while fees in first-cycle higher education are less than €100 per year, students are charged fees for repeated study of the course/subject. These fees are set differently for each higher education institution. Most countries that have tuition-free tertiary education have some percentage of private schools, and these schools already charge varying levels of fees. Germany, for example, has only around 15% of students in private schools, making the overall average fee for the whole of Germany just €1–100 per year. By contrast, Belgium, which has more than half of its students in private schools, has an average fee in the €101–1000 per year category.

The funding system for second-cycle programs is typically the same as for first-cycle programs. The exception is a group of six countries where there are significant changes. These are Greece, Ireland, Cyprus, Malta, Montenegro, Bosnia, and Herzegovina. In Greece, Cyprus, and Malta, the first cycle is free for students, but they have to pay fees for the second cycle. In Ireland, for example, the cost is €3,000, but this fee is not paid by the students themselves as it is covered by public authorities. Bosnia and Herzegovina have different systems for the first and second cycles. In the first cycle, some groups of students are exempted from the fee, but in the second cycle, everyone pays. In the case of Montenegro, there has been a systemic change in funding, and as of the academic year 2020/2021, even second-cycle students no longer pay a fee.

MATERIALS AND METHODS

Parametric and non-parametric methods can be used to calculate efficiency. According to Hollingsworth (2003), parametric approaches are dominated by the stochastic frontier analysis (SFA) method; the non-parametric approaches are dominated by the data envelopment analysis (DEA) method. Both methods attempt to construct a frontier against which to measure the situation of the subject. However, each method has different assumptions and, hence, its strengths and weaknesses. The SFA method can distinguish inefficiency from noise, which the deterministic DEA method cannot. However, the main criticism of the SFA method is that econometric estimation of efficiency can produce inconsistent parameter estimates. In our paper, we decided to use the DEA method for several reasons (Staňková, 2020):

- the DEA method allows more than one output variable to be included in the analysis, which is typical in the field of educational evaluation;
- since the evaluation is performed at an aggregate level, the risk of the DEA method results being affected by data errors (to which the method is very sensitive) is minimized;
- the DEA method allows (via the Malmquist index) a detailed view not only of the level of efficiency itself but also of changes in the efficiency frontier;
- the DEA method is not bound by any assumptions about the probability distribution or the shape of the frontier.

For the reasons mentioned above, we believe that the DEA method is more suitable than the SFA method for our research. Our conclusions are supported, for example, by De La Hoz et al. (2021) and Halásková et al. (2022), as they too claim that it is the DEA method that is the most common method in the field of evaluation of the educational process.

Since our analyses cover a very wide area, we decided to use another tool that allows us to present results in smaller (more homogeneous) groups. Cluster analysis allows us to create groups of countries that are closest to each other in terms of education. If the level of efficiency varies significantly with respect to the different clusters, we can assume that a given “strategy” of one group of countries is better than another.

To clarify and summarize our workflow, in this section, we briefly present the different steps of the research:

1. obtaining the necessary data from publicly available databases;
2. identification of homogeneous groups with regard to their differences regarding the education system;
3. calculation of efficiency and subsequently calculation of Malmquist production index;
4. presentation of results for the EU as a whole and according to the groups (clusters) created.

Data envelopment analysis model

The DEA method enables a quantitative comparison of so-called decision-making units (DMUs). In the case of the DEA method, we have many models available with different settings. The specific settings vary depending on the nature of the data and the purpose of the analysis. Considering the aggregated level of data, a model was chosen that assumes constant returns to scale like Mašková and Blašková (2021). To avoid having to determine the orientation of the model strictly, we decided to apply the non-oriented Slacks-Based Measure (SBM) model like Cossani et al. (2022). To compile a full ranking of the best countries, we decided to use the SBM model in the so-called super-efficiency variant. According to Cooper et al. (2007), we can define the super-efficiency of (x_0, y_0) as the optimal objective function value δ^* from the following program:

$$\delta^* = \min_{\bar{x},\bar{y},\lambda} \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \bar{y}_r / y_{r0}} \tag{1}$$

subject to

$$\bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j \tag{2}$$

$$\bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_j \tag{3}$$

$$\bar{x} \geq x_0 \text{ and } \bar{y} \leq y_0 \tag{4}$$

$$\bar{y} \geq 0, \lambda \geq 0, \tag{5}$$

where

$$\bar{x}_i = x_{i0}\left(1+\phi_i\right)\left(i = 1,\ldots,m\right) \tag{6}$$

$$\bar{y}_r = y_{r0}\left(1+\psi_r\right)\left(r = 1,\ldots,s\right) \tag{7}$$

$$\phi \in R^m \text{ and } \psi \in R^s. \tag{8}$$

where x_i and y_r are observed activities belonging to the production possibility set; $\bar{x}$ and $\bar{y}$ are needed to create the production possibility set with (x_0, y_0) excluded; ϕ is a semipositive variable in R^m and ψ is a semipositive variable in R^s. The model described above was constructed using DEA SolverPro version 15f.

Data used for efficiency evaluation

The choice of variables was made with the main objective in mind and based on the findings of previously conducted research, see Table 1. The data used to analyze the efficiency of the EU countries were taken from the Eurostat databases. We consider this database to be the most appropriate as it contains information from all EU members based on national statistical authorities. The data in the Eurostat database are pre-analysed and verified by these authorities. Our analysis covers the period from 2014 to 2020. More recent data could not be used at the time of the research (i.e., 2022). Calculations were based on three input and three output variables with respect to data availability. In addition to the standard used variable representing the number of graduates (like in Wolszczak-Derlacz (2017) or Mousa and Ghulam (2019)), we included in the model other variables representing the employability of the graduates in the labor market. This variable will make it possible to examine the quality and readiness of these students for working life. Specifically, the employment rate of the tertiary educated population and the employment of university graduates. This combination of variables allows us to examine the quality and readiness of these students for working life.

As in Mašková and Blašková (2021), we wanted to include public expenditure among the input variables. However, unlike the aforementioned study, we decided to include not only tertiary education expenditure but also science and research expenditure. We assume that these expenditures impact the quality of the employees themselves and the content of the study courses. In practice, it is common for a university to use the allocated funds for science and research to build a laboratory, for example. However, this laboratory can also be used (to a limited extent) by students – typically to write their thesis. Therefore, benefits are not only for the direct research activities of the employees but also for students. The experience gained then positively impacts the quality of the students and their future employability in the labor market. The Eurostat database indicates expenditure on science and research in the form of a percentage of GDP. For our analysis, we calculated the expenditure on science and research in EUR thanks to the information on the size of GDP itself. Similar to Ma and Li (2021) or Andersson and Sund (2022), we include the number of employees among the inputs. The last input variable is the percentage of non-graduates, which is defined in a given country as the ratio of students who complete the university stage to all those who enter. Therefore, if a student transfers to another university during their studies and graduates, they are treated as a successful graduate.

Authors	Input variables	Output variables
Andersson and Sund (2022)	Academic staff, other employees, number of students, area of office space	Number of employees, ECTS credits, PhD titles, publications
Mašková and Blašková (2021)	Public expenditure on tertiary education, the number of teachers in tertiary education	The employment rate of graduates of tertiary education, the number of graduates in tertiary education
Ma and Li (2021)	Academic staff and other employees, public expenditure on tertiary education, size of universities, number of books at the end of year, the value of long-term assets of higher education institutions	Number of graduates of Master's studies, graduates of Bachelor's studies or higher professional schools, published academic papers, published scientific papers, patents applied for by universities
Mikušová (2020)	Academic staff, other employees, operating costs, total expenditure, number of students, employees	Total PhD degrees awarded, number of students, graduates, grants, publications
Brzezicki et al. (2020)	Number of academic staff, total value of teaching income, government budget subsidy, value of fixed assets	Number of tertiary education graduates, doctoral degrees awarded, postgraduate certificates issued
Dumitrescu et al. (2020)	Core funding, additional funding, the value of doctoral grants	Number of students funded from the state budget (undergraduate and graduate)
Mousa and Ghulam (2019)	Academic staff, administrative staff	Number of publications in SCOPUS, graduates
Jelić and Kedžo (2018)	General government expenditure (tertiary education), financial aid to students as % of total public expenditure on education, ratio of the students and teachers	The ratio of the unemployment rate of graduates and the total unemployment rate, the population aged 15–64 with completed tertiary education, graduates aged 20–34, graduation rates
Wolszczak-Derlacz (2017)	Total income, number of academic staff, administrative staff, students	Number of publications, published scientific articles, graduates
Nazarko and Šaparauskas (2014)	Government budget subsidy, number of academic teachers and employees, licenses to award PhD degrees, licenses to award higher doctorate degrees	Weighted number of full-time students and full-time PhD students, employer preference for hiring alums, % of students studying abroad, international students, students with university scholarships

Table 1: Overview of major studies in the field of efficiency evaluation in the tertiary education sector (source: own processing)

Efficiency change over time

The analyses include the evaluation of all EU countries in the period from 2014 to 2020. Since our data is panel data, attention will also be paid to the change in efficiency over time. In this respect, either a window analysis (WA) like in Flegl et al. (2023) or a calculation via the Malmquist productivity index (MI) as in Staňková et al. (2022) are most often used. Considering the longer time period analyzed, we decided to use the decomposition of the MI in this article.

According to Křetínská and Staňková (2021), it is necessary to solve four DEA models to build the *MI*. The index itself is then compiled as a geometric mean of two efficiency ratios, where one is the efficiency change measured by the period 1 technology and the other is the efficiency change measured by the period 2 technology:

$$MI = \left[\frac{\delta^1\left(\left(x_0, y_0\right)^2\right)}{\delta^1\left(\left(x_0, y_0\right)^1\right)} * \frac{\delta^2\left(\left(x_0, y_0\right)^2\right)}{\delta^2\left(\left(x_0, y_0\right)^1\right)} \right]^{1/2}. \tag{9}$$

This index can be decomposed into two components, generally known as frontier-shift and catch-up effect. *MI* represents the overall change in the situation of a DMU. Frontier-shift (*F*) records within itself change in the frontier technology:

$$F = \left[\frac{\delta^1\left(\left(x_0, y_0\right)^1\right)}{\delta^2\left(\left(x_0, y_0\right)^1\right)} * \frac{\delta^1\left(\left(x_0, y_0\right)^2\right)}{\delta^2\left(\left(x_0, y_0\right)^2\right)} \right]^{1/2}. \tag{10}$$

Catch-up effect (C), on the other hand, provides information about relative changes in performance (i.e., efficiency):

$$C = \frac{\delta^2\left(\left(x_0, y_0\right)^2\right)}{\delta^1\left(\left(x_0, y_0\right)^1\right)}. \quad (11)$$

DEA models with the settings already described above were used to calculate the *MI* and its components. Further technical details and the DEA method can be found in Cooper et al. (2007). All DEA models were built using DEA SolverPro version 15f.

Cluster analysis

Since education systems in different countries are influenced by many factors, a cluster analysis was used to identify groups of countries with similar characteristics. Eurostat data from 2014-2020 were used for the cluster analysis to characterize the educational attainment of the EU countries. Specifically, we used information on the graduates' employment rate, the number of graduates with tertiary education, the number of the population with complete tertiary education, employment of tertiary education, the number of teachers in tertiary education, and early leavers from education. Since the quality of education is reflected in many indicators of a country's level, the variables related to tertiary education were further supplemented with the Human Development Index (HDI). The size of the HDI is proxied by education expectancy and average years of education.

Since the selected variables are in different expressions, we decided to use the standardized Euclidean distance for the pairwise distance between pairs of observations, similar to the approach in Staňková and Hampel (2017). As part of this procedure, each coordinate difference between observations is scaled by dividing by the corresponding element of the standard deviation:

$$d_{st}^2 = \left(x_s - x_t\right)V^{-1}\left(x_s - x_t\right)', \quad (12)$$

where V in the n-by-n diagonal matrix whose j^{th} diagonal element is $(S(j))^2$, where S is a vector of scaling factors for each dimension. Ward's method has proven to be a good algorithm for computing the distance between clusters in the case of Euclidean distances in many analyses; see, for example, Beneš et al. (2018).

$$d\left(r,s\right) = \sqrt{\frac{2n_r n_s}{\left(n_r + n_s\right)}}\left\|\bar{x}_r - \bar{x}_s\right\|_2, \quad (13)$$

where $\| \|_2$ represents the Euclidean distance (in our case, in the standardized version); $\bar{x}_r$ and $\bar{x}_s$ are the centroids of cluster r and s; and n is the number of elements in the cluster. The cluster analysis was performed using MATLAB computing system version 2023a. Specifically, the *pdist* (for pairwise distance between pairs of observations setting) and *linkage* (for agglomerative hierarchical cluster tree construction) functions were used.

RESULTS

Clusters of countries based on similarities in their education system

The division of countries (and, therefore, their education systems) is shown in Figure 2. Due to the large scale of the analyses, only two dendrograms are given in Figure 2, one from the beginning and one from the end of the study period. For each period, it was possible to identify five clusters (color-coded in Figure 2), with Germany being so different in each year that it did not fall into any of the clusters created (this was also the case with France in 2020). It can be concluded that the groups have not undergone dramatic changes during the whole period under review. For example, the green cluster in 2014 contained nine countries, with seven of them remaining in the same group up to 2020 – see the blue cluster in 2020. These were Belgium, Denmark, Finland, Ireland, Luxembourg, Netherlands, and Sweden. In 2014, this group also included Austria and Cyprus. Countries in this cluster have, in the long term, a large share of the population with completed tertiary education. Furthermore, these are the countries with a really active promotion of multilingual education. For example, Belgium, Finland, and Sweden managed to enroll more than 10% of students studying in a language other than their mother tongue. If we focus only on large cities that can be described as centers of tertiary education, roughly one in two students (primary education) are involved (Eurydice, 2020). In these countries, multilingual education is supported in primary education. Students who succeed in primary and secondary education have good language skills. Countries falling into this cluster also have the highest rates of inward degree-mobile graduates. Thanks to this mobility and the development of cultural and linguistic skills, students from this cluster of countries have great potential for employability in the labor market (both local and foreign).

The brown cluster was another large group of countries in 2014. The main core of this cluster (Estonia, Latvia, Lithuania, and Malta) can be seen in the yellow cluster in 2020. In addition, Poland, Slovenia, Cyprus, and Austria are here this year. This cluster can generally be characterized as a cluster with a high percentage of underachieving students. However, over the years, there have been changes in this variable, and, therefore, the cluster has also transformed, with Bulgaria, Romania, and Hungary moving to separate clusters as the percentage of non-graduates remained high for these countries. A positive trend can be seen for the remaining countries, resulting in a reduction in the share of non-graduates by about four percentage points on average. The purple cluster in 2020 can also be characterized by the very low results of the most recent PISA tests (these were conducted in 2018). These are mainly the results of students in Bulgaria and Romania (European Commission, 2020a).

The countries in the yellow cluster in 2020 (especially Lithuania, Latvia, Slovenia, Poland, and Cyprus) have significantly lower rates of employment of medium-level vocational qualification (VET) graduates compared to the overall rate for that generation. This can be seen as a signal of inefficiencies in the VET system and the inability to prepare these students for the demands of future employers (European Commission, 2020b).

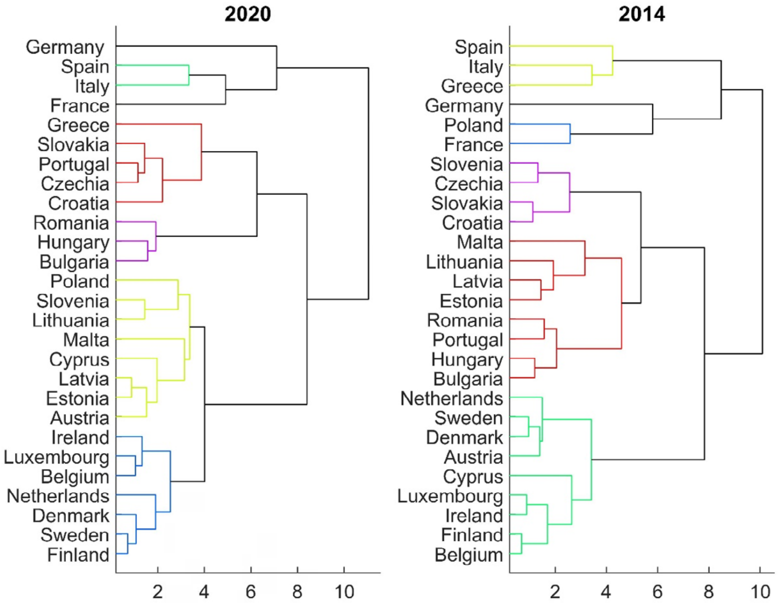

Figure 2: Identified clusters at the beginning and end of the reference period (source: own calculation)

The core of the purple cluster in 2014 (i.e., Czechia, Slovakia, and Croatia) can be found in the brown cluster in 2020. A common feature of these countries is the lower employability of tertiary graduates and the percentage of tertiary graduates between 18–25%. With the remaining brown cluster countries in 2020, they have similar employment rates.

In 2020, a purple cluster that contains only three countries was further identified. This purple cluster in 2020 is very close to the brown cluster countries in 2020. Their relative proximity can be seen in the lack of participation in early childhood education (age 4+). In these countries, there are also long-standing problems with the participation of students from disadvantaged families (European Commission, 2020a).

The last color group in 2012 was Spain and Italy (i.e., the green cluster). These two countries have education expenditure (measured as a percentage of GDP) below the EU average. The EU average is around 4.6% of GDP, but these countries have only 4%. Another typical feature of these two countries is the low level of graduate employment and the fact that vocational education is undergoing significant reform in both countries (European Commission, 2020a).

As already mentioned, Germany is not clustered with any other country. According to the cluster analysis results, this country is closest to France, but even France does not have enough common characteristics to be associated with the German system. This uniqueness of the German system is significantly influenced by the fact that students must choose their field of study at an early age.

Considering our analysis of the education systems and the resulting dendrograms, we decided to divide the EU countries into five clusters, see Table 2. Primarily, we based our analysis on the most recent results, i.e., the results of the cluster analysis in 2020. Four clusters containing at least three countries were identified this year. In addition to these four groups, four countries (Germany, Italy, Spain, and France) remained in the analysis that were quite distinct from the others. As there is a link between these countries due to the ongoing modernization of the VET system, we decided to form the last group of these four countries.

Group number	Countries
1	Austria, Belgium, Denmark, Finland, Ireland, Luxembourg, Netherlands, Sweden
2	Cyprus, Estonia, Latvia, Lithuania, Malta, Poland, Slovenia
3	Bulgaria, Hungary, Romania
4	Croatia, Czechia, Greece, Portugal, Slovakia
5	France, Germany, Italy, Spain

Table 2: Resulting country groupings (source: own processing)

Efficiency evaluation

In terms of the efficiency of the tertiary sector for the whole EU area, it can be stated that it is at a relatively high level; see the median and average efficiency values in individual years in Table 3. Although these generalized values range from 70% to 82%, the level of efficiency varies significantly between countries. Countries in Groups 2 and 3 have the highest median (and average) efficiency. The third imaginary position would go to countries in Group 4. Countries in Group 5 have the worst efficiency scores.

Detailed results of the individual SBM non-oriented models in each year are presented in Figure 3. In this figure, the countries are sorted according to the defined groups in Table 2. Here, we can see that despite the formation of homogeneous groups, individual countries can have dramatically different efficiency outcomes within the group.

Group	Char.	2014	2015	2016	2017	2018	2019	2020
All	Median	0.8213	0.7080	0.7878	0.7626	0.6995	0.7456	0.7823
	Mean	0.7829	0.7670	0.7916	0.7846	0.7763	0.7710	0.7765
1	Median	0.4427	0.4588	0.4760	0.4167	0.4261	0.4175	0.4033
	Mean	0.6414	0.6277	0.6625	0.6330	0.6265	0.6302	0.5939
2	Median	1.0329	0.8628	1.1175	1.1112	1.1014	1.0611	1.0367
	Mean	1.0492	1.0166	1.1017	1.1112	1.0887	1.0768	1.0856
3	Median	1.0810	1.0549	1.0377	1.0424	1.0634	1.0598	1.0247
	Mean	0.9194	0.9249	0.9089	0.9062	0.9157	0.9005	0.9237
4	Median	1.0481	0.8984	0.7878	0.7543	0.6995	0.7400	0.7510
	Mean	0.8464	0.8140	0.7739	0.7715	0.7463	0.7273	0.7796
5	Median	0.2351	0.2436	0.2527	0.2552	0.2649	0.2878	0.2952
	Mean	0.4182	0.4317	0.4410	0.4417	0.4621	0.4752	0.4865

Table 3: Median and average efficiency values for the EU and individual groups in each year (source: own processing)

In the case of Group 1, the results for Ireland and Luxembourg differ significantly from the other countries in this group. These two countries rank among the most efficient (or rather super-efficient) countries throughout the period under review. In contrast, the other countries have efficiency scores below 50%. Therefore, Ireland and Luxembourg have significantly increased the average values of Group 1 above their medians in Table 3. Ireland and Luxembourg are countries that have significantly higher tertiary education expenditure (including science and research expenditure) relative to the number of teachers in absolute terms than other countries; at the same time, they have a significantly lower percentage of non-graduates. This combination then resulted in an efficiency value of over 100%.

Within the created Group 2, the best performer is Malta, which is efficient (or super-efficient) throughout the period under review. By contrast, Estonia has the lowest efficiency in this group, but even for this country, the efficiency does not fall below 60%. This underperformance of Estonia relative to other countries in this group is primarily due to higher expenditure (per teacher).

Group 3 consists of only three countries. Bulgaria and Romania have similar efficiency scores, which are about 50 percentage points higher than Hungary in 2014. The ranking changed in 2020 when Romania took last place and Hungary took first place. This change in ranking is due to a significant increase in the number of graduates in that year, which was almost double the number compared to previous periods. Interestingly, this was a significant change only for this variable. The other indicators for Hungary remained at similar levels as in previous years.

In Group 4, Croatia performed best in terms of efficiency, being efficient (or super-efficient) throughout the period under review. Portugal was the worst performer in terms of efficiency. A detailed analysis of inputs and outputs for Group 4 countries shows the difference in the ratio of graduates to teachers. In this respect, Portugal lags behind other countries; for example, compared to Greece, which has an average of four graduates per teacher, Portugal has roughly half this ratio.

Our defined Group 5 consisted of four countries that were relatively significantly different from the rest of the countries in the EU. However, from the point of view of derived (in)efficiency, it would have been better to keep this group composed of only three countries, namely Germany, Italy, and Spain. These three countries have very low-efficiency scores (Spain is even the worst in the EU in terms of efficiency). The cause of this inefficiency can particularly be seen in the high rate of under-graduation.

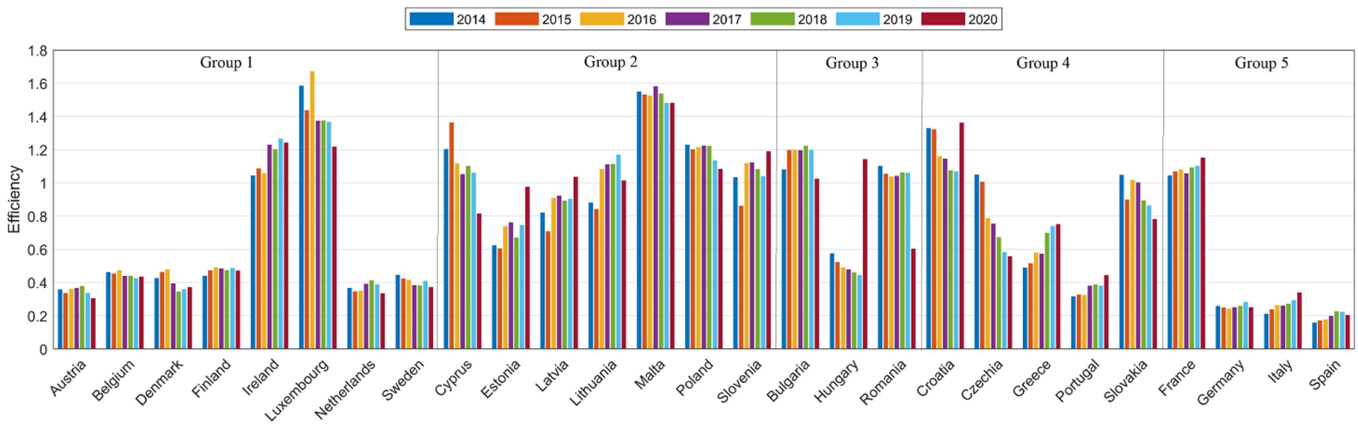

Figure 3: Country efficiency results from individual years according to the groups formed (source: own calculation)

To adequately assess changes in efficiency over time, the Malmquist index was calculated and then decomposed into a change in efficiency and a change in the production frontier. The results of the overall change (i.e., the change from 2014 to 2020) are recorded in Table 4.

Country	Malmquist	Frontier	Catch-up	Country	Malmquist	Frontier	Catch-up
Austria	0.9135	1.0715	0.8525	Italy	1.5603	0.9703	1.6081
Belgium	1.0519	1.1194	0.9397	Latvia	0.9645	0.7641	1.2622
Bulgaria	0.7617	0.8035	0.9479	Lithuania	1.0232	0.8888	1.1512
Croatia	1.0065	0.9820	1.0249	Luxembourg	0.5449	0.7093	0.7683
Cyprus	0.6777	1.0019	0.6764	Malta	0.8857	0.9268	0.9557
Czechia	0.5579	1.0478	0.5324	Netherlands	1.0248	1.1222	0.9132
Denmark	0.9973	1.1472	0.8693	Poland	0.7431	0.8427	0.8819
Estonia	1.3228	0.8454	1.5647	Portugal	1.3990	0.9944	1.4069
Finland	1.1488	1.0721	1.0716	Romania	0.5332	0.9729	0.5480
France	1.3418	1.2154	1.1040	Slovakia	0.7233	0.9691	0.7464
Germany	0.9676	1.0002	0.9674	Slovenia	1.1112	0.9643	1.1523
Greece	1.6145	1.0529	1.5333	Spain	1.2554	0.9795	1.2817
Hungary	1.8593	0.9361	1.9862	Sweden	0.9135	1.0947	0.8344
Ireland	1.3401	1.1262	1.1899	Average	1.0461	0.9860	1.0656

Table 4: Total change in the Malmquist index, including the change in individual efficiency (catch-up) and the change in the production possibilities frontier (frontier) (source: own processing)

According to the results of the overall change in the Malmquist index, Hungary and Greece experienced the greatest positive change. However, looking at the decomposition of the index into its sub-components, it can be seen that the reason for the rise in the Malmquist index was different for these two countries. In the case of Greece, there was an increase in both components, i.e., in individual efficiency (the so-called catch-up effect), but there was also an increase in the frontier of production possibilities. In the case of Hungary, it can be seen that in the case of a frontier shift, the resulting value is less than one, i.e., it is a drop, but this is compensated by a strong increase in efficiency and therefore the Malmquist index is also greater than one in the result.

At the other end of the ranking are Romania and Czechia, which have experienced a strong negative impact over the years (the Malmquist index shows that their situation has roughly halved from 2014 to 2020). In the case of Romania, we see a decline in both subcomponents of the Malmquist index. In the case of Czechia, this decline in the Malmquist index is by way of a decline in efficiency, outweighing the increase in the frontier.

In terms of Malmquist index values, 14 countries improved their overall situation between 2014 and 2020. On the other hand, 13 countries have an index value below one, thereby a deterioration of their overall situation during the period under review. Therefore, on average, there is a positive effect across the tertiary education sector in EU countries, as the average Malmquist index is greater than one. This positive change is driven by an average increase in efficiency with only a slight drop in the frontier. A detailed view of the year-on-year changes in the Malmquist index is shown in Figure 4.

Most striking in Figure 4 is the change in Hungary between 2019 and 2020. As indicated above, Hungary reported twice as many graduates in 2020, with other variables relatively unchanged. Therefore, the positive effect observed for Hungary in Table 4 was not a gradual improvement (as is the case, for example, of Spain, which has a Malmquist index score greater than one every year) but only a step change in a single period. Apart from Spain, only Portugal had systematic increases throughout the period under review. From this point of view, Czechia performed the worst, as its overall situation declined in every period, with the value of the Malmquist index always being lower than one. In the case of Czechia, a combination of several factors resulted in this bad situation for the country. Demographic factors also play a role here, as at that time, the population of weaker years was studying, and therefore, the number of graduates decreased. Furthermore, the employment rate of tertiary education graduates also decreased. For example, in 2017, this indicator was at 81%, but in 2020 it was only at 75.8%. However, in 2020, the impact of the COVID-19 pandemic may have already impacted this indicator. More detailed results for the year-on-year changes at the level of the different components of the Malmquist index are available in Figures 5 and 6.

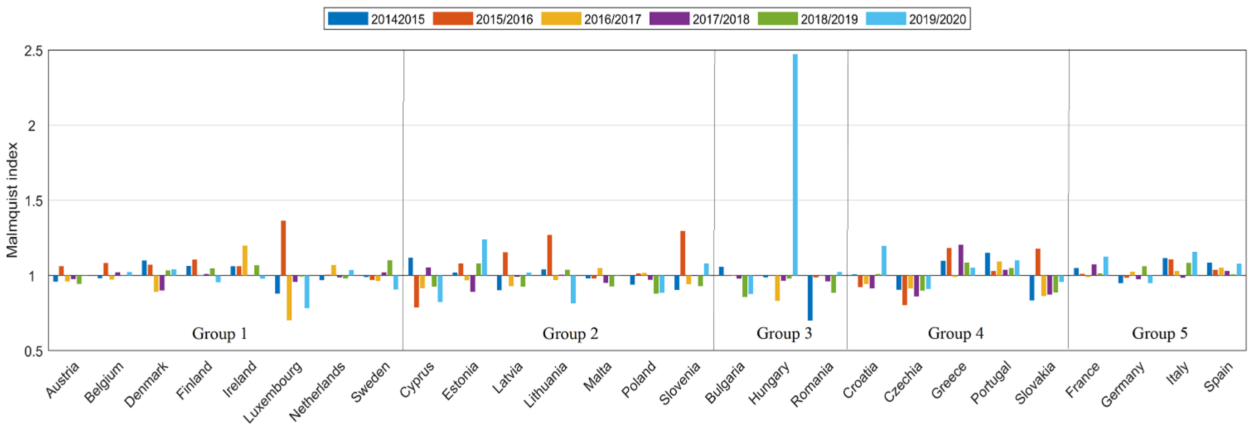

Figure 4: Year-on-year Malmquist index results for individual countries according to the groups formed (source: own calculation)

Figure 5 shows the results separately for the individual change in efficiency (the so-called catch-up effect). As mentioned above, Hungary underwent the greatest positive change in 2019/2020. On the other hand, Romania underwent the greatest negative change in 2019/2020. In the case of Romania, the inefficiency can be explained by the quality of graduates, as confirmed by the results of the World Bank (2020). The Romanian education system is currently struggling to provide graduates with skills that are currently in demand in the labor market. Unfortunately, this problem is already evident in the Romanian education system at the first stages of studies. The Romanian government is trying to reverse this situation by providing more subsidies for tertiary education. However, increasing the variable of tertiary education expenditure without adequately increasing the quality or at least the number of graduates has only reinforced the inefficiency of this country in our analysis.

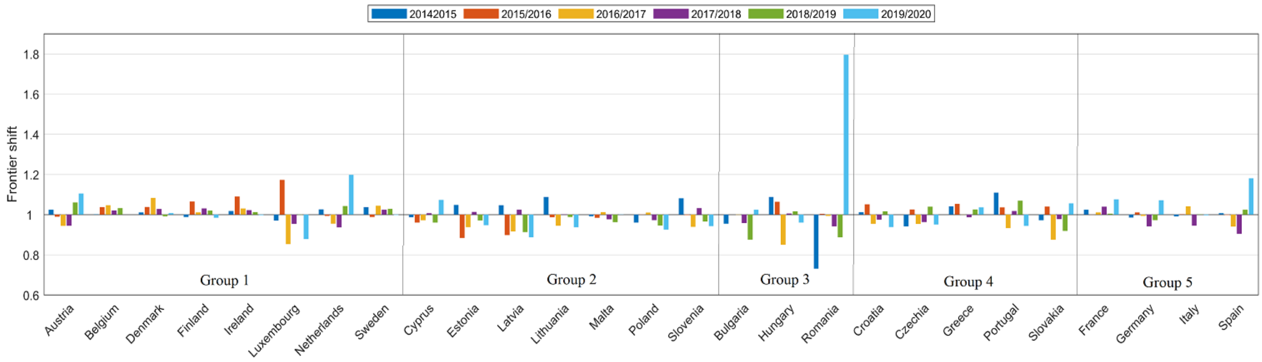

Figure 5: Year-on-year catch-up effect results for individual countries according to the groups formed (source: own calculation)

Conversely, France and Malta have the smallest year-on-year changes. However, these are two of the six countries that have efficiency scores greater than one over the whole period. Using conventional DEA models that have the highest possible efficiency score of 1 (i.e., 100%), such as the CCR model with input orientation, no change in efficiency would be identified for Bulgaria, Croatia, France, Ireland, Malta, or Poland. For this reason, the year-on-year changes in this variable can be considered negligible for these countries.

To complete the overall picture, Figure 6 also plots the year-on-year changes in the case of a frontier shift. Belgium performs best in terms of this indicator, with an increase in the frontier identified in each period. Although this is not a significant change in absolute terms, it is the only country in the EU where the frontier shift scores are greater than one throughout the period under review.

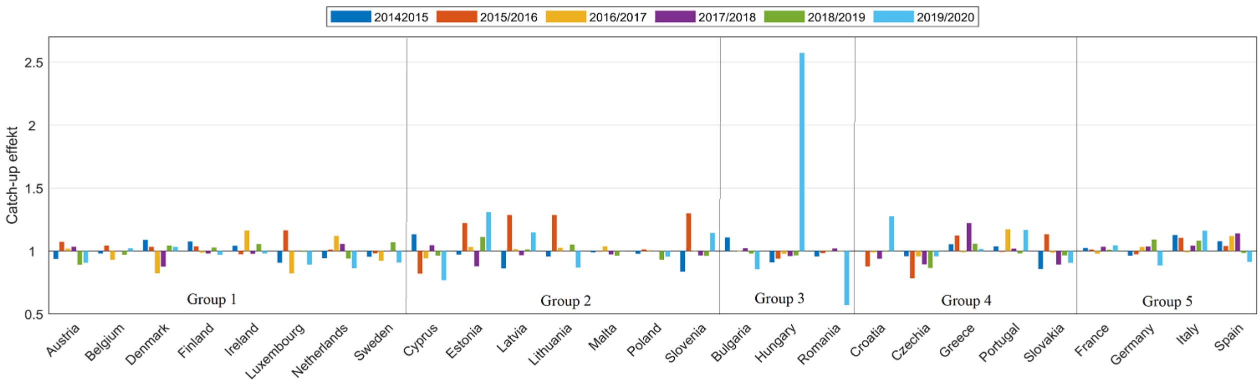

Figure 6: Year-on-year frontier shift results for individual countries according to the groups formed (source: own calculation)

DISCUSSION

Only six countries were identified in our analyses as efficient (or super-efficient) throughout the period under review, i.e., Bulgaria, Croatia, France, Ireland, Luxembourg, and Malta. The results show that countries such as France and Ireland have a very high number of graduates per teacher (in the case of Ireland, 9.7 graduates per teacher on average). They have therefore ensured their level of efficiency by producing many graduates. On the other hand, countries such as Malta and Luxembourg have gained their efficiency through quite the opposite properties. These two countries rank among the countries with the lowest ratio of students to teachers and academic staff from EU countries, and they also have the lowest percentage of people in tertiary education. Thanks to this, special conditions and a stronger, more individual approach to students have been developed at universities there. As a result, they have better employability of tertiary education graduates in the labor market, which is reflected in the results of our efficiency analysis. Inefficient countries can, therefore, choose their own path to achieve a state of efficiency in this respect. If, within this ratio, we focus on Group 2, which has the highest efficiency in terms of median values, we find a sort of guide to the intermediate level between very low efficiency and relatively high efficiency (but not always 100%) at a ratio of two to three graduates per teacher. The identified Group 2 can generally be described as countries with relatively low expenditure on science and

research and tertiary education relative to their economic strength. This relatively lower government expenditure has certainly contributed to the relatively high level of efficiency of Group 2 countries.
EU countries can largely be distinguished by the way they finance the tertiary sector. In addition to public funds, private sources can also be used. According to Andersson and Sund (2022), examining whether these government costs are used efficiently is essential. Their analysis focused on the Nordic countries. According to their results, these countries do well in using education expenditure efficiently. However, their analysis did not take into account the quality of graduates. In their analysis, Denmark and Sweden are among the best countries. Our analyses also take into account the graduate's ability to find a job in the market, with both Denmark and Sweden ranking among the highly inefficient countries. These countries were the first to devolve responsibility for the content of education to the educational institutions themselves. Moreover, these countries can be identified as countries where educational institutions have the greatest responsibility for the content of education (European Commission, 2020a).
Another option (used by other countries) is for the government to direct the process by issuing programs and development plans that regulate education content. In the case of Denmark and Sweden, however, there is strong liberalism in the content of education (European Commission, 2020a). We assume that the low efficiency of these countries can largely be explained as a consequence of this liberalism. If a situation arises where the responsibility lies primarily on the shoulders of institutions that do not adequately reflect the situation in the labor market, a mismatch will arise between the competences of graduates and the requirements of the labor market, resulting in an increase in graduate unemployment (Ho, 2015). According to the data obtained from the Eurostat database (described in the Materials and Methods chapter), this is the case for Denmark and Sweden.
Veiderpass and McKelvey (2016) combined quantitative and qualitative perspectives on education efficiency in their research. Their quantitative analysis results support our results. Both studies show that even very economically strong countries can be highly inefficient. This is particularly the case in Germany. In contrast to the EU results, Germany had a below-average share of tertiary educated people in the past decade. At the beginning of the reporting period (i.e., 2014), Germany reported only 23% of the population with a tertiary education. In contrast, by the end of the reporting period (i.e., 2020), the share increased to 27%. According to the requirements in the EUROPE 2020 strategy (European Commission, 2020b), countries should have at least 40% of the population with tertiary education (this is the share for the age group 25-34). However, Germany did not reach these required values. One reason for this may be the education system in Germany. Our analyses found that Germany has a high proportion of early leavers in tertiary education compared to other EU countries. In addition, Germany is very different from other countries and has, therefore, always stood alone in cluster analysis.
One reason it stood alone in our cluster analysis was that students in this country choose their majors earlier than is typical in surrounding countries. We also found that Germany has one of the highest numbers of early leavers. It can, therefore, be assumed that many students lack the motivation to complete their studies, and we believe that, in many cases, this is due to a hasty choice of future focus at a young age. Germany's distinctiveness may also be influenced by the fact that it is made up of individual Länder, who have their own particular authority and thus may have different educational requirements. Germany is also notable for its extensive network of vocational schools, where studies are primarily directed towards practical training as well as applied research (European Commission, 2020a).
Our results are also consistent with those of Jelić and Kedžo (2018), who looked at the efficiency of tertiary education across Europe from 2007 to 2015. Although our research period and theirs overlap in only two years, the main findings of the two studies are consistent. One of the main findings of Jelić and Kedžo (2018) is that some of the most developed countries perform worse than less developed countries. In their research, Austria and the Netherlands have fallen behind. According to our results, low-efficiency scores can be observed for these countries not only in 2014 and 2015 (which are also included in the Jelić and Kedžo (2018) analyses) but also in subsequent years.
However, the results of our analyses bring new findings that otherwise overlooked countries such as Malta or Luxembourg provide a high level of efficiency in the educational process in terms of labor market employability. These findings are also significant in contrasting migration both for educational and employment reasons. So far, people have generally had the idea of the necessity of migration from East to West, as evidenced by studies focusing on both labor migration (Johnston et al., 2014) and educational migration (Melzer, 2013). Our results show that moving to non-Western countries can also contribute to getting a good education and getting a job. Although it can be assumed that the quality of all universities will not be the same in each country, the reputation of a country, in general, may motivate the arrival of international students. Many of these students develop so many local contacts (both personal and professional) during their studies that they stay in the country after graduation (Lu et al., 2009). If these are talented and capable students who have been created through a properly set-up system, the country will improve economically. Positive results will be seen, for example, through increased labor productivity.
Education (including tertiary) was significantly affected by the COVID-19 pandemic. For example, de Boer (2021) describes the impacts in the Netherlands. According to him, due to the forced transition to online learning, schools/universities did not have a full overview of students' active participation in classes. He identified teacher-student interaction as the biggest barrier in teaching. Ahrens et al. (2021) point out that a large proportion of the students they surveyed (across different countries) complained about technical problems in online learning. However, according to the students, the pandemic also brought new opportunities – lectures and discussions with people from foreign countries who would not have come in the case of "classical" teaching. Erkut (2020) also sees the positives of restrictions due to the pandemic

as an opportunity (albeit a forced one) to adjust Turkey's outdated education system.

Unfortunately, due to the (un)availability of data, it was not possible to fully explore this period in our analysis as we only obtained data for all variables up to 2020. The inability to adequately assess the impact of the pandemic can be seen as a limitation of this research. The restrictions that were in place at the time of the COVID-19 pandemic undoubtedly impacted not only staff but also students. There are several studies addressing the impact of the pandemic; see, for example, Hosen et al. (2022) and Sahoo et al. (2021). However, these are more qualitative studies that do not evaluate the efficiency of the entire education system. Before the COVID-19 pandemic, the legislative environment in some countries already allowed the implementation of distance/online learning. Still, the restrictions due to the pandemic literally came as a shock to many subjects. Schools and teachers were suddenly forced to change the system of teaching, and many subjects discovered hidden problems in the organization of the whole study.

Based on these findings, some EU countries have started to modernize their teaching systems along with increased digitization. However, the impact of these changes has not yet been adequately analyzed in contrast to efficiency. Future research should, therefore, focus on efficiency changes considering the impacts of the COVID-19 pandemic. A comprehensive assessment will only be possible several years after the end of the restrictions. The research should be conducted after students affected by the COVID-19 pandemic graduate and become part of the country's workforce. After a few years, it will be possible to monitor whether their employability is comparable to graduates who were not affected by the pandemic during their studies. Given that the countries had slightly different restrictions (or their strength), it will also be possible to examine the efficiency changes with respect to the different strategies of each country.

Analyses could also be carried out at the level of individual universities, where individual fields of study could be analyzed. Due to the aggregated nature of the data in our research, it was not possible to distinguish in detail between the different forms of financing. However, an assessment based on data from individual universities could distinguish, for example, donations, which may represent a significant source of funding for some entities. An evaluation by individual universities or fields of study could also provide important insights in relation to the aforementioned migration.

CONCLUSION

This article focused on an evaluation of the efficiency of the tertiary education sector in EU countries. The efficiency values between 2014 and 2020 were calculated using the SBM non-oriented super-efficiency DEA model. Unlike the common analyses based on the number of graduates, we included the quality of graduates and their ability to enter the labor market. The results of our analysis show that the employability of graduates is crucial for a correct efficiency analysis. Efficiency is achieved not only by countries with a high ratio of graduates to teachers but also by countries with a low ratio and whose graduates have the necessary knowledge and skills that employers currently require in the market. Within several years, it would be appropriate to conduct an efficiency analysis with regard to the impact of the COVID-19 pandemic. It can be assumed that the restrictions have impacted students' abilities and, therefore, the efficiency of the whole education and, consequently, the employability of graduates in the labor market.

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Full research paper

A STATE-LEVEL ANALYSIS OF MEXICAN EDUCATION AND ITS IMPACT ON REGIONAL, ECONOMIC, AND SOCIAL DEVELOPMENT: TWO-STAGE NETWORK DEA APPROACH

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ABSTRACT

Education has been considered a cornerstone for human and economic development. Although there is a national educational strategy in most countries, various implementations are at the state level. This paper studies academic efficiency at the primary and secondary levels and the human development dimensions – long and healthy life, being knowledgeable, and enjoying a decent standard of life – at the state level. For this purpose, a network data envelopment analysis (NDEA) with two stages was proposed. The first stage studies the educational process efficiency, while the second evaluates its impact in the form of the human development index. The study found significant differences between the evaluated states in the education stage, where the lowest efficiencies are mainly in the southwest of Mexico. The results also indicate that better education quality leads to greater regional, economic, and social development at the state level. This study contributes to the NDEA applications on the understanding of the impact that education has in improving the development of the regions holistically.

KEYWORDS

Data Envelopment Analysis, human development index, Mexico, regional development, educational efficiency

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Highlights

- *A Network Data Envelopment Analysis model was constructed to evaluate the impact of education on regional, economic, and social development in Mexico.*
- *The best-evaluated states in education reported lower Teacher/Student and School/Student ratios compared to the less efficient states.*
- *The best-evaluated states in education have better regional, economic, and social development.*

INTRODUCTION

The education system in Mexico faces several problems mainly related to social and regional gaps. The system lacks teaching staff, educative materials, innovation of study programs and plans, and insufficient school infrastructure and services. In 2018, 25% of teaching positions at primary and secondary levels were not contracted, which resulted in an average of 34 students per teacher (García, 2018). This situation improved during the last years, and by 2022 the student-teacher ratio was 23.71 in primary education, 15.55 in secondary education, and 11.77 in the high school level (SEP, 2022). Still, the OECD average is around 13 students per teacher (OECD, 2022).

This goes in hand with the government expenditures on education. In OECD countries, expenses per student in primary to tertiary education grew by an average of 1.7% between 2012 and 2019. However, in Mexico, average spending per student fell by 0.3-0.5% per year as students' numbers grew faster than educational expenditures (OECD, 2022). Consequently, nationwide, primary school teachers are paid around 40% less than the OECD average during the first

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ten years of teaching experience and approximately 26% lower at the secondary level (OECD, 2022). Furthermore, as García (2018) stated, 40% of teachers did not complete required training programs, and 3 out of 10 teachers in primary education do not have a higher education degree.

The lack of quality education and, consequently, inadequate social development and shortage of economic opportunities have led to a higher migration to more prosperous and more developed regions (Eggert et al., 2010). Access to education is lower for vulnerable groups, especially in the rural areas. Limited access to schools due to a long distance is considered a significant barrier to education (Ama et al., 2020; Falch et al., 2013; Liu and Xing, 2016), as lower population density and longer distances can make education investments costly (Cattaneo et al., 2022). Regarding Mexico and rural communities, 6 out of 10 persons from 15 to 17 years old live isolated and without nearby schools, 13.2% of children and youth in extreme income poverty do not attend compulsory education, and 3 out of 10 students drop out the school due to lack of money (García, 2018).

Limited access to education is crucial in primary school completion and transition to the secondary school level. According to SEP (2022), the net enrollment rate in Mexican primary education dropped from 94.8% in 2014 to 89.8% in 2022. In addition, the terminal efficiency in primary education was 96.7% nationwide, 91.0% in secondary education, and 64.9% in high school. In this case, allocating more resources to educational programs may mitigate such interregional migration and increase regional economic performance (Eggert et al., 2010).

This study aims to evaluate Mexican education's efficiency and its impact on regional, economic, and social development. For this purpose, a two-stage network Data Envelopment Analysis (NDEA) model is proposed. The analysis uses data from the Mexican National Educative system and data related to Human Development Index in Mexico, both for all 32 Mexican states. This analysis targets to respond to the following research questions:

- *RQ1: What is the efficiency level of education process regarding the analyzed academic levels?*
- *RQ2: Can significant differences in educational efficiency be observed regarding the academic level?*
- *RQ3: What factors lead to higher educational efficiency?*
- *RQ4: Does higher educational efficiency lead to better regional, economic, and social development in the Mexican states?*

The rest of the article is divided as follows: In the next section, we present a brief literature review of Data Envelopment Analysis (DEA) applications in education and regional and economic development; in Materials and methods, we describe the two-stage DEA methodology and introduce the model structure and dataset; in Results, we calculate the efficiency scores and investigate a relationship between education and regional, economic and social development; in Discussion, the obtained results are analyzed, we suggest possible implications of the results and mention several limitations of the analysis; finally, we conclude the article with future research directions.

Literature review

Non-parametric efficiency evaluations

Data Envelopment Analysis (DEA) is a non-parametric technique used to evaluate efficiency and productivity with a comprehensive record of successful applications in numerous sectors (Emrouznejad and Yang, 2018; Liu et al., 2013; Mahmoudi et al., 2020). For example, Avilés-Sacoto et al. (2020) used DEA methodology to investigate the regional efficiency of innovation systems; Ferro and Romero (2021) constructed a DEA model to determine countries' efficiency in producing codified knowledge. Flegl and Hernández Gress (2023) applied DEA to evaluate the efficiency of public security in Mexico; Moghaddas et al. (2022) assessed a resource allocation in a sustainable supply chain based on DEA modeling; Wu and Lin (2022) applied a DEA model to measure the performance of cultural tourism of several Asian tourist destinations.

The value of the DEA methodology is its capability to evaluate the individual efficiency or performance of a Decision-Making Unit (DMU) within a set of homogeneous DMUs operating in a specific application domain (Liu et al., 2013). DEA requires very few assumptions about the variables´ selection, and it is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data, DEA tries to stay on top of the observations by calculating an efficiency frontier (Cooper et al., 2011).

Efficiency evaluations in education

The DEA methodology has a long history of applications in education. These applications differ regarding the educational, institutional, and/or regional level point of view. For example, considering recent publications, many authors evaluated the efficiency at an institutional level. Ben Yahia et al. (2018) assessed the educational efficiency of 105 public secondary schools in Tunisia. Chen et al. (2021) employed a two-stage DEA model to measure the operating efficiency of 52 universities in China regarding teaching and research activities. Halásková et al. (2022) investigated the efficiency of 26 private and public secondary education schools in Slovakia through the DEA analysis. Sagarra et al. (2017) investigated the research and teaching efficiency at 55 universities in Mexico. Santos Tavares et al. (2021) used a network DEA model to evaluate the financial, undergraduate, and graduate-level performance of 45 Brazilian federal universities. Shamohammadi and Oh (2019) employed a two-stage network DEA to evaluate the efficiency of 57 Korean private universities.

From a cross-regional/country perspective, Delprato and Antequera (2021) applied a DEA model to evaluate private-public schools' efficiency gap at the secondary level in Latin America. Minuci et al. (2019) used a DEA analysis to estimate the technical efficiency of West Virginia school districts, whereas Ramzi et al. (2016) analyzed the efficiency of primary and secondary education in 24 governorates in Tunisia. See et al. (2022) applied the hierarchical DEA model to assess the quality of higher education systems in 50 countries listed in the U21 National Higher Education Systems 2020 ranking. Williams et al. (2013) evaluated the performance of national higher education systems in 48 countries included in the National Science Foundation ranking.

Regarding study programs or course satisfaction applications, Fuentes et al. (2016) composed a three-stage DEA model to assess teaching efficiency in higher education to optimize the quality of the teaching process. Mendoza-Mendoza et al. (2023) used a DEA model to evaluate industrial engineering programs offered at Colombian higher education institutions.

Data Envelopment Analysis and Education Quality

Education quality is a measure of the efficiency of an educational process. It can be viewed from different perspectives, as quality is a complex multi-dimension concept (Ahmad, 2015), including multiple factors. These factors should synergize to satisfy all stakeholders (Velásquez Rodríguez et al., 2022). These factors usually include educational resources and infrastructure, students, teachers, administrative employees, and teaching and learning outcomes (Flegl and Andrade Rosas, 2019; Gambhir et al., 2016; Jalongo et al., 2004; Sahu et al., 2013; Udouj et al., 2017; Velásquez Rodríguez et al., 2022).

From the perspective of the DEA models, education quality can be understood as a process of transforming the available resources into teaching and learning outcomes. In this way, school quality can be grasped as a capability to prepare students to perform well on standardized tests and the labor market during their professional life (Flegl and Andrade Rosas, 2019; Hanushek and Woessmann, 2008). Considering this definition, the common set of inputs in DEA models consists of expenditures in education or Research & Development (Santos Tavares et al., 2021; See et al., 2022;); funding (Chen et al., 2021; Shamohammadi and Oh, 2019; Williams et al., 2013); Number of students and international students (Chen et al., 2021; See et al., 2022;); Number of academic and non-academic employees (Chen et al., 2021; Minuci et al., 2019; Sagarra et al., 2017; Shamohammadi and Oh, 2019).

On the other hand, the outputs usually cover enrollment rates (Santos Tavares et al., 2021; See et al., 2022); number of graduates (Sagarra et al., 2017; Williams et al., 2013); standardized test results (Delprato and Antequera, 2021; Minuci et al., 2019; Ramzi et al., 2016); dropout levels (Ben Yahia et al., 2018); graduates' employment (See et al., 2022); scientific outcomes, such as published scientific articles (See et al., 2022; Shamohammadi and Oh, 2019; Williams et al., 2013); granted research funds (Chen et al., 2021); generated patents (Chen et al., 2021; Santos Tavares et al., 2021; Shamohammadi and Oh, 2019); or international scientific collaboration (Williams et al., 2013).

Efficiency evaluations of regional and economic development

DEA has also been successfully applied for evaluating regional developments from various perspectives. For example, Chen (2017) deployed a DEA model to measure efficiency in Taiwan's counties regarding economic development, public security, social welfare, and education. Giménez et al. (2017) used a DEA model with desirable and undesirable outputs to evaluate the efficiency of generating social welfare regarding Mexico's Human Development Index (HDI). Marshall and Shortle (2016) used a DEA model to evaluate the quality of life within Mid-Atlantic states in the USA. Min et al. (2020) investigated regional technology development and commercialization efficiencies in South Korea using a two-stage DEA model. Moreno and Lozano (2016) measured public finance management efficiency concerning social welfare in 29 European governments. Qu et al. (2022) used a three-stage DEA model to observe regional sustainability performance regarding economic growth, waste disposal, and health protection.

Considering the impact of education on regional developments, Berbegal-Mirabent et al. (2013) assessed the efficiency of Spanish universities regarding knowledge transfer activities to enhance local industry systems. Rodionov and Velichenkova (2020) observed the link between universities and regional innovation system development in 85 regions in Russia. Vliamos and Tzeremes (2006) applied a DEA model to evaluate the efficiency of higher education systems in 20 OECD countries regarding their contribution to economic development.

Materials and methods

Data Envelopment Analysis

Charnes et al. (1978) developed the mathematical methodology known as Data Envelopment Analysis (DEA). It is used to compare the relative efficiency of a group of entities, commonly referred to Decision Making Units (DMUs). DEA lets compute the performance of each DMU in relation to every other DMU in the set by using mathematical programming tools. After calculating the efficiency ratings, DEA establishes an efficient frontier where the top-performing DMUs are situated. The remaining units outside the efficiency frontier are referred to as inefficient. However, DEA offers the frontier a chance to identify how the inefficient DMUs should modify in order to become efficient by radial projection (Cooper et al., 2011).

DEA is a linear programming technique that can handle multiple measures in a single integrated model. The measures are inputs, which are resources or factors that one aims to diminish, or outputs, which are outcomes or results that one seeks to maximize (Avilés-Sacoto et al., 2021). Two "return to scale" strategies are provided by DEA - the Constant Return to Scale (CRS) and the Variable Return to Scale (VRS). According to Avilés-Sacoto et al. (2020), the VRS is an extension of the CRS. Either the input orientation or the output orientation can be used to view CRS and VRS. The input orientation is used when evaluating how much input for a DMU can be decreased while maintaining performance. The output orientation is used when the output side needs to be improved and the inputs are difficult to control (Avilés-Sacoto et al., 2021).

Through time, the DEA's initial idea has been expanded in literature, covering a variety of theoretical and applied research fields. One is the Network DEA (N-DEA), particularly a two-stage DEA process. For example, the studies of Liang et al. (2006), Kao (2009), Tone and Tsutsui (2009), Cook and Zhu (2014), and Cook et al. (2010) present a review of network models, including a two-stage process or multi-stage situations in DEA. Among the different two-stage structures analyzed in DEA is the serial process. In this type of setting, the outputs from the first stage serve as the inputs to the second stage; this is the most frequent two-step setting examined in the DEA literature. Other two-stage systems are closed -in that nothing enters or exits the system in between the stages. Some variations of this allow outputs from Stage 1 to leave the system and inputs to Stage 2 to enter the system at that point (Avilés-Sacoto et al., 2015).

For the paper herein, it was considered a serial process, where the outputs from the first stage serve as the inputs to the second stage.

Model structure and research questions

The structure of the DEA model is presented in Figure 1. The analysis uses a two-stage network process design divided into the education and development stages. The first stage aims to evaluate the educational process regarding three academic levels: Primary school (ISCED level 1, equivalent of *primaría* level in Mexico), Junior high school (ISCED level 2, equivalent of *secundaría* level in Mexico), and High school (ISCED level 3, equivalent of *preparatoría* level Mexico) (UNESCO, 2012).

Considering the common DEA model structures in education and the evaluated three academic levels, the teacher-student ratio (TSR) represents the first input. Educational analyses and statistics usually utilize a student-teacher ratio (e.g., Brunello and Checchi, 2005; Vliamos and Tzeremes, 2006). However, reflecting the DEA methodology, the bigger the TSR is, the more time a teacher can devote to each student's needs, and less amount of class time is needed to deal with disruptions, which should be reflected in higher outcomes and school attainment (Kedagni et al., 2021), i.e., securing better education quality. Similarly, the second input constitutes the school-student ratio (SSR), which reflects the accessibility of education. A similar approach was also used by Ramzi et al. (2016) and Halásková et al. (2022), who used the number of teachers per 100 students, the number of classes per 100 students, and the number of schools per million inhabitants as measures describing schools' quality.

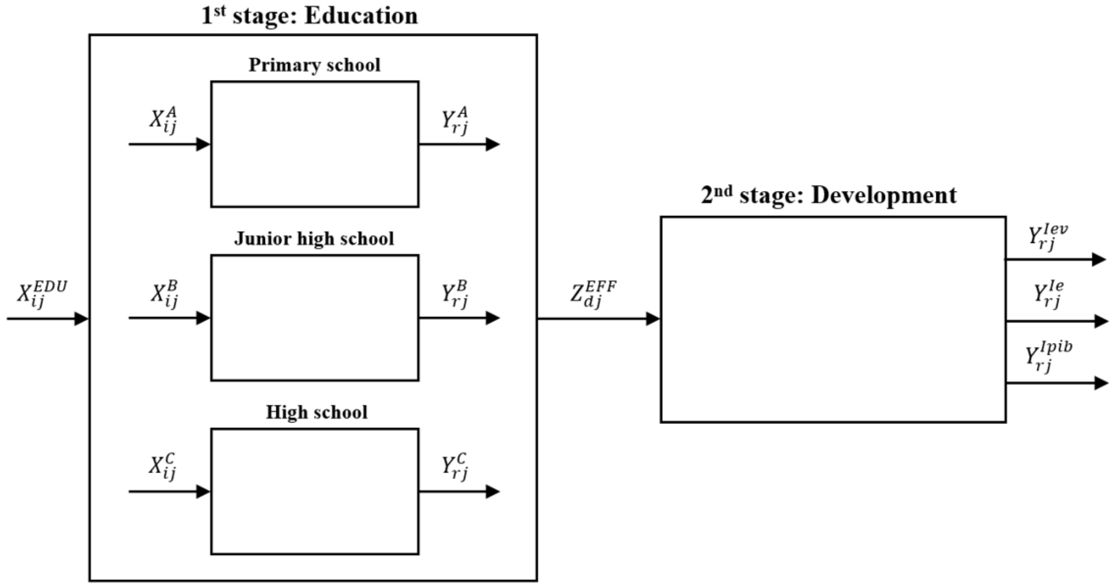

Figure 1: Two-stage model structure (own elaboration)

On the other hand, the outputs of the 1st stage consist of terminal efficiency (TE), enrollment rate (ER), and dropout rate (DR). The TE represents a percentage of students who completed an academic level on time according to the number of years programmed, i.e., a proportion of a cohort that finishes the academic level in the established time. The ER is the proportion of the total enrollment of a determined academic level, with respect to the population of official age to study the level. This indicator shows the percentage of the potential demand for a given academic level being met. A higher gross enrollment rate for an academic level is interpreted as a higher school attendance by the population in the statutory ages[1]. Finally, the DR is the percentage of students who drop out of school activities during the school year and at the end of it, compared to the total number of students enrolled in the school year[2]. The dropout rate represents an undesirable output (Chen et al., 2018; Flegl and Hernández Gress, 2023; Seiford and Zhu, 2002) of each academic level. Each sub-model (primary school, junior high school, and high school) has the same input-output structure with data linked to its corresponding academic level.

The second stage of the DEA model aspires to investigate the impact of education on regional, economic, and social development. In this scope, excluding the above-mentioned educational variables, the DEA models incorporate variables linked to the unemployment rate (Chen, 2017; Murias et al., 2006; Vliamos and Tzeremes, 2006); income (Murias et al., 2006; Vliamos and Tzeremes, 2006); gross domestic product

1 It is important to mention that this indicator is sensitive to the migration of the population and figures greater than 100% can be reached if students from neighboring states register as new students.

2 When the indicator is positive, it is probable that dropout will only occur to a degree in a given school cycle; sometimes the percentage can be negative, due to the fact that during the school year under study there were more students who enrolled as ''admitted'' than those who stated that they were ''withdrawn'' from school.

(Giménez et al., 2017; Moreno and Lozano, 2016; Qu et al., 2022; Rodionov and Velichenkova, 2020); literacy (Giménez et al., 2017; Marshall and Shortle, 2016); life expectancy (Qu et al., 2022); innovative activities (Rodionov and Velichenkova, 2020); among others.

So, to intend capturing development in all three areas, we take the Human Development Index (HDI) as the outcome of this stage. The HDI measures the average achievement in several key dimensions of human development, such as (i) a long and healthy life, (ii) being knowledgeable, and (iii) having a decent standard of living. The HDI has been calculated as the geometric mean of the normalized indices for each of the three dimensions (UNDP, 2023):

$$\mathrm{HDI} = \frac{1}{3} I_{LEI} + \frac{1}{3} I_{EI} + \frac{1}{3} I_{GDP} \quad (1)$$

where I_{LEI} is the Life expectancy index (LEI), I_{EI} is the Education index (EI), which is calculated as 2/3 of Literacy level and 1/3 of Net enrollment rate, and I_{GDP} is Gross domestic product (GDP) per capita. To secure comparability between GDP and the other two outputs, we used an ideal normalization of GDP. In this case, the highest GDP equals 100, and the rest GDPs vary between 0 and 100 correspondingly. We assume that LEI represents regional development, EI represents social development, and GDP represents economic development. These three dimensions of the HDI are then used as independent outputs for the 2nd stage of the analysis.

This idea takes a similar approach as Murias et al. (2006), who decomposed a synthetic economic well-being index based on the Index of Economic Well-being (Osberg and Sharpe, 1998) to evaluate the economic situation of 50 Spanish provinces regarding consumption capacity, wealth stocks, inequality, and economic insecurity. The HDI as an output in DEA models has been used by several authors (e.g., Despotis, 2005; Giménez et al., 2017; Van Puyenbroeck and Rogge, 2020).

The obtained efficiency scores in the 1st stage from the three academic levels defined above were used as the inputs for the 2nd stage. Thus, considering a two-stage DEA process described, for example, by Kao and Hwang (2008) or Chen et al. (2018), these inputs were considered as intermediates variables.

Data

The state-level analysis includes records for all 32 Mexican states for 2021. More precisely, in the case of education, the data covers the school year 2020/2021 in all three academic levels- primary (PRI), junior high (JHS), and high school (HS). The TSR, TSS, TE, ER, and DR indicators for the first stage of the DEA model were collected or calculated from the Interactive education statistics consultation system of the Secretary of Public Education (Secretaría de Educación Pública) published by the Mexican National Institute of Statistics and Geography (INEGI, 2023a). Table 1 summarizes the descriptive statistics of the selected indicators.

Academic level	Indicators	Max	Min	Mean	Standard deviation
Primary school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.124	0.068	0.089	0.015
	School/Student Ratio (SSR)	0.028	0.007	0.015	0.006
Output (y)	Terminal Efficiency (TE)	103.100	89.200	97.478	3.275
	Enrollment Rate (ER)	114.300	87.500	96.428	4.966
	Dropout Rate (DR)	2.000	-2.000	0.363	0.838
Junior high school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.201	0.055	0.115	0.035
	School/Student Ratio (SSR)	0.035	0.002	0.012	0.008
Output (y)	Terminal Efficiency (TE)	96.800	78.500	90.950	3.577
	Enrollment Rate (ER)	111.200	73.500	83.797	6.795
	Dropout Rate (DR)	8.100	-0.900	2.944	1.707
High school					
Input (*x*)	Teacher/Student Ratio (TSR)	0.151	0.049	0.097	0.026
	School/Student Ratio (SSR)	0.008	0.002	0.005	0.001
Output (y)	Terminal Efficiency (TE)	76.200	55.300	64.922	4.566
	Enrollment Rate (ER)	98.400	50.200	62.163	8.711
	Dropout Rate (DR)	16.500	1.000	12.788	3.191

Table 1: Introduction of indicators and descriptive statistics of the data set for the education stage

For the second stage of the DEA model, the Life expectancy of the population was obtained from Demography and Society – Population statistics published by the Mexican National Institute of Statistics and Geography (INEGI, 2023b). The Literacy level and Net enrollment rate required for calculating the Education index (EI) were obtained from the Interactive Education Statistics Consultation System of the Secretary of Public Education (INEGI, 2023a). Finally, gross domestic product (GDP) per capita was acquired from the Mexican National Institute of Statistics and Geography (INEGI, 2023c). The GDP per capita was normalized to secure comparability between all three indexes (outputs) used in the second stage of the analysis. Table 2 presents the descriptive statistics of the indexes.

MaxDEA Ultra 7 software was used for all the efficiency calculations. In this case, a CCR output-oriented DEA model was performed in both stages; to eliminate possible drawbacks in determining the best efficient DMUs when $\varepsilon = 0$, as several

	Indicators	Max	Min	Mean	Standard deviation
Output (y)	Life Expectancy Index (LEI)	76.600	73.300	75.219	13.108
	Education Index (EI)	93.798	83.975	90.463	15.939
	Gross Domestic Product (GDP)	100.000	23.823	49.190	18.925

Table 2: Introduction of indicators and descriptive statistics of the data set for the development stage

inputs and outputs can be omitted from the model (Dyson et al., 2001; Toloo, 2014), the non-Archimedean element ε was set equal to 0.3 (i.e., an absolute weight restriction) after several simulations. IBM SPSS Statistics 26 was used for the statistical part of the analysis.

RESULTS

This study is divided into two parts. First, the educational process results are described; second, the education's impact on regional, economic, and social development is investigated.

1st stage: education

The first stage of the analysis is divided into three sub-models. Regarding the Primary school level, the average efficiency was 0.740 with a standard deviation (StDev) of 0.194. The highest efficiency was obtained by Ciudad de México (1.000), Yucatán (1.000), Baja California (0.962), Querétaro (0.925), and Quintana Roo (0.922). On the other hand, the worst efficiency can be observed in Michoacán (0.471), Veracruz (0.492), Durango (0.538), Chiapas (0.552), and Hidalgo (0.690). With greater detail, the Top 5 states registered 13.16% lower TSR and 33.94% lower SSR compared to the national average. However, on the other hand, these states reported 6.15% bigger ER, 254.48% lower DR, and 2.53% bigger TE. Comparing this with the five worst states, which registered +23.97% TSR, +54.27% SSR, -0.44% ER, +192.41% DR, and -2.44% TE compared to the national average. The complete results are summarized in Table 3.

Considering the Junior high school level, the average efficiency was 0.630 with a StDev of 0.200. This represents an efficiency drop of 0.110 compared to the previous education level (Table 3). The best-evaluated states are Ciudad de México (1.000), Yucatán (1.000), Nuevo León (0.964), Sonora (0.902), and Querétaro (0.791), whereas the worst-evaluated states are Oaxaca (0.353), Chiapas (0.389), Michoacán (0.430), Guerrero (0.462), and Durango (0.469). Using the same detail about the inputs and outputs of this sub-model, the best-evaluated states have TSR -33.94% and SSR -54.62% compared to the national average, with ER +8.26%, DR -66.71% and ET +3.79%. The worst-evaluated states record opposite tendencies: TSR was +45.44% and SSR +104.80%, ER -8.35%, DR +74.61%, and ET -5.66%.

Finally, the high school educational level obtained an average efficiency of 0.791 with a StDev of 0.175. This result indicates that the high school level is the best of the three sub-models, with the lowest variability among the states. The best-evaluated states are Chiapas (1.000), Ciudad de México (1.000), Jalisco (1.000), Tabasco (1.000), and Nuevo León (0.974). The worst-evaluated states are Morelos (0.626), Colima (0.635), Nayarit (0.675), Veracruz (0.684), and Chihuahua (0.693) (Table 3). In this case, the top 5 states registered -11.07% TSR, -34.23% SSR, +7.24% ER, -36.03% DR, and +0.89% TE compared to the national level. On the other hand, the worst five states registered +18.82% TSR, +37.07% SSR, -5.83% ER, +12.14% DR, and -4.35% TE.

Based on the obtained results and regarding the RQ3, the analysis revealed that although the best-evaluated states register more students per teacher and school ratios, they achieve higher enrollment rates, terminal efficiency, and lower dropout rates. This suggests that better educational results instead depend on quality than the quantity of teaching staff. In this case, teaching quality is linked to teachers' education, experience, and training (Canales and Maldonado, 2018; Clotfelter et al., 2007; Ome et al., 2017).

Considering the RQ2 and applying the Tuckey test, there are significant differences between the efficiencies of each academic level. More precisely, the JHS efficiencies are significantly lower compared to the HS efficiencies ($p < 0.001$) and the PRI efficiencies ($p = 0.008$).

2nd stage: development

The second stage of the analysis evaluates the impact of education on the regional, economic, and social development expressed by the HDI. For this, the obtained efficiency scores from the previous stage are used as the inputs, and HDI indicators are used as the outputs. The average efficiency of the development stage is 0.842 with StDev 0.098 (Table 3). These numbers indicate a high efficiency across all the analyzed states with a low variation. Both parameters are the highest/lowest considering the three sub-models in the 1st stage.

The highest efficiency was obtained by Colima (1.000), Michoacán (1.000), Oaxaca (1.000), Veracruz (1.000), and Durango (0.980). On the other hand, the lowest efficiencies were obtained by Yucatán (0.665), Estado de México (0.714), Ciudad de México (0.721), Tabasco (0.721) and Puebla (0.730). In most cases, we can see an inverse position of the states considering the first stage of the analysis (Table 3). For example, Ciudad de México was ranked within the top 5 in all three academic levels, Yucatán was in the top 5 in Primary and Junior high school levels, and Tabasco was within the best-evaluated in High school level. Similarly, Michoacán, Oaxaca, and Veracruz were ranked among the worst-evaluated at each level.

In more detail, the worst efficient states in the 2nd stage reported higher educational efficiencies in PRI (+15.75%), in JHS (+25.33%), and in HS (+19.76%) compared to the national average. Their education quality also resulted in higher HDI, +0.19% in regional development, +12.36% in economic development, and +1.01% in social development. However, these developments were not significantly higher than the most-efficient states in the 2nd stage. Putting this into context with the best-evaluated states in the 2nd stage, these states obtained 24.77% lower efficiency in PRI, -28.27% in JHS, and -10.60% in HS levels compared to the national average. Even though their HDI indicators are -0.48% in regional development, -3.36% in social development, and -12.38% in economic development, their impact of education on HDI is relatively higher than the worst-evaluated states.

So, considering the RQ4, we can conclude that higher education quality leads to higher regional, economic, and social development. However, this development is not reflected in higher efficiency in the development stage. This means that the impact of education on development should be much higher. Figure 2 summarizes the results of the three sub-models from the first stage and the efficiency results in the second stage. It can be seen that there is no clear relationship between educational quality and development stages.

State	Efficiency PRI	PRI position	Efficiency JHS	JHS position	Efficiency HS	HS position	Efficiency HDI	HDI position
Aguascalientes	0.889	6	0.633	16	0.709	23	0.806	19
Baja California	0.962	3	0.776	7	0.697	27	0.809	18
Baja California Sur	0.806	11	0.654	13	0.732	21	0.878	12
Campeche	0.620	26	0.538	22	0.783	15	0.863	15
Chiapas	0.552	28	0.389	31	1.000	1	0.943	6
Chihuahua	0.839	9	0.789	6	0.693	28	0.801	20
Ciudad de México	1.000	1	1.000	1	1.000	1	0.721	30
Coahuila	0.814	10	0.683	9	0.773	16	0.770	24
Colima	0.659	23	0.529	23	0.635	31	1.000	1
Durango	0.538	29	0.469	28	0.707	25	0.980	5
Estado de México	0.721	18	0.655	11	0.795	12	0.714	31
Guanajuato	0.748	16	0.558	19	0.705	26	0.782	22
Guerrero	0.514	30	0.462	29	0.847	9	0.791	21
Hidalgo	0.690	20	0.655	12	0.741	20	0.937	7
Jalisco	0.842	8	0.639	15	1.000	1	0.867	13
Michoacán	0.471	32	0.430	30	0.746	19	1.000	1
Morelos	0.688	21	0.556	20	0.626	32	0.912	9
Nayarit	0.678	22	0.507	24	0.675	30	0.916	8
Nuevo León	0.885	7	0.964	3	0.974	5	0.735	27
Oaxaca	0.623	25	0.353	32	0.763	17	1.000	1
Puebla	0.699	19	0.649	14	0.912	6	0.730	28
Querétaro	0.925	4	0.791	5	0.783	14	0.739	26
Quintana Roo	0.922	5	0.552	21	0.824	11	0.864	14
San Luis Potosí	0.608	27	0.478	26	0.848	8	0.906	10
Sinaloa	0.802	13	0.609	17	0.718	22	0.845	16
Sonora	0.804	12	0.902	4	0.763	17	0.760	25
Tabasco	0.741	17	0.657	10	1.000	1	0.721	29
Tamaulipas	0.765	14	0.722	8	0.708	24	0.829	17
Tlaxcala	0.757	15	0.565	18	0.857	7	0.770	23
Veracruz	0.492	31	0.477	27	0.684	29	1.000	1
Yucatán	1.000	1	1.000	1	0.825	10	0.665	32
Zacatecas	0.626	24	0.505	25	0.787	13	0.882	11
Average	**0.740**	-	**0.630**	-	**0.791**	-	**0.842**	-
StDev	**0.194**	-	**0.200**	-	**0.175**	-	**0.098**	-

Table 3: 1st stage and 2nd stage efficiency results (own elaboration)

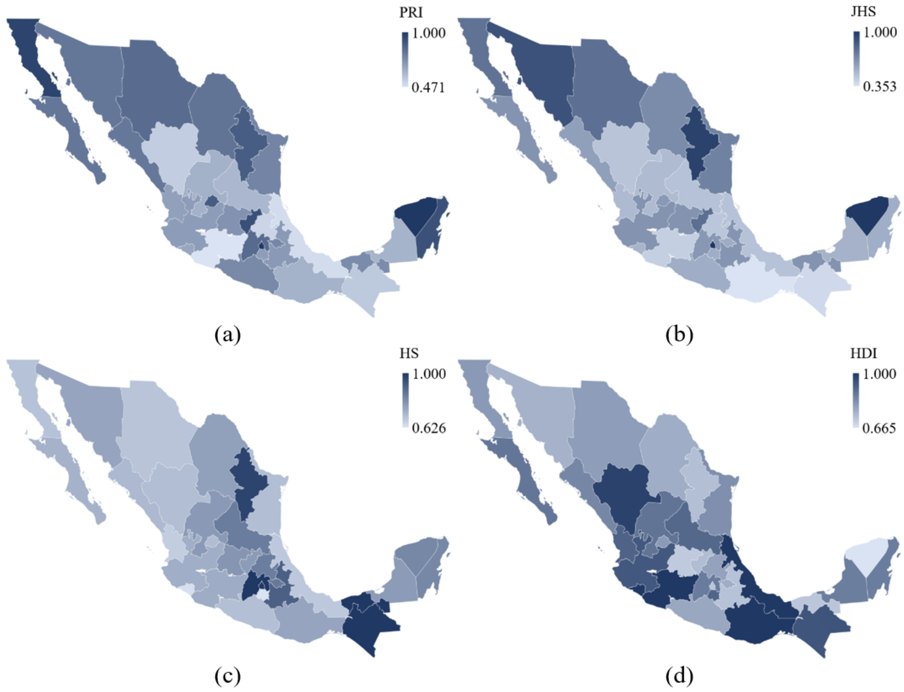

Figure 2: Results of the two-stage network process: (a) Primary school level efficiency; (b) Junior high school level efficiency; (c) High school level efficiency; (d) Human development index level efficiency (own elaboration using GeoNames, Microsoft, TomTom tool)

DISCUSSION

The article's main objective was to investigate Mexican education's efficiency and its impact on regional, economic, and social development. Regarding the first stage (RQ1), the analysis indicates a congruence in the obtained scores to some extent. In many cases, the best and worst-evaluated states remain similar in all three levels, and the differences between both sides of the ranking are significant. For example, at the PRI level, the two worst-evaluated states obtained an educational efficiency of 0.471 and 0.492, respectively. Similarly, at the JHS level, the worst-evaluated states had an efficiency of 0.353 and 0.389, whereas at the HS level, 0.626 and 0.653. So, we can conclude that significant differences in educational efficiency can be observed regarding the academic level (RQ2).

Considering the definition of education quality, the observed differences can be linked to the states' capability to transform available resources into teaching and learning outcomes. The DEA model supposed that a bigger teacher-student ratio and better access to education (expressed by the school-student ratio) would lead to better educational results. However, the analysis did not confirm this, as the best-evaluated states in all levels reported lower TSR and SSR compared to the less efficient states (RQ3). For example, at the JHS level, the best-evaluated states had TSRs of 33.94% and SSRs of 54.62% lower than the national average. This is in contradiction, for example, with Brunello and Checchi (2005) and Kedagni et al. (2021), who found that the lower students–teacher ratio (meaning higher teacher-student ratio) is positively correlated with higher educational attainment.

The results indicate that the quality of teaching and school infrastructure play a more critical role than the quantity of both. Regarding teaching quality, our results align with Clotfelter et al. (2007), who observed a positive effect of teacher experience, test scores, and regular licensure on students' achievements. Similarly, Buddin and Zamarro (2009) and Canales and Maldonado (2018) also found a positive effect of teachers' experience on students' learning outcomes. From the perspective of school infrastructure, Barragan Torres (2017) and No et al. (2016) investigated that school characteristics are an important factor in students' school attendance, dropout rates, and increased transition outcomes between educational levels. Similarly, Ben Yahia et al. (2018) observed that more resources should be spent on improving school buildings and materials to enhance educational efficiency and decrease dropout numbers.

Further, as shown in Figure 2, the lowest educational efficiencies are mainly in the southwest of Mexico, which may result in lower regional development and economic opportunities due to the higher concentration of highly skilled workers in other parts of the country (Eggert et al., 2010; Giménez et al., 2017). If we leave the efficiency point of view, then the best-evaluated states in the 1st stage of the DEA model have better HDI indicators. For example, Ciudad de México reached 1.000 efficiencies in all three sub-models in the first stage and has a 1.84% bigger life expectancy index, 3.38% bigger education index, and 103.29% bigger GDP per capita. Similarly, Estado de México has an LEI of +3.00%, EI of +10.14%, and GDP of +86.54%, whereas Puebla +2.18%, +6.22%, and +36.55%, respectively. This result corresponds with the research presented by Giménez et al. (2017), who demonstrated the highest efficiency in generating HDI in Aguascalientes, Baja California Sur, Campeche, Ciudad de México, Colima, Estado de México, and Nuevo León. In contrast, Coahuila, Durango, Hidalgo, Michoacán, Oaxaca, Sinaloa, and Veracruz were the least efficient states.

However, if the efficiency point of view of the 2nd stage is considered, the analysis did not prove the impact of better educational process on bigger regional, economic, and social development (RQ4). The results revealed that the least efficient states in the education stage were the most efficient states in the development stage. For example, Oaxaca and Veracruz reached a development efficiency of 1.000, although Oaxaca was ranked 25th in PRI, 32nd in JHS, and 17th in HS, and Veracruz ranked 31st, 27th, and 29th. On the other hand, the least efficiency in the development stage was obtained by Ciudad de México (0.770), Estado de México (0.714), and Yucatán (0.665), i.e., states with high efficiencies in PRI, JHS, and HS. Therefore, we can conclude that higher education quality leads to better regional, economic, and social development, but the difference is not significant, resulting in lower technical efficiency of Ciudad de México, for example.

Study limitations

The presented analysis has several limitations. First, the state-level analysis may be misleading as significant differences between municipalities in each state exist (expressed by marginality index, for example). So, it would be desirable to apply the DEA model on a municipality level to precise the obtained results. However, the availability of some indicators may limit the feasibility of such an analysis. Second, the analysis used only one school period (2020/2021). This may result in biased results in some cases due to extraordinary events (such as local pandemic closures of schools, natural disasters, etc.), resulting in worse educational outcomes. Therefore, the analysis should be extended to cover more periods. The Malmquist index or Window Analysis models could be used from the DEA methodology to evaluate the efficiency developments. Third, we were unable to incorporate government expenditures in education into the model due to its unavailability. The education expenditures may enhance the obtained results considering resource allocation.

CONCLUSION

This study developed a NDEA to answer four questions. The research found that the states with better education quality are not necessarily related to educational efficiency. We also found that the three academic levels are different in terms of educational efficiency. Lastly, we also found that educational efficiency is not improving the state's development. These findings suggest that education policymakers could allocate more resources to achieve academic quality rather than quantity and align academia with local needs. On the other hand, as politicians are allocating fewer resources to education, efficiency is a must, but effectiveness is needed first; effectiveness in this context has to do with improving the quality of life of the people in the state; efficiency in this context has to do with providing quality education with fewer resources.

Future research may go in several ways. Considering the mentioned limitations, the analysis can incorporate more school years into the evaluation to investigate the development of all parameters. Similarly, the other way can incorporate demographic parameters to assess the state's or regional specifics' impact on the efficiencies. A progression of this work also consists of measuring the NDEA robustness and considering a longitudinal study.

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RANKING OF EUROPEAN UNIVERSITIES BY DEA-BASED SUSTAINABILITY INDICATOR

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ABSTRACT

The paper introduces a novel approach to university rankings that considers a university's contribution to sustainable development. It addresses the usual controversies surrounding the construction of rankings using composite indicators. The conventional approach typically involves normalizing sub-indicators and applying subjective weights for aggregation, which raises concerns about the reliability of the rankings. In response to this issue, we propose an alternative method based on Data Envelopment Analysis (DEA) that utilizes flexible weights. Our approach is applied to the data from the UI-GreenMetric World University Ranking. We initially employ a general Benefit of the Doubt DEA model and subsequently enhance its discrimination power by computing super-efficiency. In the third model, we impose weight restrictions on sub-indicators. The results of our analysis offer valuable insights for all stakeholders, as illustrated by the implications derived for Czech universities included in the sample. Furthermore, we compare the results of universities in various European countries, establishing a connection between rankings and the fulfillment of Sustainable Development Goals (SDG) within individual countries. This research contributes to a more comprehensive understanding of the relationship between university performance, sustainability, and the associated implications for policy and benchmarking.

KEYWORDS

Composite index, Data Envelopment Analysis, sustainability goals, university ranking

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Highlights

- *The paper presents an alternative to the UI-GreenMetric World University Ranking with lower sensitivity to sub-indicator weighting.*
- *Moreover, the methodology used in our study allows for identifying areas with potential for improvement and peer units for benchmarking purposes.*
- *The analysis results demonstrate positive correlations between university rankings and the fulfillment of sustainable development goals in their respective countries.*

INTRODUCTION

As a reaction to global challenges our planet faces, the United Nations General Assembly established the global Sustainable Development Goals (SDGs) for 2015–2030 (United Nations, 2014). Governments, civil societies, private companies, and other organizations are supposed to conduct their activities in accordance with these goals, see Table 1. Countries are assessed using the so-called SDG Index (Sachs et al., 2022) to measure how far they are on the road towards development, balancing social, economic, and environmental sustainability. The level of SDG attainment in the European countries ranges from 70.41% (Turkey) to 86.51% (Finland); the values are depicted in the map in Figure 1. Over the years 2015-2020, the EU has generally made progress toward achieving most sustainable development goals, with varying advancement rates across different goals. SDG 16, which focuses on peace, justice, and strong institutions, notably saw significant improvements. Reductions in poverty and enhancements in the EU's health situation (SDG 1 and SDG 3) also showed positive trends, although these assessments predate the COVID-19 pandemic. The pandemic has had a noticeable impact on the economy, labor market, education, gender equality, inequality, and global partnerships (SDG 8, SDG 4, SDG 5, SDG 10, and SDG 17), resulting in interruptions and deteriorations in these areas. Moderate progress has been observed in sustainable cities, consumption and production, sustainable agriculture, and R&D and innovation (SDG 11, SDG 12, SDG 2, and SDG 9). However, the assessments are based on data predating the pandemic. SDG 13, climate action, has seen neutral progress, influenced by both positive trends in climate mitigation and negative impacts of climate change. SDG 7 and SDG 15, however, show slight deviations from sustainable development objectives, primarily due to increased energy consumption and ongoing pressure on ecosystems and biodiversity, respectively (Sachs et al., 2022).

Goal	Description
SDG1	End poverty in all its forms everywhere
SDG2	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture
SDG3	Ensure healthy lives and promote well-being for all at all ages
SDG4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
SDG5	Achieve gender equality and empower all women and girls
SDG6	Ensure availability and sustainable management of water and sanitation for all
SDG7	Ensure access to affordable, reliable, sustainable and modern energy for all
SDG8	Promote sustained, inclusive and sustainable economic growth, full and productive employment, and decent work for all
SDG9	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation
SDG10	Reduce inequality within and among countries
SDG11	Make cities and human settlements inclusive, safe, resilient, and sustainable
SDG12	Ensure sustainable consumption and production patterns
SDG13	Take urgent action to combat climate change and its impacts
SDG14	Conserve and sustainably use the oceans, seas and marine resources for sustainable development
SDG15	Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss
SDG16	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels
SDG17	Strengthen the means of implementation and revitalize the global partnership for sustainable development

Table 1: The goals of the UN's 2030 Agenda for Sustainable Development (Source: United Nations. Sustainable Development, https://sustainabledevelopment.un.org/)

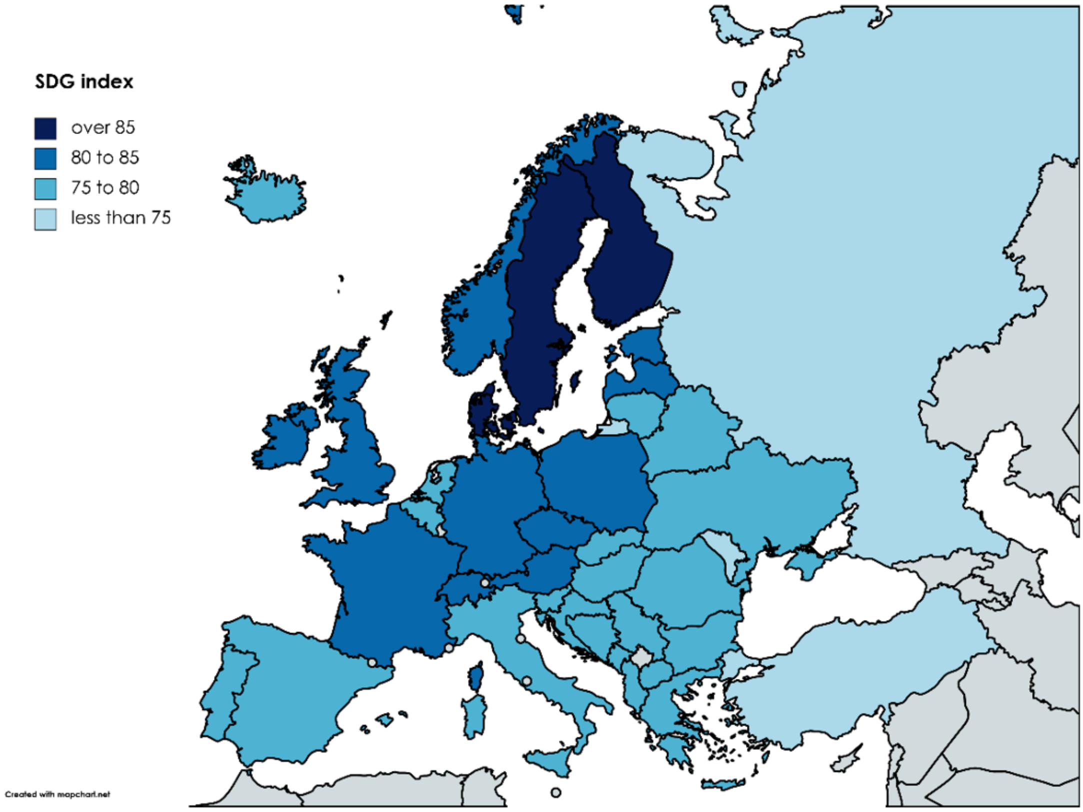

Figure 1: SDG index (Source: mapchart.net, Sachs et al., 2022)

Education is probably one of the most influential factors in this effort. Education for sustainable development received recognition and description in Agenda 21 for promoting education, awareness, and training (UNESCO, 1992). It explicitly articulates the responsibility of both formal and non-formal education systems to cultivate the necessary attitudes in the population, enabling active participation in sustainable development activities and matters. The effect of education on the attitude and awareness of young people towards sustainability is explored by many authors, e.g., Kaur and Kaur (2022), Nousheen et al. (2020), Tang (2018). Another important aspect is how educational institutions themselves follow the SDG strategies. The involvement of universities in global sustainable development and the role of SDGs as fundamental aspects of their strategy concerning teaching, research, and third-mission activities is subject to many scientific papers (e.g., Lozano, 2006; Lozano et al., 2015; Purcell et al., 2019; Mori Junior et al., 2019; Klußmann et al., 2019; Ceulemans et al., 2015).

Part of meeting sustainability goals is comparing with others, for example, through participation in international rankings. However, most major university ranking schemes often stress the importance of research and academic reputation, followed by educational indicators, whereas environmental issues have received little or no attention. As an example, we can name the best-known ranking systems, such as the *Times Higher Education World University Rankings* (THE), sponsored by Thomson Reuters, or the *QS World University Rankings. Both rankings include sustainable development only in auxiliary assessments covering just a partial sample of* higher education institutions (HEIs); see THE Impact Rankings (Thomson Reuters, 2023) and QS Sustainability Rankings (Quacquarelli Symonds, 2023). Nevertheless, rankings that really include environmental aspects and sustainability issues have also begun to emerge, such as the one providing data for our analysis: UI GreenMetric World University Ranking 2022, a survey-based global self-assessment tool for higher education institutions. UI GreenMetric Ranking (UI-GMR) initiative started in 2010 by ranking 95 universities from 35 countries. It became increasingly recognized and prestigious, so in 2021, more than 950 universities from 80 countries participated in the ranking. The universities are ranked according to the values of the composite indicator aggregating information from six areas (environment and infrastructure, energy and climate change, waste, water, transport, education, and research). The relationship between academic performance measured by recognized rankings and environmental responsibility measured by UI-GMR was explored by Galleli et al. (2022) and Atici et al. (2021).

However, certain aspects of the UI-GMR ranking are criticized by some authors. Ragazzi and Ghidini (2017) identified several issues that need to be addressed in order to improve the ranking method, among others, the relativity of scores and the high sensitivity of the ranking. Boer (2013) provides a discussion on alternate evaluation frameworks, among others, a U.S. campus sustainability rating system, The Sustainability, Tracking, Assessment and Rating System (STARS) originating in 2006, Auditing Instrument for Sustainability in Higher Education (AISHE) from the year 2012, Assessing Responsibility In Sustainable Education (ARISE), and the Audit and certification method which reflects ISO methods. As mentioned by Dalal-Clayton and Bass (2002), various approaches can be utilized to assess and report sustainability, such as accounts, converting raw data to a common unit (monetary, area, or energy), or narrative assessments combining text, maps, graphics and tabular data. Nevertheless, the mainstream is represented by indicator-based strategies.

Composite indicators (CI) are regularly used for benchmarking performance but equally often stir controversies about the unavoidable subjectivity that is connected with their construction. In constructing CIs, the normalized sub-indicators are usually added, sometimes with certain weights associated with the sub-indicators. We will depart from that approach in our study using flexible weights obtained by Data Envelopment Analysis (DEA). Engaging the DEA in developing a composite index can address two significant issues: the undesirable reliance on preliminary normalization of sub-indicators and the subjective weighting used for aggregation. Additionally, flexible weighting can promote buy-in from relevant stakeholders, making the final results more widely accepted. Lastly, it is worth noting that DEA analysis can offer valuable insights into the relative performance of evaluated units, such as identifying peer units for those that are inefficient. DEA-based approaches have been used in the context of university evaluations many times, e.g., Thuan et al. (2022) or Ferro and D'Elia (2020).

The objective of this study is twofold. The first aim is to construct an alternative to the global ranking of HEIs focusing on sustainability while mitigating the shortcomings of existing ranking systems. The second objective is to explore the differences between the ranking of universities from different European countries and to find the connection between the position of the HEI in the ranking and the extent to which the country fulfills the Goals of Sustainable Development (SDG). Our results show a significant positive association between the ranking of HEIs and the value of the SDG index in countries of their origin. The rest of the paper is organized as follows: In the second chapter, we describe the data sample and three models used to create an alternative sustainability indicator for universities. The resulting rankings of universities and their comparison with the original UI-GMR ranking are presented in Chapter three. We also demonstrate the interpretation of additional results obtained using tools of DEA methodology (slack analysis and identification of peer units) and possible recommendations in the case of Czech universities. The third chapter ends by comparing results across European countries and investigating their relationship with SDG fulfillment in these countries. The results are discussed in the fourth chapter, and the final chapter concludes the study.

MATERIAL AND METHODS

Composite indicator construction using DEA

The approach used in our study is based on using DEA as an aggregation tool in Multiple Criteria Decision Making (MCDM). In the context of composite indices, it was first used by Mahlberg and Obersteiner (2001) to reassess the Human Development Index. Since then, DEA-based CIs have been used in many application areas, such as assessing European social inclusion policy (Cherchye et al., 2004), technology achievement (Cherchye et al., 2008) or road safety (Shen et al., 2013). A similar model has been tested to assess progress towards achieving the so-called Lisbon objectives (European Commission, 2004, p. 376-378). Many other applications are mentioned in the survey of Greco et al. (2019). The basic properties of the DEA-based CIs are described in the paper of Cherchye et al. (2007), which refers to the method as the Benefit-of-the-Doubt (BoD) approach.

The scientific studies also point out one major issue that often

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occurs while applying this method as a result of the absence of further constraints: After the optimization process, a multiplicity of the units are assigned the maximum possible value of „efficiency,“ so their order cannot be determined. That is why we also introduce two alternate approaches to solving this problem. The first one is based on the computation of super-efficiency. In the second one, we allow for more constraints given by the decision maker, controlling, for instance, the lower and upper bounds of the weights of each sub-indicator or their ratios.

Model 1

Driven by the above-mentioned ideas, we first adopted the typical DEA setup for our MCDM-DEA model, which only requires the endogenous weights to be nonnegative. To introduce DEA as a tool for constructing composite indicators, we consider variables in the form of values of m sub-indicators for n units (universities), with the value of sub-indicator i in unit j. In the following, and in line with the more common DEA terminology, we will often refer to sub-indicators as outputs. In contrast to the typical DEA setup, in our analysis, we do not consider any inputs, or more precisely, we use a single input with a uniform value of 1 for all Decision-Making Units (DMUs). Following the ideas formulated in the literature on BoD indicators (e.g., Cherchye et al., 2008), let's define single-valued CI, defined as the weighted average of the m sub-indicators; we use v_i to represent the weight of the i-th sub-indicator. As discussed above, the available expert information does not allow us to specify a priori a unique vector of generally acceptable weights. Therefore, we endogenously select those weights that maximize the value of the composite indicator for the unit under consideration. This gives the following linear programming problem for each j:

$$CI_j = \max_{v_i} \sum_{i=1}^{n} v_i\, y_{ij} \quad (1)$$

subject to

$$\sum_{i=1}^{n} v_i\, y_{ik} \le 1, \forall k = 1,\ldots,n, \quad (2)$$

$$v_i \ge 0,\ \forall i = 1,\ldots,m. \quad (3)$$

We obtain $CI_j \le 1$ for each unit j, with higher values indicating better relative performance. The indices of constraints binding in optimal solutions identify peer units for „inefficient“ units. As mentioned by Despotis (2005), this model formally corresponds to the original input-oriented, constant-returns-to-scale DEA model using the sub-indicators to represent the individual outputs and allocating a single 'dummy input' with value unity to each unit.

Model 2

One of the issues of basic DEA models is ranking units having identical scores of unity. To address this problem, Andersen and Petersen (1993) proposed a super-efficiency model used to complete ranking. The model involves executing standard DEA models, assuming that the unit under evaluation is excluded from the reference set, so in the second model, instead of the constraint (2), we consider its modification,

$$\sum_{i=}^{n} v_i\, y_{ik} \le 1, \forall k = 1,\ldots,n, k \ne j \quad (4)$$

In the case of output-oriented models, the super-efficiency score provides a measure of the proportional reduction of outputs that a unit could experience without losing its "efficient" status relative to the frontier created by the remaining units. Additionally, the super-efficiency score serves as a measure of stability. In other words, if the data is subject to changes or errors over time, the score provides a means of evaluating the extent to which these changes could occur without violating the efficient status of the unit (Zhu, 2001). However, it should be noted that under specific conditions concerning returns to scale, the super-efficiency DEA model may not have feasible solutions for some units. A well-known result from the DEA literature is that the super-efficiency model preserves the scores of non-efficient units obtained by the basic model (Andersen and Petersen, 1993).

Model 3

In the last model, we include the ordinal information about the weights of the individual sub-indicators determined by the experts from the GreenMetric team. This is done by adding additional restrictions on the relative weights to the basic DEA model to obtain the so-called Assurance Region (AR) model. These models impose restrictions in the form of lower bounds (LB) and upper bounds (UB) for outputs (or inputs) weights or bounds for their ratios, as in our application:

$$LB_i \le \frac{v_i}{v_{i+1}} \le UB_i,\ \forall i = 1,\ldots,m-1 \quad (5)$$

These models were first used by Thompson et al. (1990) to improve the discrimination power of the basic DEA model. Since then, such weight restrictions have been applied in various applications, and among them, absolute restrictions on weights or the constraints of type (5) are the most common. They are particularly suitable when there is à priori information on marginal substitution rates between inputs and/or outputs. The difference between multi-criteria decision analysis and DEA is that the former aims to identify the trade-off exactly. At the same time, DEA leaves some weight flexibility, see e.g., Dyson and Thanassoulis (1998). In some applications, models with different weights restrictions were used, i.e., Luptáčik and Nežinský (2022), where they measured income inequalities using MCDM-DEA composite indicator with weights restrictions favoring a higher income share in the lower quantiles. Unlike absolute weight restrictions, Charnes et al. (1990) and Thompson et al. (1990) pointed out that by using relative weight restrictions, different oriented DEA models produce consistent results. The issue of imposing additional a priori weights has attracted considerable attention in the DEA literature; see, e.g., Allen et al. (1997) for a survey.

Data

We use the data from UI GreenMetric World University Ranking (2022). The sample covers 950 universities worldwide, but we focused on the European countries only.

While the sample selection can be subject to discussion, it is not feasible to include just countries comparable in terms of climate, legislation, culture, and other conditions. Therefore, considering the sample size, we included not only members of the European Union but also countries whose territories lie fully or at least partially on the European continent. The number of universities representing one country ranged from 1 to 52. The total size of the dataset used in our analysis is 273 HEIs, with some European countries (including Austria, Belgium, Bulgaria, Norway, Serbia, and Sweden) uncovered, as their HEIs do not participate in the UI GMR initiative, so no data is provided from them.

The methodology of UI-GMR is continuously evolving; in the current performance evaluation tool, they collect data on 39 indicators categorized into 6 groups. The relative performance of the universities is measured by sub-indicators corresponding to these categories, see Table 2.

We took the values of the 6 UI-GMR sub-indicators as the output variables in our analysis. Instead of the weighted aggregation of sub-indicators used by the UI-GMR team, we apply the MCDM-DEA model (1) with constraints (2), (3), or (4) (and (5)). As the weight vector of 2022 Ranking was set to $v = (0.15, 0.21, 0.18, 0.1, 0.18, 0.18)$ by experts of the UI-GMR team, we preserve the order of the weights by imposing the inequalities $v_4 \le v_1 \le v_3 = v_5 = v_6 \le v_2$ as the constraints formulated in (5).

Dimension	Indicators
Setting & Infrastructure	• The ratio of open space area to total area • Area on campus covered in forest • Area on campus covered in planted vegetation • Area on campus for water absorbance • The total open space area divided by the total campus population • University budget for sustainable effort
Energy & Climate Change	• Energy-efficient appliances usage are replacing conventional appliances • Smart building implementation • Number of renewable energy sources on campus • The total electricity usage divided by the total campus population (kWh per person) • The ratio of renewable energy produced to energy usage • Elements of green building implementation as reflected in all construction and renovation policy • Greenhouse gas emission reduction program • The ratio of total carbon footprint divided by campus population
Waste	• Recycling program for university waste • Program to reduce the use of paper and plastic on campus • Organic waste treatment • Inorganic waste treatment • Toxic waste handled • Sewerage disposal
Water	• Water conservation program implementation • Water recycling program implementation • The use of water-efficient appliances (water tap, toilet flush, etc.) • Treated water consumed
Transportation	• The ratio of total vehicles (cars and motorcycles) divided by the total campus population • Shuttle service • Zero Emission Vehicles (ZEV) policy on campus • The ratio of Zero Emission Vehicles (ZEV) divided by the total campus population • Ratio of the parking area to total campus area • Transportation program designed to limit or decrease the parking area on campus for the last 3 years • Number of transportation initiatives to decrease private vehicles on campus • Pedestrian path policy on campus
Education & Research	• The ratio of sustainability courses to total courses/subjects • The ratio of sustainability research funding to total research funding • Number of scholarly publications on environment and sustainability published • Number of scholarly events related to environment and sustainability • Number of student organizations related to environment and sustainability • Existence of a university-run sustainability website • Existence of a published sustainability report

Table 2: Dimensions and partial indicators of UI-GMR index (Source: GreenMetric World University Ranking, 2022)

RESULTS

By applying individual models, we obtained a ranking of universities as an alternative to the UI-GMR ranking. Figure 2 shows scatterplots of evaluations of all units involved in the analysis, comparing the results of our models with the original evaluation. The results of Model 3 are depicted on the right-hand side of the figure, while the left-hand side represents the results of Model 2. The results of Model 1 would correspond to

Model 2 with values censored from above at 1 on the vertical axis. The higher similarity of the results of Model 3 with the original evaluation is evident, which corresponds to our expectations.

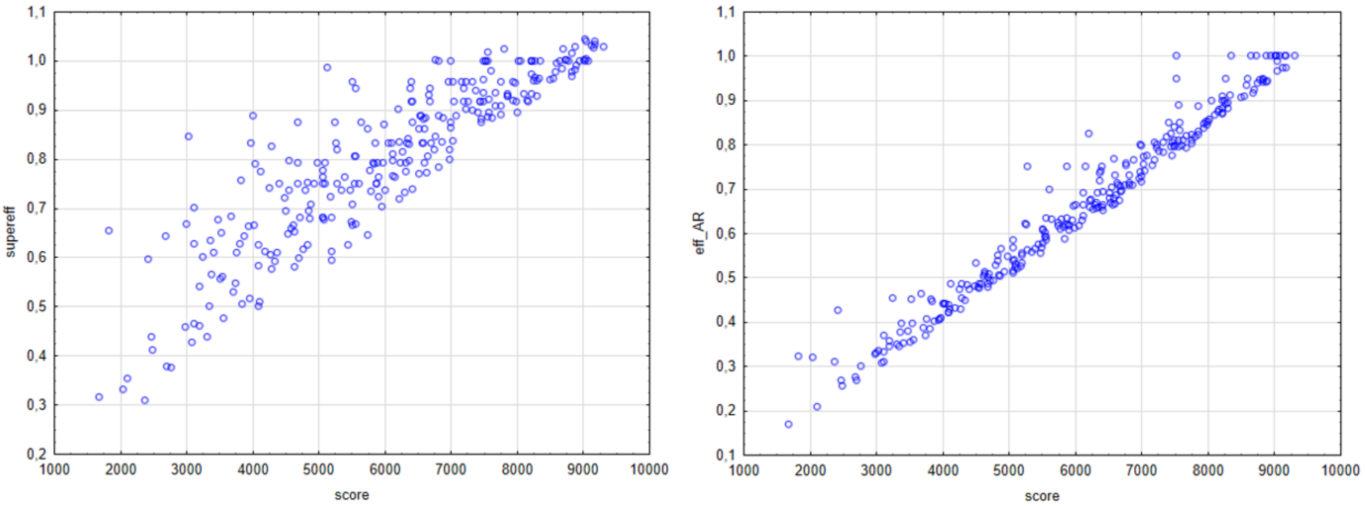

Figure 2: Scores of Models 2, 3 vs. UI-GMR scores (Source: Own calculations)

The Spearman correlation between the results of Model 1 (MCDM-DEA model) and the original UI-GMR ranking of European countries was relatively high, $r_s = 0.95$. However, a drawback of our approach is the inability to compare a large number of universities at the top, as 35 universities reached the highest achievable score of efficiency. Moving to Model 2 (super-efficiency model), we increased the discriminatory power of the analysis, obtaining 16 units with efficiency values higher than one (so-called super-efficient units). In contrast, the ranking of other units remained unchanged. The overview of super-efficient units is presented in Table 3. The rank correlation coefficient between the scores of Model 2 and the original UI-GMR ranking is $r_s = 0.96$.

University	Country	UI-GMR Rank
Wageningen University & Research	Netherlands	1
Leiden University	Netherlands	9
Nottingham Trent University	United Kingdom	2
Universita di Bologna	Italy	8
University of Nottingham	United Kingdom	3
Umwelt-Campus Birkenfeld (Trier University of Applied Sciences)	Germany	5
Politecnico di Torino	Italy	15
University of Groningen	Netherlands	4
Universidad de Alcalá	Spain	22
Perm National Research Polytechnic University	Russia	54
Russian State Agrarian University - Moscow Timiryazev Agricultural Academy	Russia	66
Universita degli Studi di Torino	Italy	17
Universitat Bremen	Germany	7
Kastamonu University	Turkey	11
Universita degli Studi dell’Aquila	Italy	20
Dublin City University	Ireland	103

Table 3: Top-ranked units under Super-efficiency model (Model 2) (Source: Own computations, GreenMetric World University Ranking, 2022)

We achieved the highest level of agreement with the original UI-GMR ranking using Model 3 (AR model), taking into account the order of weight assigned to sub-indicators. The correlation coefficient reached the value $r_s = 0.99$. Similar to Model 1, the maximum score is 1, making it impossible to distinguish the order of units that reach this maximum. Fortunately, only 13 universities are indistinguishable in terms of ranking compared to the baseline Model 1. Table 4 provides an overview of these universities. While the incomparability issue does not arise in the original UI-GMR ranking, the methodology used in our analysis provides far more benchmarking opportunities and recommendations to individual universities.

The dataset includes six Czech universities, so we present their position within the rankings and use them as an example showing how to use the results to derive recommendations for improvement. The applied methodology allowed for the identification of peer units for each university, which opened up space for establishing new cooperation and spreading good practices in the area of social and environmental responsibility. At the same time, we determined dimensions with nonzero slacks that indicate areas with the highest potential for

University	Country	UI-GMR Rank
Wageningen University & Research	Netherlands	1
University of Nottingham	United Kingdom	3
University of Groningen	Netherlands	4
University College Cork	Ireland	6
Leiden University	Netherlands	9
University of Southern Denmark	Denmark	10
Dublin City University	Ireland	11
Hame University of Applied Sciences	Finland	12
Politecnico di Torino	Italy	15
Universidad Complutense De Madrid	Spain	21
University of Eastern Finland	Finland	24
Cyprus International University	Turkey	29
Universita degli Studi di Bari Aldo Moro	Italy	67

Table 4: Top-ranked units under the Assurance region model (Model 3) (Source: Own computations, GreenMetric World University Ranking, 2022)

improvement. They can be interpreted as directions in which university management should concentrate their effort. Detailed information can be found in Table 5. The codes used for the individual dimensions are SI (Setting & Infrastructure), ECC (Energy & Climate Change), WST (Waste), WTR (Water), T (Transportation), and ER (Education & Research). The rankings obtained by Models 1 and 2 are the same as the shift from efficiency to superefficiency, which is order-preserving, and even the scores of nonefficient units remain the same (which is the case of all Czech units in the analysis).

University	UI-GMR rank	Nonzero slacks	Models 1,2	Rank	Model 3	Rank
Czech University of Life Sciences	25	ECC, T	0.996	36	0.950	20
Masaryk University	43	SI, ECC, WST, WTR	0.934	70	0.869	48
Mendel University	128	WST, WTR, T	0.797	150	0.718	119
Palacký University Olomouc	160	SI, WST	0.645	225	0.618	160
University of Hradec Králové	169	WTR, T, ER	0.708	199	0.577	174
Tomas Bata University	209	ECC, WTR, T, ER	0.667	217	0.504	205

Table 5: Scores and rankings of Czech universities (Source: Own computations)

The *Czech University of Life Sciences Prague* (CULS) achieved the highest position in the original UI-GMR ranking, which improved its performance using our DEA-MCDM methodology with one peer unit identified as Politecnico di Torino. The second of Czech universities was *Masaryk University* (MUNI), with two peers from Italy: Politecnico di Torino and Universita di Bologna. Two Italian universities (Politecnico di Torino and Universita degli Studi di Torino) should also be used as a benchmark for the third of Czech HEIs, *Mendel University in Brno* (MENDELU). *Palacký University Olomouc* (UPOL) switched positions with others after the change of methodology; it ranked last among Czech universities in the new evaluation with two Italian peers, Politecnico di Torino, Universita di Bologna, and another peer from The Netherlands: Wageningen University & Research. The ranks of two remaining Czech HEIs remained relatively stable: *University of Hradec Králové* (UHK) with one peer (Wageningen University & Research) was followed by *Tomas Bata University* (UTB) with the same peers as MUNI, Politecnico di Torino and Universita di Bologna.

Based on the Slack analysis, we can identify areas where Czech universities should focus their efforts to improve their performance in the ranking. In Table 5, we can see that the most problematic areas for most Czech universities remain transportation (with the exception of MUNI and UPOL) and water (with the exception of CULS and UPOL). There are also strengths in Czech educational institutions, with particularly strong results in the areas of Setting & Infrastructure (except for MUNI and UPOL) and Education & Research (except for UHK and UTB).

In the last part of the analysis, we compare the performance of universities from different countries and explore its association with the fulfillment of sustainable development goals. First, we present a boxplot of the Model 3 scores of universities in Figure 3 (countries are ordered according to the mean of UI-GMR score). The best results were achieved by universities from the countries at the top positions of the SDG ranking, namely the Netherlands (17.), the UK (11.), Germany (6.), Ireland (9.), Italy (25.), Denmark (2.), and Finland (1.). The number in the brackets represents the country rank among all 163 SDG Ranking 2022 participants (Sachs et al., 2022).

The intensity of the association between UI-GMR performance and the SDG Index can be measured by the Spearman correlation coefficient; in Table 6, we present positive correlations that are statistically significant at the level of 95%. Although the analysis cannot capture the direction of effect or prove causality, it shows a clear positive relationship between university rankings and the SDG index score, showing the level of attainment of sustainability goals in their respective countries.

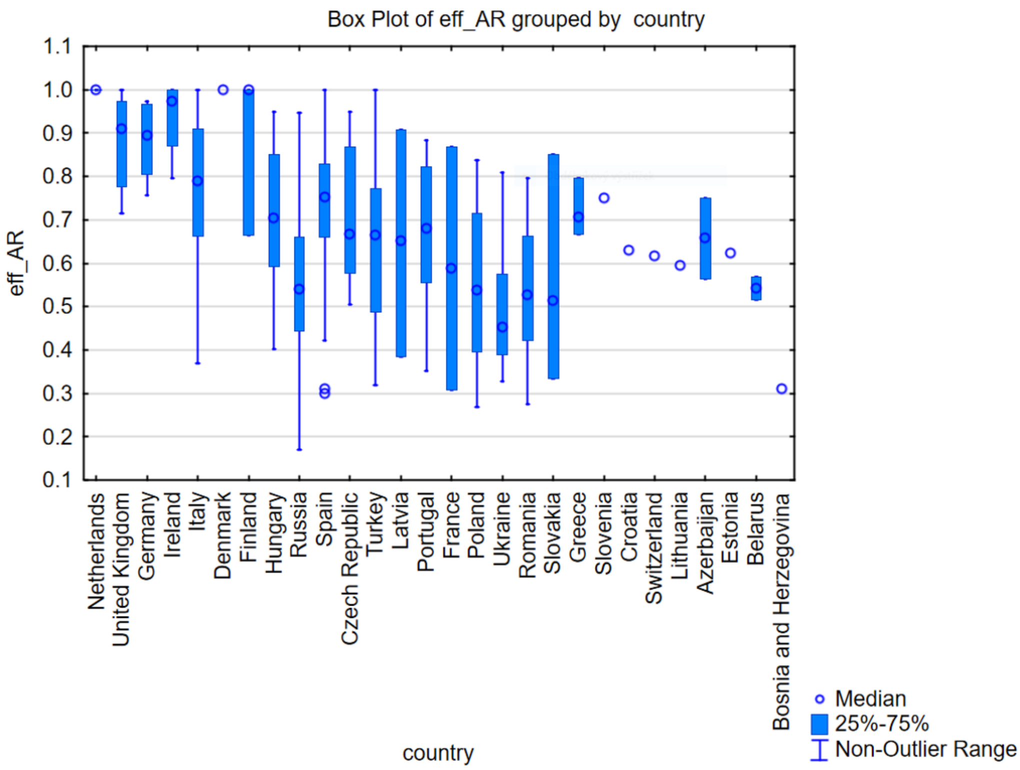

Figure 3: Scores of Model 3 grouped by countries (Source: Own calculations)

SDG index	UI-GMR score	Model 1 score (DEA)	Model 2 score (superef)	Model 3 score (AR)
overall	0.58	0.58	0.57	0.52
Goal 3	0.80	0.76	0.75	0.75
Goal 5	0.52	0.48	0.48	0.46
Goal 6	0.70	0.63	0.63	0.59
Goal 7	0.45	0.46	0.45	0.40
Goal 8	0.50	0.45	0.45	0.48
Goal 9	0.75	0.70	0.70	0.68
Goal 11	0.59	0.55	0.55	0.55
Goal 16	0.62	0.65	0.64	0.64

Table 6: Correlations of UI-GMR score and its alternatives with SDG index (Source: Own computations, Sachs et al. (2022), GreenMetric World University Ranking, 2022)

All methods yield the same results in terms of the sign of the coefficient and its statistical significance. The coefficient values themselves are comparable across methods as well. The strongest correlations are observed for Goals 3 (Good health and well-being) and 9 (Industry, innovation, and infrastructure), followed by Goals 6 (Clean water and sanitation) and 16 (Peace, justice, and strong institutions). Surprisingly, we did not observe a significant correlation between Goal 4 (Quality education) and some of the goals in the area of environmental sustainability. This is noteworthy as one of the common criticisms of the UI-GMR methodology is that it favors environmental goals at the expense of other areas.

An overview of the level of fulfillment of the individual significant SDGs is shown in Figure 4. Here, you can see a generally higher level of goal fulfillment in the northern countries; on the contrary, the worst results can be observed in the southeast. Some of the countries with universities at the top of the UI-GMR ranking also occupy leading positions in the fulfillment of individual SDGs (Finland, Denmark), while others, on the contrary, lag behind in selected goals. As an example, we can name Ireland and the United Kingdom, which have poor performance in SDG7 (Sustainable energy). However, we must point out that this particular goal is largely determined by the geographical and natural conditions of the given country, so it is difficult to influence it through education.

DISCUSSION

There are many studies explaining the potential of HEIs to impact sustainable growth and innovation at the regional level positively. According to research by Fritsch and Aamoucke (2017), the presence of HEIs in a region can benefit regional sustainability by creating and performing new firms. Additionally, the proximity between HEIs and new firms seems to affect the quality of spillovers generated between agents, as Pedro et al. (2022) noted. HEIs should focus on collaborative

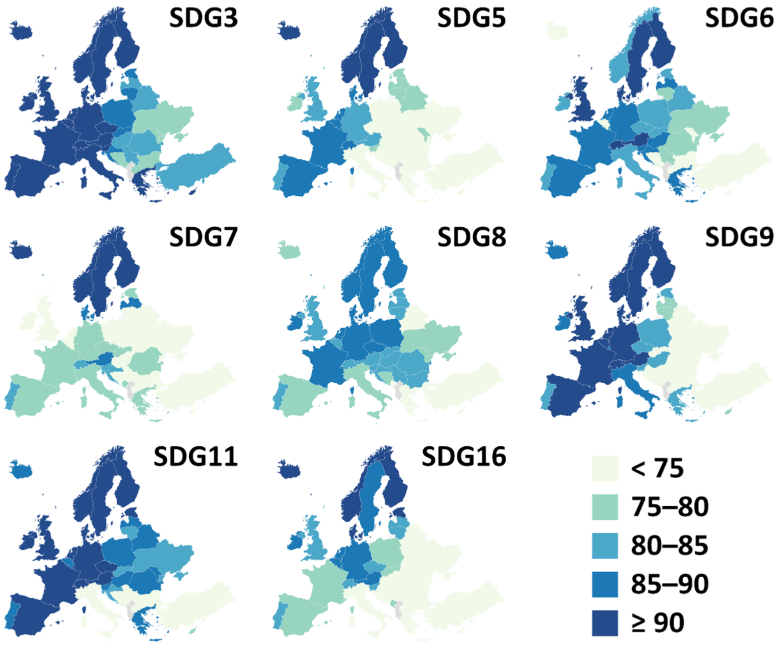

Figure 4: The level of the selected SDGs (Source: Sachs et al., 2022)

activities with industry, government, and society to further reinforce this impact. This can be especially important in structurally weak regions, see Baptista et al. (2011).

Other authors also stress other roles of HEIs beyond the ones mentioned above. According to Kohl et al. (2022), implementing a whole-institution approach toward sustainability could lead to a policymaking role for higher education. HEIs could be more active in policymaking if sustainability was at the core of their own practice. The same authors mention the long-standing tradition of universities' networking to expand knowledge and join forces in teaching, research, and furthering exchange. Hence, the influence of HEIs can be realized through new networks focusing on sustainability, such as the Higher Education Sustainability Initiative (HESI), Association for the Advancement of Sustainability in Higher Education (AASHE), Sustainable Development Solutions Network (SDSN), SDG Accord led by the Global Alliance of Tertiary Education and student Sustainability Networks, etc. In the Czech context, we can mention the UNILEAD project initiated by 24 universities (Masaryk University, 2022). The project aimed to strengthen the role of universities as efficient, responsible, and inclusive public organizations by ensuring more effective cooperation in the transfer of good practices in implementing sustainable development goals.

According to the project participants, „Cooperation between universities and the transfer of good practice helps to remove internal obstacles, whether it is a lack of structure or the belief that it can't be better because there is no monitoring and a clearly defined goal for further improvement. In addition, they have the opportunity to approach sustainable development in a truly comprehensive way, rather than limiting themselves to partial measures." Other initiatives and declarations are mentioned by Filho (2011), such as COPERNICUS 'Universities Charter on Sustainable Development' (1994), Luneburg Declaration on Higher Education for Sustainable Development (2001), Ubuntu Declaration on Education and Science and Technology for Sustainable Development (2002), Graz Declaration on Committing Universities to Sustainable Development (2005), or G8 University Summit Sapporo Sustainability Declaration (2008). However, the level of formal commitment to concrete efforts resulting from such declarations varies, as mentioned by Filho (2011). The study also mentions results of the survey identifying possible misconceptions preventing universities from the more efficient implementation of sustainable development in their programs and operations, including the following statements: „Sustainability is too abstract", „Sustainability is too broad", „We have no personnel to look after it", „The resources needed do not justify it", „The theme has no scientific basis", „There is much competition for funds and resources for sustainability initiatives".

We hope that insights like the one provided by our study can greatly help the efforts to reach SDG. One of the benefits of the methodology used in our study is the identification of slacks and peer units, which helps to foster the sharing of good practice. Using DEA, the benchmarks are not based upon theoretical bounds but as a linear combination of observed best performances that are close to a unit under evaluation. We have reason to believe that setting achievable targets and comparisons within clusters of similar institutions will serve as a better incentive than if universities were to strive for unattainable goals. The analysis also allows for possible extensions, including dynamic performance evaluation, to measure the progress over time. Similarly, Zaim et al. (2001) proposed a DEA-based aggregate performance index assessing intertemporal performance shifts. Their approach has the advantage of being decomposable into a *catching-up* component, which assesses individual improvement, and an *environmental change* component, which focuses on best practice changes between periods. Consistent assessment of universities' progress toward sustainable development is, therefore, a potential area for further research.

Although composite indicators represent a very popular tool for benchmarking performance in various areas, on the other hand, they are often criticized for the subjectivity connected with their construction. Data Envelopment Analysis helps to overcome some issues, particularly the dependence of final results on the preliminary normalization of sub-indicators and the subjective nature of the weights used for aggregating. The analysis can thus provide more acceptable results to subjects under evaluation. The need for flexible weights is evident, especially in a competitive environment or in a context where tensions between the evaluator and individual units may be present. That is why, besides academic contributions, practical applications are also emerging. For example, the European Commission has employed a flexible weighting scheme to assess member states' performance concerning the Lisbon objectives (European Commission, 2004).

While some issues are overcome by the methodology used in our study, others, e.g., those related to using UI-GMR data as mentioned by Ragazzi and Ghidini (2017) or Lauder et al. (2015), remain unaddressed. The key limitations and potential areas for improvement are the selection of sub-indicators and the number of universities participating in the GreenMetric Ranking survey. Possible broadening of the scope and the extent of the survey can bring more relevance to the results and conclusions. As mentioned by Boiocchi et al. (2023), some UI-GMR sub-indicators need to be more adequate for effectively and fairly measuring sustainability development; others require contextual adjustments.

Ranking universities based on sustainable development is a sensitive and complex task that requires careful consideration of context-specific factors. Universities operate in diverse environments, each facing distinct challenges in their pursuit of sustainability. Neglecting the heterogeneity among HEIs can lead to inherently biased results, potentially causing misleading rankings that impact universities' reputations. So, this opens up another promising path for future research in this area: to focus on addressing the heterogeneity of the DMUs. A notable advantage of the DEA-based ranking construction is the possibility of incorporating relevant geographical and socio-economic factors directly into the computational model. The strategies to achieve this are well described in the scientific literature, e.g., Banker and Natarajan (2008). Homogenizing the data plays a crucial role in ensuring that universities are evaluated fairly and meaningfully, and only when considering contextual factors in the analysis can we understand the unique challenges and opportunities that each university encounters.

CONCLUSIONS

The attainment of the Sustainable Development Goals necessitates the active involvement of all stakeholders. This requires having the skills and mindsets t o contribute to the challenges on the path towards sustainability. Universities are influential institutions and can serve as opinion leaders. When they adopt certain practices, they inspire and provide models for other segments of society to adopt and emulate. By studying HEIs' social and environmental responsibility in different institutional and regional contexts, we can gain new insights into their contributions at the regional and national levels, leading to sustainable economic development and promoting innovation and technological entrepreneurship.

It is desirable for the sustainability aspects and considerations presented above to be disseminated further into the awareness of authorities and creators of recognized rankings like THE or the QS World Ranking. These rankings are often seen as proxies for quality and are also used as marketing tools. Placement in a prestigious ranking can significantly increase the number of high-quality students HEI attracts and, consequently, boost its influence on the economy and society. If the university's contribution to SDG goals attainment becomes a direct component of recognized evaluations (e.g., in the form of an expansion of THE Impact ranking), it may act as an inhibitor for their more vigorous promotion. For instance, governments and educational authorities may be more inclined to allocate resources to HEIs that excel in sustainability rankings, thereby promoting environmentally responsible policies at both the institutional and national levels. Furthermore, when sustainability is a prominent factor in rankings, it sends a clear signal to HEIs that integrating sustainability into their curricula is socially responsible and advantageous in terms of their overall performance and reputation. This, in turn, leads to the development of new courses and study programs, equipping students with the knowledge and skills needed to address pressing global issues. In sum, sustainability evaluation and ranking of HEIs go beyond just measuring social and environmental responsibility. They catalyze change, drive policy reforms, inspire curriculum adjustments, and promote sustainable institutional practices.

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Full research paper

ASSESSING THE RELATIVE IMPACT OF COLOMBIAN HIGHER EDUCATION INSTITUTIONS USING FUZZY DATA ENVELOPMENT ANALYSIS (FUZZY-DEA) IN STATE EVALUATIONS

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ABSTRACT

This research aims to design a helpful methodology for estimating universities' relative impact on students as a sustainability factor in higher education. To this end, the research methodology implemented a two-stage approach. The first stage involves the relative efficiency analysis of the study units using Fuzzy Data Envelopment Analysis. The second stage consists of a predictive evaluation of the efficiency of the study units. Consequently, among the most relevant results of the research, it is observed that the methodology identifies the institutions that need to strengthen the academic competencies of the industrial engineering program. Additionally, we developed a benchmark analysis called Efficient Route to help inefficient units achieve efficiency, associating efficiency, and sustainability as pillars of higher education processes.

KEYWORDS

Efficiency, higher education, machine learning, predictive evaluation

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Highlights

- *An empirical methodology is presented to evaluate, calculate, and predict the relative contribution under a fuzzy approach.*
- *The evaluation of homogeneous universities allows for correctly determining academic performance and associating efficiency with educational sustainability.*
- *The comparison of equivalent entities yields different average efficiency values for the global analysis.*

INTRODUCTION

Globalisation has catalysed what is now known as the integration of economies, societies, and cultures. Generally, these integrations manifest as global political ideas such as Education for Sustainable Development (Cars and West, 2015). Education for Sustainable Development is an instrument created in December 2002 by the United Nations General Assembly in its resolution 57/254. This instrument aims to provide comprehensive education in values, knowledge, and attitudes for discerning decisions and executing an action plan, considering a country's social, environmental, and economic context.

According to the United Nations, Educational Institutions are vital allies in this educational strategy due to their role as transformers of society through education. Various studies reveal a positive association between economic growth and the number of professionals (Hoeg and Bencze, 2017; Sharma et al., 2018). Meanwhile, Bianchi and Giorcelli (2020) show how countries with higher levels of education have higher levels of innovation, as represented in patent registrations. Corlu and Aydin (2016) demonstrated that science, technology, engineering, and mathematics education increases enterprise creation.

Therefore, it is necessary to overcome the challenges faced by educational institutions in Colombia to provide their students with the best education. The reports from the Organization for Economic Co-operation and Development are alarming, as they indicate the poor academic performance of Latin American countries. Figure 1 shows that Latin American countries rank at the bottom of the list of 79 evaluated countries in the areas assessed by the PISA test. The nation's average score is below the estimated population's average result.

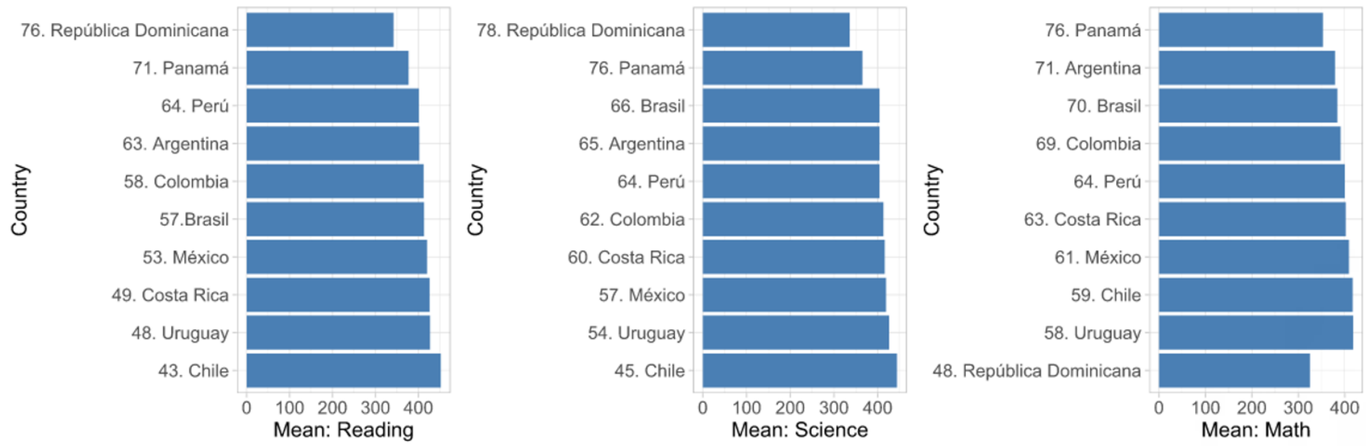

Figure 1: Ranking of PISA evaluation results for the year 2018 (OECD, 2019)

Academic Performance in Higher Education in Colombia

The results of internal assessments conducted in Colombia to evaluate the quality of secondary education confirm the issue of low academic performance (see Figure 2). Since 2016, the average evaluation score administered to students in professional training programs at Higher Education Institutions (IES) in Colombia has been below the value of 150.

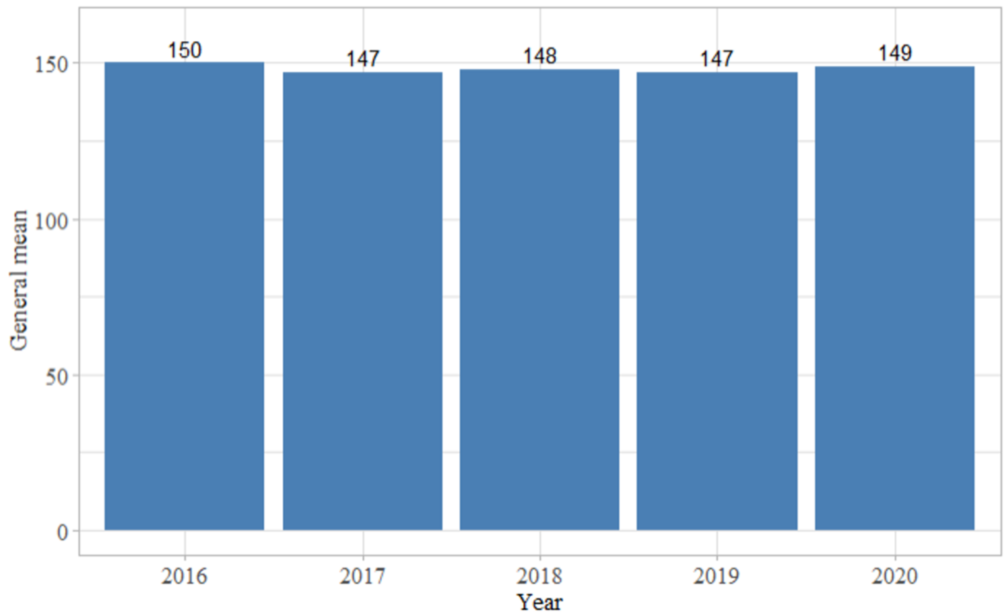

Figure 2: Average of the overall score between 2016 and 2020 (ICFES, 2022)

Previous reports on student academic performance are an issue that must be analysed, addressed, and resolved if the goal set by the United Nations for countries worldwide concerning Education for Sustainable Development is to be met. This is justified through the Sustainable Development Goals (SDGs), a series of targets set by the United Nations to address the world's most pressing global challenges to promote sustainable development worldwide. These objectives cover many areas, from poverty eradication to climate action and quality education (Chankseliani and McCowan, 2021). Specifically, one of the SDGs is Goal 4, which aims to "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all." Quality education is essential for achieving sustainable development, as it equips individuals with the skills and knowledge required to understand current and future challenges and find innovative solutions (Ferrer-Estévez and Chalmeta, 2021).

In engineering, quality education plays a crucial role in promoting sustainability. Students and professionals in engineering are fundamental in creating sustainable solutions to social, economic, and environmental challenges. Therefore, it is vital that quality education addresses the principles of sustainability and equips students with the necessary skills to design, develop, and manage projects that are socially responsible, environmentally friendly, and contextually appropriate (Kopnina, 2020) Education for Sustainable Development (ESD).

In this vein, engineering programs incorporating sustainability into their curriculum raise awareness of the environmental and social impacts of engineering projects. Thus, it teaches students to consider energy efficiency, waste management, responsible use of natural resources, and social equity when designing technical solutions. At the same time, students must also evaluate and communicate the impacts of their projects in terms of sustainability (Chankseliani and McCowan, 2021). Additionally, engineering education can directly contribute to the achievement of several SDGs, such as SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 11 (Sustainable Cities and Communities). By equipping future engineers with knowledge about renewable energies, clean technologies, and sustainable urban design, the groundwork is being laid for more sustainable and resilient development. Therefore, quality engineering education that addresses sustainability principles prepares students to tackle current and future challenges from a responsible and sustainable perspective. Integrating sustainability into engineering education can drive innovation and promote more equitable, resilient, and environmentally respectful development (Avelar et al., 2019) but evolving, field. To conceptualize the phenomenon, accumulated ideas from a total of 193 articles were extracted through a secondary data source, the Web of Science™. The analysis proceeds in two sequential steps. First, the bibliometric analysis identified the networks of co-authorship, periodicals, higher education institutions (HEI).

However, all of this is overshadowed by the context of low performance presented at the beginning of this section. In response to this concern, various authors consider the possible causes of low academic performance, which may include i) the quality assessment approach for educational institutions (OECD, 2019), ii) how variables of interest are analysed (Rodríguez and Huertas, 2016), and iii) differing information on variables that determine academic performance (Pérez, 2019). These causes may also be due to the lack of an educational management tool to analyse student academic information and make accurate decisions regarding academic performance.

The first possible cause of low academic performance contemplates that the quality assessment for educational institutions is obtained by fulfilling three substantive activities (teaching, research, and social outreach or extension) and other specific requirements according to the accreditation requested. Additionally, Duque Oliva and Chaparro Pinzón (2012) consider that quality in education has different focuses: quality as prestige-excellence, quality based on resources, quality as a result, quality as change (added value), quality as an adjustment to purposes, quality as perfection or merit, quality as a program's conformity with prior minimum quality standards through accreditation processes, quality as a cost-value ratio, and quality as suitability for meeting the needs of the recipients or clients.

In Colombia, since 2016, the quality of educational institutions is estimated using the concept of quality as a result, which largely depends on the performance that students from the institution achieve in various evaluations, and quality as change (added value), which is granted based on the influence that the institution has on student performance (ICFES, 2022), it is worth noting that education experts suggest using this approach (Gamboa et al., 2003; Quintero Caro, 2018).

The second cause is that each approach mentioned considers different sets of factors or variables that intervene in educational processes based on an analysis, this makes quality in education a complex concept to define and possibly a multi-dimensional concept with multiple methods for its estimation (Santos et al., 2020) this process requires the development of a theoretical framework in order to analyse the impact of universities' social responsibility strategies on service quality and students' satisfaction with higher education. The present study sought to identify the factors defining students' perceptions of university social responsibility (USR). In the case of quality estimation in Colombia, Pérez (2019) states that the controls carried out on education measure a specific moment of education without considering the evolution of students, evidencing a poor understanding of the situation and, consequently, incorrect solutions to this problem.

The quality of higher education institutions in Colombia is estimated through information from the Saber PRO evaluations (conducted by final-year students in professional programs) (ICFES, 2022). Table 1 presents the variables collected for the evaluation model, and it is observed that they are qualitative; moreover, only the socio-economic information of the student is considered, and no past academic level is taken into account. Therefore, the inferences about the results may not be sufficient to understand current academic performance.

Variable	
Age	Sex
Socio-economic status	Scholarship
Region	Student loan
Type of institution	Head of the household
Tuition fee	Father's education
Hours on the internet	Mother's education
Semester	Public school
Socio-economic level	Private school

Table 1: Survey Variables in the Saber PRO Assessment Used for the Quality Evaluation Model

Lastly, the third cause relates to how variables are analysed, as they are crucial for generating accurate conclusions. According to Rodríguez and Huertas (2016), there are degrees of correspondence between deficient, acceptable, and outstanding academic performance. These authors argue that quality evaluation should consider, for instance, to what extent performance is deficient if an institution exhibits poor academic results. Similarly, if an institution has an acceptable academic performance, to what extent is it considered acceptable? Moreover, if an institution has an outstanding academic performance, to what extent is it considered outstanding?

Considering the challenges above, this research aims to answer the question: What tool should Higher Education Institutions utilise to identify the trajectory (in terms of benchmarking) they should follow to improve their students' academic performance?

LITERATURE REVIEW

Overview of the Colombian Higher Education System

The higher education system in Colombia is characterised by its diverse range of institutions, which include public and private universities, technological institutes, and technical professional institutions (Altbach et al., 2009). The system is governed by the Ministry of National Education, which defines policies and regulations and evaluates and accredits institutions (Ntshoe and Letseka, 2010) and quality assurance, movements have become highly contested issues in the advent of new managerialism1 in higher education. This is because while the notion of quality is critical to institutional autonomy and academic freedom, there are no universal criteria to determine quality in the current conditions of global competitiveness and new managerialism. In this chapter we analyze quality measures and the quality assurance movement in the current global market economy. We investigate ways in which the quality assurance movement has shaped higher education policy and practice and impacted national, regional, and international priorities. The chapter's emphasis is on the following areas: (a. There has been significant growth in higher education enrollment over the past two decades, with a notable increase in private institutions (Barr and Turner, 2013).

Despite the growth of the higher education sector, Colombian higher education institutions (HEIs) face several challenges, such as improving access, equity, and quality (Acosta and Celis, 2014). Moreover, there is a need to enhance teaching and research effectiveness and increase the internationalisation of Colombian HEIs (Navas et al., 2020). On the other hand, the higher education sector also presents opportunities for growth and improvement, such as the potential for collaboration between institutions, innovative teaching and learning methods, and the integration of new technologies (Castro, 2019) dynamics, and actors' interactions, particularly concerning technological innovations. This paper aims to identify some of the most promising trends in blended learning implementations in higher education, the capabilities provided by the technology (e.g., datafication).

State evaluations of higher education institutions play a crucial role in assessing the quality and performance of these institutions, providing valuable information for decision-making processes, and promoting accountability (Shriberg, 2002). State evaluations typically include assessments of teaching, research, community engagement, governance, and management (Abelson et al., 2003). Consequently, national or regional agencies conduct these evaluations and can serve various purposes, such as accreditation, funding allocation, or performance benchmarking (Font, 2002).

In Colombia, state evaluations of higher education institutions are conducted by the National Council for Higher Education Accreditation (CNA) and the Colombian Institute for the Evaluation of Higher Education (ICFES). The CNA is responsible for accrediting institutions based on their compliance with established quality criteria, while the ICFES evaluates the performance of students and programs through standardised tests. These evaluations are a basis for developing national policies and strategies to improve the higher education sector.

Application of Fuzzy Data Envelopment Analysis in Higher Education Performance Evaluation

Fuzzy Data Envelopment Analysis (Fuzzy-DEA) has developed as an essential method for evaluating the performance of higher education institutions, especially when data are imprecise, ambiguous, or subjective. Accounting for the inherent imprecision of input and output characteristics, Fuzzy-DEA has been utilised in several studies to assess the efficiency of higher education institutions in diverse scenarios.

Nojavan et al. (2021) utilised Fuzzy-DEA to evaluate eight higher education institutes in Iran. The study resolved the ambiguity of assessing research quality and its effect on overall efficiency scores by applying fuzzy logic. Their study indicated considerable differences in research efficiency across the examined institutions, shedding light on the aspects contributing to successful research performance.

Similarly, Nazarko and Šaparauskas (2014) applied Fuzzy-DEA to assess the efficiency of university departments, considering the uncertainty associated with the inputs and outputs variables such as number of professors, number of students, equipment and income. Their study found substantial differences in efficiency scores among the university departments, with most institutions operating below their maximum efficiency levels. Their research findings highlighted the need for resource equipment and space improvements to enhance overall performance in the higher education sector.

Aparicio et al. (2019) used Fuzzy-DEA to evaluate the performance of US students and schools participating in PISA (Programme for International Student Assessment) 2015. Their study provided a more robust and comprehensive assessment of educational performance by accounting for the imprecision and subjectivity of input and output factors. The results provide a framework to set the notion of fuzziness in some variables, such as students' socio-economic status or test scores.

In addition to these studies, Fuzzy-DEA has also been used to assess the efficiency of higher education institutions in other countries, such as Phillipines (Mirasol-Cavero and Ocampo, 2021), Taiwan (Liu and Chuang, 2009), and India (Singh et al., 2022). These studies have demonstrated the value of Fuzzy-DEA as a flexible and robust tool for evaluating the performance of higher education institutions, particularly in contexts where data are subject to uncertainty, imprecision, or subjectivity.

In Colombia, the use of Fuzzy-DEA in evaluating the performance of higher education institutions remains restricted, giving a potential for more study and analysis. By introducing fuzzy logic into the DEA framework, the present study attempts to provide a more thorough and nuanced evaluation of the relative contribution of Colombian higher education institutions based on state evaluations. Thus, this study aims to create a tool for educational management to evaluate students' academic performance in the industrial engineering program. Additionally, it is necessary to consider i) the quality assessment approach for educational institutions, ii) how the variables of interest are analysed, and iii) the variables that determine academic performance.

Consequently, it is essential to recognise the research that has been conducted to date in this field. Table 2 presents a summary of the literature review, in which only quantitative research studies were considered due to the focus of this study. Additionally, it is important to note that the identified research has an added-value approach for quality assessment (used in Colombia) due to the implementation of Data Envelopment Analysis models (De La Hoz et al., 2021).

Authors	Variables	Location	Population
Johnes (2006)	Academic scores, number of undergraduate and graduate students, library expenditure (Fuzzy logic approach)	England	130 universities
Nazarko and Šaparauskas (2014)	Financial expenses, faculty, student-to-administrative staff ratio	Poland	19 universities
Do and Chen (2014)	Staff, expenses, university area, credit-hours, publications, and scholarships (Fuzzy logic approach)	Vietnam	18 universities
Galbraith and Merrill (2015)	Academic performance and Burnout measures	United States	350 graduate students in economics and business
Alabdulmenem (2016)	Faculty and administrative staff, number of students, number of graduates	Saudi Arabia	25 universities
Visbal-Cadavid et al. (2017)	Financial resources, quality indicators, accreditations, and achievements	Colombia	32 universities
Wolszczak-Derlacz (2017)	Faculty, total income, number of students, bibliographic production, number of graduates	Europe and United States	500 universities
Aparicio et al. (2019)	PISA 2015 assessment outcomes (Fuzzy logic approach)	PISA Tests	United States
Agasisti et al. (2019)	Faculty, government investment, and PISA results	Europe	24 countries
Kalapouti et al. (2020)	Faculty and administrative staff, spending on research and development, and patents	United States	182 regions
Nojavan et al. (2021)	Outcomes of academic performance evaluations for HEIs (Higher Education Institutions) (Fuzzy logic approach)	Iran	30,000 Iranian students
Aparicio et al. (2021) the so-called plausible values, which are frequently interpreted as a representation of the ability range of students. In this paper, we focus on how this information should be incorporated into the estimation of efficiency measures of student or school performance using data envelopment analysis (DEA)	PISA 2015 assessment outcomes (Fuzzy logic approach)	PISA Tests	72 countries

Table 2: A literature review of papers using the fuzzy data envelopment analysis model

MATERIALS AND METHODS

The current research focuses on three fundamental concepts: Fuzzy Logic, Data Envelopment Analysis, Machine Learning and Methodology.

Fuzzy Logic

The objective of fuzzy logic is to mathematically represent the ambiguity of expressions or events that are observed in everyday life. In other words, the fuzzy numbers represent the uncertainty generated at the borders of the qualifiers (high, medium, low) that describe an event, for example, a student's performance (Rodríguez and Huertas, 2016).
On the other hand, mathematically, a fuzzy set is defined as presented in equation (1).

$$A=\{(x,\mu_A(x))\},x\in X \quad (1)$$

Thus, the expression $\mu_A(x)$ represents the membership level of x in A and μ_A is the membership function associated with A. The equation defines the level at which each element of X belongs to the fuzzy set; it should be noted that X take values in $R:[-\infty,+\infty]$.
Finally, there exists a series of fuzzy numbers whose usage depends on the event or linguistic variable one wishes to represent. Figure 3 shows the graphical representation of a triangular fuzzy set (a) and another triangular fuzzy set (b). It should be noted that these are the most commonly used sets. The difference lies in the results for the membership function according to the same value of X.

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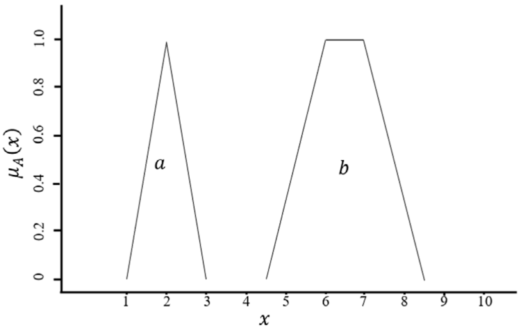

Figure 3: Graphical representation of a triangular fuzzy set (a) and a trapezoidal fuzzy set (b)

Data Envelopment Analysis

The Data Envelopment Analysis (DEA) methodology proposed by Charnes, Cooper, and Rhodes (Charnes et al., 1978) is a non-parametric approach for estimating the relative efficiency of Decision Making Units (DMUs). The outcome of the DEA model is a frontier made up of the most efficient DMUs in the study; it is essential to note that only the DMUs on this frontier are considered efficient.

To construct the DEA model, it is necessary to establish its configuration, which consists of scale return and orientation. First, the scale return can be either constant or variable. It is constant when estimating the system's overall efficiency, which involves understanding all the parts contributing to efficiency outcomes. On the other hand, variable returns are used to observe resource utilisation for each system unit. In other words, this scheme focuses on one aspect of efficiency; therefore, efficiency with variable returns will always be higher than with constant returns.

Additionally, orientation is important for the model's configuration and can be either input-oriented or output-oriented. Input orientation implies that resources or inputs can be reduced to achieve a greater or equal level of outputs. Conversely, an output-oriented model suggests that products or outcomes can be increased using the same input level.

Lastly, equation (2) presents the linear programming model of DEA (León et al., 2003). This model compares the ratio of outputs to inputs. It is worth noting that one DMU will be more efficient than another based on its ability to generate higher output levels with a given input level.

$$\begin{aligned}
&\min \theta_0 \\
&Subject\,to: \sum_{j=1}^{n} \lambda_j \bar{x}_{ij} \leq \theta_0 \tilde{x}_{i0}, i = 1, \dots, m \\
&\sum_{j=1}^{n} \lambda_j \bar{y}_{rj} \geq \tilde{y}_{r0}, r = 1, \dots, s \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \geq 0, j = 1, \dots, n
\end{aligned} \tag{2}$$

where, θ_0 is the value of the efficiency of DMU 0, λ_j is the weighting of DMU j, $\bar{x}_{ij}$ is the fuzzy amount of resource i consumed by DMU j, $\tilde{x}_{i0}$ is the fuzzy amount of resource i consumed by DMU 0, $\bar{y}_{rj}$ is the fuzzy amount of output r produced by DMU j, $\tilde{y}_{r0}$ is the fuzzy amount of output r produced by DMU 0, n is the number of DMUs, m is the number of resources, and s is the number of outputs.

Consequently, equation (3) presents the DEA model in its version for fuzzy data analysis (León et al., 2003).

$$\begin{aligned}
&P_T^h \min \theta_0 \\
&subject\,to: \sum_{j=1}^{n} \lambda_j x_{ij} - (1-h) \sum_{j=1}^{n} \lambda_j \alpha_{ij} \leq \theta_0 x_{i0} - (1-h)\theta_0 \alpha_{i0}, i = 1, \dots, m \\
&\sum_{j=1}^{n} \lambda_j x_{ij} + (1-h) \sum_{j=1}^{n} \lambda_j \alpha_{ij} \leq \theta_0 x_{i0} + (1-h)\theta_0 \alpha_{i0}, i = 1, \dots, m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - (1-h) \sum_{j=1}^{n} \lambda_j \beta_{rj} \geq y_{r0} - (1-h)\beta_{r0}, r = 1, \dots, s \\
&\sum_{j=1}^{n} \lambda_j y_{rj} + (1-h) \sum_{j=1}^{n} \lambda_j \beta_{rj} \geq y_{r0} + (1-h)\beta_{r0}, r = 1, \dots, s \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&h = 0, \dots, 1 \\
&\lambda_j \geq 0, j = 1, \dots, n
\end{aligned} \tag{3}$$

where, x_{ij} is the amount of resource i consumed by DMU j, h is the possibility level, α_{ij} is the alpha cut-off level for resource i consumed by DMU j, x_{i0} is the amount of resource i consumed by DMU 0, α_{i0} alpha cut-off level for resource i consumed by DMU 0, y_{rj} is the quantity of output r produced by DMU j, β_{rj} is the betha cut-off level for output r produced by DMU j, y_{r0} is the amount of output r produced by DMU 0, and β_{r0} is the alpha cut-off level for output r produced by DMU 0.

Machine Learning

Two machine learning algorithms are used to support this research's development: Random Forest and Logistic Regression Boosted.

Random Forest

The Random Forest (RF) technique is a supervised machine-learning model and is mainly used for classification (De La Hoz et al., 2021). This model makes use of the democracy criterion, which consists of the creation of multiple responses that will be counted and the final response is classified according to the highest frequency (Louppe, 2014). On the other hand, the main parameters of the RF technique are number of trees (k) and number of variables needed to divide the nodes (m).

Logistic Regression

The Logistic Regression technique proposes the probability ratio (odds). This is the ratio between success and failure in a Bernoulli event. This algorithm predicts the probabilities of success of the diverse levels of the response variable, using the inverse of the logarithm of the probability ratio as a function of the linear predictor.

Boosting Models

The algorithms belonging to the Boosting model family aim to achieve robust and sophisticated predictions from a single model. These algorithms train multiple weak models to generate a robust final model that feeds on information from the weak models (Chen and Guestrin, 2016). This algorithm is also known as a generic and non-specific algorithm, so it is crucial to define the base model (for example, DT, GLMNET, NB, among others) and then it will be improved. This research will apply Boosting to the Logistic Regression model (LogitBoost).

Methodology

The current research is divided into two stages (See Figure 4): efficiency analysis and predictive assessment. In the first stage, fuzzy data analysis is conducted using the technique of Fuzzy Data Envelopment Analysis to estimate the relative efficiency of the Decision-Making Units. Then, in the second stage, a predictive analysis of the efficiency profiles found in the first stage is designed. The results of these two stages allow for generating useful information for decision-making in educational environments.

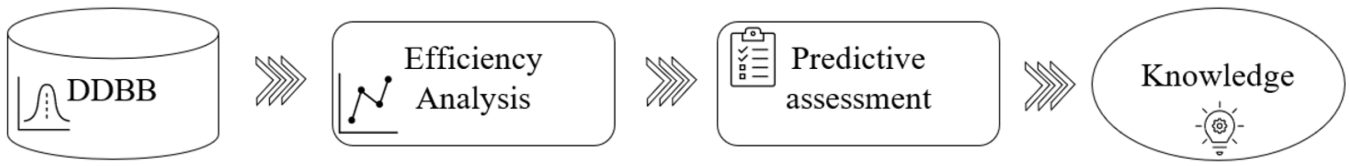

Figure 4: Research methodology (own elaboration)

Data

The data corresponds to the Mendeley's repository of the paper by Delahoz-Dominguez et al. (2020). For the present research, 92 universities (DMUs) are evaluated to summarise the results of the standardised evaluations of high school (Saber 11 - inputs) and university (Saber PRO – outputs) of 4,976 students of the Industrial Engineering program in Colombia (See Table 3). It is important to note that: first, 57% of the institutions evaluated in the database are private. Second, characteristics such as size and age are not homogeneous. And finally, 13.27% of the analysed universities are in socio-economic level 1 (low), 68.37% in level 2 (medium-low), 7.14% in level 3 (medium-high) and 11.22% in level 4 (high).

Variable	Full name	Test	Average	Deviation
MAT_11	Math	Saber 11	61.84	6.96
CR_11	Critical Reading	Saber 11	58.83	5.10
CS_11	Citizenship skills	Saber 11	58.93	5.11
BIO_11	Biology	Saber 11	61.71	6.43
ENG_11	English	Saber 11	58.67	7.50
QR_PRO	Quantitative Reasoning	Saber PRO	73.45	12.33
CR_PRO	Critical Reading	Saber PRO	57.74	12.81
CS_PRO	Citizenship skills	Saber PRO	54.71	11.92
ENG_PRO	English	Saber PRO	62.46	14.72
WC_PRO	Writing Communication	Saber PRO	50.94	8.79
FEP_PRO	Formulation of Engineering Project	Saber PRO	145.84	24.50
ACCP	Academic Program	-	-	-

Table 3: Data summary

On the other hand, for the information analysis, the R software is used (Coll-Serrano et al., 2018; R Core Team, 2013).

RESULTS

Stage 1: Efficiency Analysis

As mentioned, the models used correspond to the two-scale returns of the classic DEA model (CRS Constant, VRS Variable) and scale performance (RTS = CRS/VRS). Table 4 presents the efficiency results of the constant scale model; Table 5 presents the efficiency results of the variable scale model and Table 6 presents the efficiency results of scale performance.

The tables mentioned (4, 5 and 6) contain the level of possibility (h-level or alpha cut), the count of efficient DMUs (Count eff) and the percentage of efficient DMUs, the average (Mean), standard deviation (SD), minimum value (min), quartile one, two and three of the efficiency levels of the DMUs.

Considering the above, Table 4 shows how level h affects efficiency. As the h level increases, the number of efficient DMUs, the average efficiency level, the minimum efficiency value and the quartiles decrease.

On the other hand, although the efficiency model with variable scale return presents a similar behaviour as the model with a constant scale, the efficiency level is higher (see Table 5).

Finally, the model scale performance results equal the constant scale model. This indicates the difficulty that some DMUs could have in achieving the system's overall efficiency, so it is necessary to generate strategies to increase the efficiency of these DMUs.

Consequently, Table 7 presents a non-random sample of the top 10 DMUs for the model with constant scale, variable scale, and scale performance. Table 7 shows a similar efficiency behavior as in the summary tables (4, 5 and 6). For example, for the model with constant scale, no DMU of the sample has crisp efficiency; that is, the DMU is always efficient for the distinct levels of the possibility of h. On the other hand, for the model with variable scale the DMUs U3, U4, U5, U6, U9 and U10 have crisp efficiency. Finally, the efficiency of the scale performance has results comparable to the model with constant scaling; therefore, it does not have DMU with crisp efficiency. It should be noted that for the possibility level $h = 0$, the efficiency scores are always higher than those that would be obtained in the conventional evaluation of the centers of fuzzy triangular numbers ($h = 1$).

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	68 (69%)	0.992	0.017	0.911	0.994	1.000	1.000
0.100	59 (60%)	0.990	0.019	0.903	0.990	1.000	1.000
0.200	57 (58%)	0.986	0.023	0.894	0.981	1.000	1.000
0.300	52 (53%)	0.982	0.027	0.883	0.972	1.000	1.000
0.400	43 (44%)	0.977	0.032	0.871	0.960	0.996	1.000
0.500	37 (38%)	0.970	0.038	0.859	0.950	0.990	1.000
0.600	36 (37%)	0.962	0.044	0.836	0.931	0.980	1.000
0.700	31 (32%)	0.953	0.051	0.803	0.913	0.971	1.000
0.800	29 (30%)	0.943	0.058	0.773	0.894	0.961	1.000
0.900	26 (27%)	0.932	0.065	0.745	0.877	0.949	1.000
1.000	20 (20%)	0.921	0.073	0.716	0.857	0.938	0.997

Table 4: Results of the efficiency model with constant scale

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	85 (87%)	0.998	0.006	0.962	1.000	1.000	1.000
0.100	85 (87%)	0.998	0.007	0.957	1.000	1.000	1.000
0.200	82 (84%)	0.997	0.007	0.953	1.000	1.000	1.000
0.300	80 (82%)	0.997	0.008	0.948	1.000	1.000	1.000
0.400	77 (79%)	0.997	0.009	0.943	1.000	1.000	1.000
0.500	71 (72%)	0.996	0.009	0.939	0.999	1.000	1.000
0.600	68 (69%)	0.995	0.010	0.935	0.996	1.000	1.000
0.700	65 (66%)	0.994	0.011	0.931	0.993	1.000	1.000
0.800	63 (64%)	0.993	0.012	0.927	0.989	1.000	1.000
0.900	56 (57%)	0.992	0.013	0.923	0.988	1.000	1.000
1.000	52 (53%)	0.991	0.015	0.919	0.986	1.000	1.000

Table 5: Results of the efficiency model with variable scale

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	68 (69%)	0.994	0.014	0.927	0.999	1.000	1.000
0.100	59 (60%)	0.992	0.017	0.918	0.993	1.000	1.000
0.200	57 (58%)	0.989	0.021	0.910	0.989	1.000	1.000
0.300	52 (53%)	0.985	0.025	0.894	0.981	1.000	1.000
0.400	43 (44%)	0.980	0.030	0.879	0.969	0.998	1.000
0.500	37 (38%)	0.974	0.035	0.863	0.955	0.994	1.000
0.600	36 (37%)	0.966	0.042	0.836	0.937	0.984	1.000
0.700	31 (32%)	0.958	0.049	0.803	0.918	0.980	1.000
0.800	29 (30%)	0.949	0.056	0.773	0.900	0.975	1.000
0.900	26 (27%)	0.940	0.064	0.745	0.883	0.966	1.000
1.000	20 (20%)	0.929	0.072	0.716	0.866	0.953	0.998

Table 6: Model scale performance efficiency results

CRS – Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	0.956	0.961	1.000	0.999	0.974	0.911	0.962	0.981
0.100	0.999	1.000	0.949	0.948	1.000	0.993	0.954	0.903	0.955	0.974
0.200	0.989	1.000	0.941	0.934	1.000	0.982	0.935	0.894	0.950	0.968
0.300	0.977	1.000	0.930	0.921	1.000	0.968	0.922	0.883	0.939	0.960
0.400	0.957	0.997	0.912	0.901	0.992	0.955	0.912	0.871	0.928	0.952
0.500	0.938	0.990	0.892	0.870	0.982	0.941	0.900	0.859	0.917	0.942
0.600	0.922	0.983	0.871	0.836	0.964	0.928	0.886	0.842	0.902	0.929
0.700	0.908	0.976	0.849	0.803	0.940	0.913	0.872	0.823	0.884	0.914
0.800	0.892	0.968	0.826	0.773	0.918	0.898	0.855	0.803	0.861	0.898
0.900	0.873	0.957	0.804	0.745	0.896	0.880	0.836	0.782	0.838	0.882
1.000	0.854	0.943	0.781	0.716	0.874	0.859	0.817	0.761	0.816	0.864
VRS - Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000
0.100	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000
0.200	1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.982	1.000	1.000
0.300	1.000	1.000	1.000	1.000	1.000	1.000	0.997	0.981	1.000	1.000
0.400	1.000	1.000	1.000	1.000	1.000	1.000	0.994	0.980	1.000	1.000
0.500	1.000	1.000	1.000	1.000	1.000	1.000	0.991	0.980	1.000	1.000
0.600	1.000	1.000	1.000	1.000	1.000	1.000	0.989	0.979	1.000	1.000
0.700	1.000	0.998	1.000	1.000	1.000	1.000	0.986	0.978	1.000	1.000
0.800	0.998	0.994	1.000	1.000	1.000	1.000	0.983	0.976	1.000	1.000
0.900	0.994	0.991	1.000	1.000	1.000	0.999	0.980	0.975	1.000	1.000
1.000	0.990	0.987	1.000	0.999	1.000	0.999	0.976	0.973	1.000	0.999
RTS - Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	0.956	0.961	1.000	0.999	0.974	0.927	0.962	0.981
0.100	0.999	1.000	0.949	0.948	1.000	0.993	0.954	0.918	0.955	0.974
0.200	0.989	1.000	0.941	0.934	1.000	0.982	0.935	0.910	0.950	0.968
0.300	0.977	1.000	0.930	0.921	1.000	0.968	0.925	0.900	0.939	0.960
0.400	0.957	0.997	0.912	0.901	0.992	0.955	0.917	0.889	0.928	0.952
0.500	0.938	0.990	0.892	0.870	0.982	0.941	0.908	0.877	0.917	0.942
0.600	0.922	0.983	0.871	0.836	0.964	0.928	0.897	0.861	0.902	0.929
0.700	0.908	0.978	0.849	0.803	0.940	0.913	0.884	0.842	0.884	0.914
0.800	0.894	0.973	0.826	0.773	0.918	0.898	0.870	0.823	0.861	0.898
0.900	0.879	0.966	0.804	0.745	0.896	0.881	0.854	0.803	0.838	0.882
1.000	0.863	0.955	0.781	0.716	0.874	0.860	0.837	0.782	0.816	0.865

Table 7: Sample efficiency result for 10 DMUs

Table 8 also generates a concept called fuzzy set of effective units. In this sense, a fuzzy set is represented as the name of the DMU and the value of the maximum level h with which the DMU is still efficient, for example, for the model with constant scale the DMU U1 is efficient for the values h equal to 0, 0.1 and 0.2, then the set is (U1, 0.2).

Model	Effective diffuse assembly
CRS	(U1, 0.2), (U2, 0.4), (U5, 0.3), (U6, 0)
VRS	(U1, 0.8), (U2, 0.7), (U3, 1), (U4, 1), (U5,1), (U6, 1), (U7, 0.3), (U9, 1), (U10, 1)
RTS	(U1, 0.1), (U2, 0.4), (U5, 0.3), (U6, 0.1)

Table 8: Fuzzy set of effective units for 10 DMUs

On the other hand, the advantage of the model is the creation of an efficient route (see Table 9), the path that a non-efficient DMU must follow to become efficient and reach the maximum level of efficiency projected for its group. Two efficient routes were created that correspond to the low-medium efficiency levels (range between the 0th percentile and the 66th percentile of efficiency) and high efficiency (range between the 67th percentile and the 100th percentile of efficiency). For the development of the two routes, all the non-efficient DMUs of the model with constant scale were compared and grouped by efficiency level. Then, the score value of the references between DMUs of the model (lambdas) was observed and ordered from lowest to highest. Finally, DMU sequences were selected more frequently.

Name group	Efficiency path	Efficiency level
Path 1	U61 - U48 - U45	[0 - 0.94]
Path 2	U39 - U48 - U69	(0.94 - 1]

Table 9: Efficient paths

The efficient routes are composed of the DMUs of Table 10, each route has an expected increase from the competencies of Saber 11 to the competencies of Saber PRO (Diff). For example, path 1 generates a 14.7% increase in learning outcomes from Saber 11 to Saber PRO. It should be noted that the increase must be gradual, that is, it must first reach the efficiency of the first DMU of the route, then the second DMU and so, until reaching the last DMU of the route, consequently, the DMU that passes through the path will be efficient.

Finally, this section presents the analysis of two population variables: type of institution and socio-economic level. Table 11 presents a summary of the efficiency of public and private institutions.

Similarly, Table 12 shows the efficiency analysis according to the universities' socio-economic level.

Path	DMU	Saber 11						Saber PRO						Diff
		MAT	CR	CC	ENG	BIO	Mean	QR	CR	CC	ENG	WC	Mean	
1	U61	72.96	67.69	67.68	65.50	72.05	77.67	91.53	81.41	77.19	78.72	59.50	69.18	10.9%
	U48	61.88	59.52	61.02	59.74	61.52	70.38	89.32	70.22	55.18	69.94	67.22	60.74	13.7%
	U45	66.08	63.65	62.61	71.69	66.53	77.51	81.07	70.46	71.82	86.75	77.43	66.11	14.7%
2	U39	68.83	64.12	64.36	63.52	66.79	74.50	92.48	74.87	70.96	75.56	58.61	65.53	12.0%
	U48	61.88	59.52	61.02	59.74	61.52	70.38	89.32	70.22	55.18	69.94	67.22	60.74	13.7%
	U69	70.04	65.08	63.67	70.86	68.63	79.28	86.87	74.97	77.97	85.08	71.52	67.65	14.7%

Table 10: Characterisation of efficient paths

University	Count eff			Mean			Standard deviant		
	CRS	VRS	RTS	CRS	VRS	RTS	CRS	VRS	RTS
Private	13	27	13	0.935	0.990	0.944	0.068	0.013	0.065
Public	7	25	7	0.902	0.991	0.910	0.076	0.017	0.076

Table 11: Description of the efficiency of public and private universities

Socio-economic level	Count eff			Mean			Standard deviant		
	CRS	VRS	RTS	CRS	VRS	RTS	CRS	VRS	RTS
L1	2	6	2	0.916	0.985	0.930	0.071	0.019	0.073
L2	10	36	10	0.904	0.991	0.912	0.073	0.015	0.071
L3	2	3	2	0.977	0.993	0.984	0.020	0.007	0.018
L4	6	7	6	0.994	0.996	0.998	0.010	0.007	0.005

Table 12: Description of the efficiency of the university's socio-economic levels

Stage 2: Prediction Analysis

Finally, this stage seeks to suggest a model for predictive evaluation for non-efficient universities in the group analysed. In this sense, the route universities must follow to achieve maximum efficiency is established as a response variable, on the other hand, as predictor variables, the academic competencies of the Saber 11 evaluation and the training program are selected.

The construction of the model consists of two stages: training and evaluation. The data is divided into two groups, corresponding to 70% for training and 30% for evaluation. In summary, two models are used for the training phase: Random Forest and LogitBoost. In addition, the cross-validation technique with 10 folds is used in this phase. The results show that the best-performing model is Random Forest (see Table 13).

Model	Metric	AUC	Accuracy	F1	Sensitivity	Specificity
Random Forest	Mean	0.641	0.650	0.725	0.892	0.600
	SD	0.157	0.093	0.072	0.142	0.274
LogitBoost	Mean	0.593	0.571	0.684	0.883	0.300
	SD	0.146	0.145	0.114	0.153	0.222

Table 13: Results of model training

Then, the models are evaluated with 30% of the study population, and their results are benchmarked. However, as in the training phase, in the evaluation phase, it is observed that the Random Forest model performs better (see Table 14).

Model	AUC	Accuracy	F1	Sensitivity	Specificity
Random Forest	0.710	0.700	0.727	0.667	0.800
LogitBoost	0.570	0.577	0.649	0.545	0.800

Table 14: Results of model testing

Finally, to generate additional information to understand the model with the best performance, Table 15 is constructed. Table 15 shows the importance of the variables of the Random Forest model. It is possible to identify that the variable with greater weight is the academic program, followed by English, Mathematics, Biology, Citizenship Skills, and Critical Reading.

Variable	Weight	Variable	Weight
ACCP	0.035	ENG_11	0.025
MAT_11	0.001	CR_11	0.000
BIO_11	0.000	CS_11	0.000

Table 15: Importance of the variables of the Random Forest model

DISCUSSION

Data Envelopment Analysis using fuzzy data offers an interesting approach for creating decision-making tools in the educational field. First, a significant advantage of this tool is its ability to incorporate uncertainty when formulating the evaluation model. Moreover, the results allow for analysing efficiency level changes concerning the decision variable - results not provided by a classical DEA model. In other words, if there is a substantial change from one level h of measurement to another $h+1$, then it can be asserted that the evaluated Decision-Making Unit (DMU) is sensitive to the measurement variable. This could be a persuasive argument for using the fuzzy approach to evaluate education quality using DEA models. It should be noted that it is essential to understand the context to adapt the model to the situation.

On the other hand, multiple efficiency measures allow for the creation of various alternatives within an action framework. That is, decision-makers can establish an h level for a student's academic competencies and then observe the efficiency level and its efficient path (if it is not already efficient). In this vein, one could know a student's efficiency level in advance to create an action plan that improves their level of academic competencies and, consequently, the efficiency of the university.

According to the research results, variations in competency levels cause significant differences in educational institutions' efficiency. Consequently, the efficiency level of a student's basic competencies greatly impacts the university's efficiency level. In other words, even if a university has an excellent training program, the student's competency level can be critical and decisive in determining the university's efficiency.

The findings on the economic aspect analysed complement this. For example, in the present analysis, the socio-economic level of the university is presented as a factor that has a small impact on university academic efficiency. Also, the diversity in efficiency within each socio-economic level suggests that institution-specific strategies, beyond their economic context, are crucial to achieving efficiency in higher education. And finally, the consistent efficiency in specific academic programmes indicates that the focus and quality of educational provision may be more critical than socio-economic status. Considering the above, it is necessary to generate crisply efficient DMUs, meaning that a DMU can be efficient at any level of academic competencies. This implies that higher educational institutions should have a prior plan that contributes to raising the level of academic competencies, not just for the university's efficiency level but also because a student's academic performance significantly determines their future professional performance.

Additionally, it is necessary to compare the present research with similar works. For example, the research by Nazari-Shirkouhi et al. (2020) develops a tool for evaluating academic performance based on an integrated fuzzy multicriteria decision-making approach. Unlike our research, Nazari-Shirkouhi et al. (2020) emphasise using the Fuzzy Decision-Making Trial and Evaluation Laboratory and Fuzzy Analytic Network Process tools to determine the indicators' weight for the model. This creates a robust framework for variable selection and model construction. In contrast, the research by Contreras et al. (2020) implemented classification models (decision tree, KNN, and perceptron) to predict academic performance. A differentiating point in Contreras et al.'s research is the use of data mining methodology for predicting academic performance; however, failing to consider the fuzzy aspect of information could be a weakness.

Similarly, Valdés Pasarón et al. (2018) research develops an empirical model combining qualitative and quantitative characteristics about the education system to estimate education quality. A point in favor of Valdés Pasarón et al.'s research is the addition of qualitative variables to provide more information for training models using the fuzzy approach. On the other hand, the research by Lee et al. (2019) constructs a model for evaluating and analysing e-learning systems through a matrix. In Lee et al.'s research, a differentiating point is avoiding the problem of potential sampling errors and the complexity of collecting fuzzy linguistic data through evaluative matrix systems.

Lastly, it should be noted that this model does not require expensive or specialised software, but can be implemented using standard DEA or linear programming packages. This could greatly assist researchers who are just starting to develop efficiency models.

CONCLUSION

The present research aimed to design a tool for educational management in a context of uncertainty. To accomplish this, we utilised Data Envelopment Analysis methodology within a framework of uncertainty represented by fuzzy inputs. The research provided a new perspective on evaluating quality in education using DEA models. The designed tool successfully identifies an "efficient path" consisting of universities with standard or ideal efficiency levels, serving as a reference point for universities identified as inefficient to find a path or goal towards increased efficiency. A crucial point in this development is that uncertainty is inherent in every process within the service and production areas. Therefore, the foundation of this research adapts classical DEA models into equivalent "crisp" linear programming formulations.

In addition, the findings show that there is a representation of both public and private efficient universities, with a slightly higher percentage of private universities; however, there is no clear trend indicating that one type of institution (public or private) is more efficient than the other in terms of the academic programmes evaluated. Additionally, some academic programmes, such as Electronic Engineering, Chemical Engineering, Civil Engineering, Mechanical Engineering, and Industrial Engineering, consistently stand out in terms of efficiency, regardless of socio-economic level.

Lastly, this research broadens the scope of knowledge to models that analyse the quality level in education, providing a tool for predictive evaluation under a fuzzy approach. Additionally, future research will consider incorporating Machine Learning models into efficiency evaluation with fuzzy data.

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Full research paper

EDUCATION PERFORMANCE OF CZECH PUBLIC HIGHER EDUCATION INSTITUTIONS USING DATA ENVELOPMENT AND PANEL REGRESSION ANALYSIS

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ABSTRACT
The priority goals of the development of Czech higher education include ensuring the quality of its activities, improving the availability and relevance of flexible forms of education, and increasing efficiency in teaching and research. Several professional articles evaluated educational efficiency, but the proposed models did not include unemployed graduate students. The paper assesses education efficiency at public universities in the Czech Republic in 2020-2021 using an extended Data envelopment model with undesirable outputs, non-proportional and non-radial measures of distance from the efficient frontier. The influence of selected economic, social, regional and institutional factors on education efficiency is estimated by a panel regression model using the Feasible generalized least squares method. The results document the level and development of education efficiency and find insufficient reduction of unemployed graduates as a critical problem of inefficiency. More prominent universities achieve higher education efficiency. The main statistically significant factors influencing changes in education efficiency are population density, the unemployment rate, the location of the university in larger urban centres and the number of students per university employee.

KEYWORDS
Czech environment, Data Envelopment Analysis, education efficiency, education factors, panel regression model, public universities

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Highlights

- *Analysis of education efficiency of higher education institutions in the Czech Republic.*
- *Changes in education efficiency as a result of dividing universities into groups.*
- *The effects of selected factors on education efficiency.*

INTRODUCTION
The Czech education system, including higher education institutions (HEIs), has unique characteristics and structure. The structure is as follows:

- Pre-school Education - optional and available for children between the ages of 3 and 6 (the last year is compulsory).
- Primary Education - compulsory for children aged 6 to 15 in two cycles: the first lasts five years and the second 4 years.
- Secondary Education - optional; students can attend various types of secondary schools, such as grammar schools, technical schools, and vocational schools.
- Higher Education Institutions (HEIs) - optional; students can choose from various higher education institutions, including universities, colleges, and institutes. These institutions may be public and private.

The number of students enrolled in tertiary education within the European Union was around 14.3 million in the years 2015-2020, and there was an annual growth of 2.28% in 2021 (Eurostat, 2023a). The development of these students in the Czech Republic decreased since 2013, from 370.6 thousand to 285 thousand students in 2020, and followed an annual growth of 3.36% in 2021 (Eurostat, 2023a). The tertiary education system in the Czech Republic included 26 public universities, two state universities and 53 private universities in 2021. The number of graduates from public and state universities was 52,328 in 2021 (89%), and for private schools, 5,726 students (11%).

Most HEIs in the Czech Republic are public, which means they receive government funding. Private HEIs operate alongside them, typically funded by tuition fees. The Czech HEIs are subject to quality assurance and accreditation processes to ensure high education standards. The Czech Republic has a National Accreditation Bureau responsible for accrediting programs and institutions. Czech higher education follows the Bologna Process, which aligns with the European Higher Education Area (EHEA). This includes using the three-cycle system (bachelor's - 3 years program (Bc.), master's – 1.5-2 years program (Mgr. or Ing.), and doctoral degrees - 3-4 years program (PhD)) and the European Credit Transfer and Accumulation System (ECTS). Czech HEIs offer various study fields, including humanities, sciences, engineering, and business. Czech universities are involved in research and innovation in various fields. The country has a rich scientific tradition and has contributed to science and technology. There are numerous research centres at the HEIs institutions, and Czech HEIs are active participants in international research collaborations. Many Czech HEIs offer programs mainly in the Czech language. However, there is an increasing number of English programs. Czech higher education is known for its quality and internationalisation. The country attracts students worldwide due to its rich academic tradition, affordable tuition, and diverse study options.

Public and private HEIs in the Czech Republic differ in crucial aspects, including funding, governance, and admission policies. More precisely:

1. Funding - public HEIs in the Czech Republic receive a significant portion of their funding from the government. This funding allows them to offer education at lower tuition fees, primarily to Czech and European Union (EU) or European Economic Area (EEA) citizens. Public HEIs typically have more resources for research and facilities. Private HEIs are funded primarily through tuition fees, research grants, donations, and private investments. Private HEIs have more financial autonomy and rely on student enrollment for revenue.
2. Tuition Fees - tuition fees at public HEIs in the Czech Republic are generally lower, especially for Czech and EU/EEA students. Tuition fees for non-EU/EEA international students vary but are typically higher than for EU/EEA students. Private HEIs often have higher tuition fees for all students.
3. Governance - public HEIs are typically under the authority of the Ministry of Education, Youth, and Sports. They are subject to government regulations and policies, and public sector rules and oversight influence their governance structures. Private HEIs have more autonomy in their governance and decision-making processes.
4. Admission Policies - admission to public HEIs in the Czech Republic is often highly competitive, particularly for popular programs. There are centralised admission procedures for Czech and EU/EEA students. The specific requirements and admission processes vary by institution and program. Private HEIs may have more flexible admission policies and procedures.
5. Programs and Specializations - public HEIs typically offer a wide range of programs and specialisations, including those in high-demand fields. They may have more extensive academic and research resources. Private HEIs may focus on specific fields of study or niche programs. They often tailor their offerings to meet the needs of specific student populations.

It is important to note that public and private HEIs in the Czech Republic are subject to quality assurance and accreditation processes to ensure the quality of education. Nowadays, there are many problems all around the world, especially in the financing of public institutions. To analyse the topic properly with a homogenous group of the HEIs, just the public HEIs are taken, primarily based on the funding.

The Czech higher education system needs more financial resources, especially for public and state universities. Therefore, the critical question is whether the Czech labour market has sufficient capacity to accept university graduates who no longer want to continue their studies, with the growing number of such graduates and the structure of professional orientation. If we follow the unemployment rate of graduates of all universities (*ur_abs*) in the Czech Republic (see Figure 1), it is clear that it decreased from 2013 to 2019 and then oscillated between 4.2% and 4.9%. The figure also shows the difference between public universities (*ur_abs_public*) and private universities (*ur_abs_private),* with lower graduate unemployment rates. The Ministry of Education, Youth and Sports is faced with the question of how to allocate limited financial resources to universities (especially public and state ones), how to evaluate the effectiveness of educational and research activities at universities so that graduates of these universities contribute positively to the development of society and do not burden the social support system unemployed?

The priority goals of the strategic plan for the development of Czech universities after 2021 (MEYS, 2021) include ensuring the quality of their activities, improving the availability and relevance of flexible forms of education, increasing the efficiency and quality of doctoral studies, strengthening strategic management and effective use of capacities in the field of research, teaching and other creative activities, including those of an international nature. Higher education governance should be conceptual, data-driven, and funding-efficient. Therefore, the next part is devoted to evaluating and analysing the education efficiency of universities in the Czech Republic for 2020 – 2021.

This paper proposes a Data Envelopment Analysis (DEA) model to measure and evaluate the efficiency of the educational process at selected universities and analyse the influence of selected economic, social, regional and institutional factors on the development of this efficiency. The proposed DEA model uses the non-proportional directional output distance function (DDF) introduced by Chung et al. (1997), and the DEA model includes undesirable outputs of unemployed college graduates. The goal of the DEA analysis is to find out the leading causes of the failure to achieve effective behaviour of universities. The subject of the investigation will also be the influence of classifying public universities into more homogeneous groups and monitoring group differences. To reveal the influence of

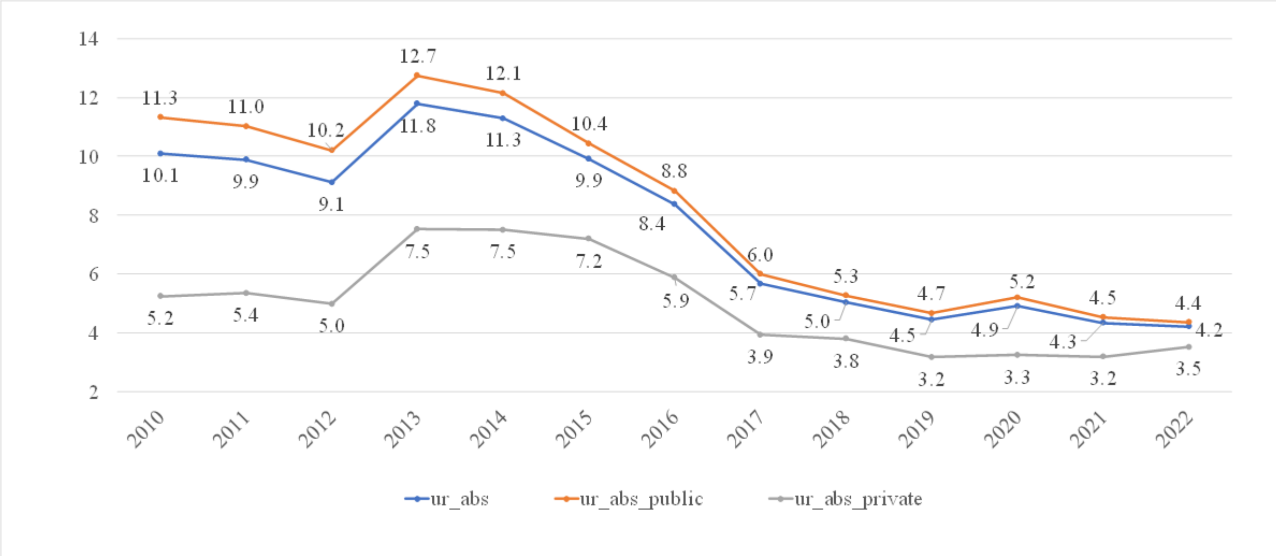

Figure 1: Development of the unemployment rate of university graduates in the Czech Republic, 2010-2022 (data source: Education Policy Center (2022), own calculation)

the factors on the level of education efficiency in the examined period, a panel regression model will be estimated using the FGLS method.

The paper is organised into five sections. Section 2 reviews literature related to the selection of inputs, outputs and the structure of the educational system of universities, the definition of factors affecting the efficiency of the educational process and the specification of the evaluation of education at Czech universities. The description of the input data, the proposal of the new DEA model, and the definition of the methodology for estimating the panel regression model are developed in Section 3. The following section includes the application of the proposed DEA model in the analysis of 26 higher education institutions (HEIs) in the Czech Republic in 2021 and 2021, followed by the estimation of the panel regression model, including the analysis of the results. Section 4 discusses the obtained key results, which are further confronted with other professional literature. Finally, the results are summarised, the limits of the proposed DEA model are defined, and some direction for future research is proposed.

LITERATURE REVIEW

The Bologna Process seeks to ensure the coherence of higher education systems across Europe by creating a European Higher Education Area that facilitates the mobility of students and workers, increases the inclusiveness and accessibility of that education in Europe and strengthens competitiveness on a global scale (European Education and Culture Executive Agency, 2020). A three-level higher education system was introduced: bachelor's, master's and doctoral studies. Conditions were created to ensure the mutual recognition of qualifications abroad and the evaluation of the quality of education. Evaluating higher education, identifying areas for improvement, and ensuring the cooperation of educators and policymakers serve the educational system's effective functioning and sustainable development. Higher education institutions (HEIs) drive economic, social, and regional development. They generate innovation, knowledge creation and human capital formation, all essential for sustainable growth and social progress.

There are different approaches to educational performance assessment. A large group consists of optimisation models of Data Envelopment Analysis, which measure the efficiency of the educational system. Mikušová dealt in the evaluation of educational and research activities at HEIS in both publications, which are discussed below. She used DEA methods, more precisely CRS and VRS model. The first publication (Mikušová, 2015) deals with the DEA applied to Czech public schools from 2013, where academic staff and other costs were used as inputs, whereas graduates and students of bachelor and master programs, and doctoral graduates and students were the outputs of the model. Two analyses were carried out: 1) comparing universities with each other, where the specificities of universities were demonstrated; 2) a comparison of universities divided into three groups with similar cost coefficients, which helps eliminate the high differences in inputs and in outputs led to more accurate results and an understanding of the redistribution of finance at universities in relation to performance. In the second analysis (Mikušová, 2017), an updated analysis with the newest data was performed to confirm the observed division of universities regarding the cost coefficients. The educational system contains academic units (HEIs) that transform inputs into outputs using educational "technologies and processes". The result is finding an efficient boundary where the HEIs with the best practice are identified. For HEIs that are not efficient, the causes of this inefficiency can be identified and quantified. Evaluating higher education's effectiveness can occur at different levels of study programs, departments, faculties, universities, countries, etc. As Mikušová (2017) suggests, it is more appropriate to divide the analysis into smaller and more specific substructures; this helps the condition of better homogeneity of decision-making units, i.e. according to the groups of overall economic difficulty coefficients of the KEN (it is therefore a more specific branch focus). This is more difficult for the Czech Republic to ensure, since there are not so many identical faculties or departments in the Czech Republic. This article focuses on educational units – public HEIs. The key activities of universities are not only education in the sense of teaching but also research and other activities such as lifelong learning, support of the local government or new business of students, etc. This article focuses only on teaching at the bachelor's, master's and doctoral levels.

The global and complex evaluation model of HEIs is documented in the article by Navas et al. (2020). The authors proposed a DEA model for evaluating the performance of 289 HEIs in Colombia from 2010 to 2015. The authors established four models: general and partial models of teaching, employment and research. The average general efficiency of the Colombian HEIs was 0.95. The results were then subjected to a cluster discussion according to various criteria (sub-models, institution size, changes in the number of inputs and outputs). Similarly, the academic effectiveness of 256 study programs was examined in the article by De la Hoz et al. (2021) for 135 public and private universities in Colombia. The study programs were divided into two clusters according to critical competencies. The applied DEA analysis of the effectiveness of the study programs showed that 16% of the study programs were effective. Random Forest and Decision Tree techniques were applied to predict academic effectiveness. Performance assessment in Czech HEIs involves evaluating various dimensions, such as teaching quality, research output, student outcomes, and community engagement. These assessments often inform policy decisions, accreditation processes, and funding allocation. However, the complex nature of HEIs and their diverse range of activities pose challenges for measuring and comparing performance effectively.

In the Czech Republic, Flegl and Vltavska (2013) focused on evaluating the effectiveness of economics faculties in public HEIs comparing 2006-2010 and 2007-2011 periods. The classic output-oriented DEA model was modified by including weighted inputs/outputs. The authors considered three inputs (actual labour costs, number of academic staff, number of students) and one output (research points) The paper evaluates the effectiveness of research and teaching at the Faculty of Economics in public universities in the Czech Republic in two periods (2006-2010 and 2007-2011). The authors use the Data Envelopment Analysis and Index method. Data Envelopment Analysis measures research efficiency according to weighted inputs (average salary of academic staff, number of academic staff and average number of students) to weighted output (RIV points). Teaching effectiveness is measured by weighted performance (average number of graduates). The index approach compares changes between productivity measured in two different ways (RIV points per academic staff, number of students per academic staff) and changes between average wages adjusted for the average rate of inflation. The results of both methods are very similar - for example identifying the "most efficient HEI". However, there are also differences, for example, DEA is considered better in the area of determining efficiency levels and therefore the possibility of compiling a ranking of HEIs according to efficiency and at the same time the possibility of recommendations on how to improve. In contrast, the index method gives the possibility of decomposition and therefore a better understanding of the given area.

Mikušová (2017) also addressed the measurement and evaluation of the effectiveness of public universities in the Czech Republic in 2015. A set of 26 public universities was evaluated using two DEA models assuming (a) constant returns to scale (CCR, Charnes et al., 1978) and (b) variable return to scale (VRS, Banker et al., 1984). The inputs were presented by the number of academic staff, indicator A (number of students in study programs) and indicator K (quality and performance). These indicators are used by the Ministry of Education, Youth and Sports of the Czech Republic when distributing financial resources to universities. Two outputs were presented: the bachelor's and master's graduates and the doctoral graduates. The results show that the average efficiency in the monitored set of HEIs was 0.819 under CRS conditions and 0.885 under VRS conditions. The number of effective HEIs was 50% for the second model. The results were also compared and discussed for three more homogeneous groups divided according to the coefficient of economic difficulties. The main conclusion of this part showed that a higher efficiency of education was achieved in the three more homogeneous groups than in the whole group and that more prominent universities (in terms of number of students) had higher teaching efficiency.

Finally, considering study programs, Flegl, Ticha, and Stanislavska (2013) investigated research efficiency for 29 doctoral study programs at the Czech University of Life Sciences Prague between 2007 and 2011. The DEA model included two inputs (number of PhD students and average length of study) and three outputs (number of graduated PhD students, research quality and a proportion between the number of PhD students and the number of PhD supervisors). The DEA model was based on increasing outputs with given inputs under CRS conditions. It was found that there is a need to improve students' research experiences, provide appropriate conditions for PhD students in departments and improve communication between PhD students and supervisors.

A Literature Search of Used Data

Demosthenous (2017) divided four key factors influencing the educational process – economic, social, cultural and developmental. The author concluded that the measurement and evaluation of the effectiveness of education contribute to the accumulation and growth of human capital and further to the increase of competitiveness on both the micro and macro levels.

Numerous studies have shown a strong correlation between college education and economic development. Economic theory argues that education, as the primary institutional mechanism for the accumulation, production and diffusion of human capital, is also an externality for the spread of market and non-market interests. The importance of education or human capital in the growth process was emphasized by Campbell and Üngör (2020), Fatima et al. (2020), Rossi (2020), Oyinlola and Adedeji (2021) and Braunerhjelm (2022). Similarly, Qi et al. (2022) analysed China's domestic labour market and observed that there was a limited demand for tertiary graduates due to an unbalanced industrial structure, with a weak contribution to economic performance over the past decade. HEIs produce a highly skilled workforce, fostering productivity gains and technological advancements that stimulate economic growth. Research has consistently shown that countries with more college graduates experience higher per capita income, increased labour market participation and reduced unemployment rates (for example the publication by Ferro and Romero (2021)). The main economic factors are labour market needs, innovation and entrepreneurship, economic inequality and industry-academia collaboration.

The effectiveness of public spending on education was analysed by Dufrechou (2016). The study compared the efficiency of 11 upper-middle-income Latin American economies and 24 high-income countries from 1970-2010. Efficiency scores were obtained by applying the DEA model and followed by simulation using bootstrapped truncated panel regressions to estimate the influence of other determinants to explain efficiency. Dufrechou (2016) established one input (real per capita education spending) and two outputs (years of schooling, share of population with secondary education) to evaluate effectiveness, and the basic output-oriented DEA model under VRS was applied. The key conclusion of this study was the finding of a positive trend in the efficiency of public spending, except for an economic slowdown in the years 1973-1990. It has been confirmed that it is necessary to invest in education. The level of globalisation and democracy emerged as the main determinants of efficiency improvement when comparing two groups of countries.

The question of the influence of the *social responsibility* of HEIs on sustainable regional growth and innovation was investigated by Pedro et al. (2022). Effectiveness for 23 public Portuguese HEIs was monitored using teaching and learning, research and technology, and social responsibility activities based on data from semi-structured interviews from 2018-2019. Based on the evaluation of technical efficiency using the output-oriented DEA model under CRS conditions, the influence on sustainable regional growth and innovation intensity of HEIs was determined in the next step using Tobit regressions. The results documented that higher social efficiency was demonstrated by larger HEIs located in large urban centres. Furthermore, the positive effect of teaching and social effectiveness on the regional gross domestic product for peripheral HEIs was proven. Higher education also plays an essential role in the context of social advancement in the form of transformation of individual lives, promoting social mobility and fostering social progress.

Furthermore, HEIs also play a pivotal role in *regional development*, particularly in peripheral or economically disadvantaged areas. They drive regional innovation systems as centres for research, entrepreneurship and collaboration between academia, industry and local communities. Studies have highlighted the positive impact of universities and colleges on local economies, including job creation, increased business activity, and the attraction of external investments, Bukhari et al. (2021). Furthermore, HEIs often contribute to regional development by offering relevant programs tailored to the needs of the local labour market, thus addressing skill gaps and promoting local talent retention (OECD, 2023). Therefore, regional disparities, local labour market, community engagement, infrastructure and connectivity are essential regional factors.

Several professional articles are dedicated to measuring and evaluating education efficiency and research efficiency through DEA models, which are classic single-stage or multi-stage models, usually in the form of network DEA. An example is the article by Wegener and Soummakie (2020) who studied research efficiency of 50 Turkish higher institutions using output-oriented DEA under VRS. This was followed by a beta regression analysis to investigate the influence of external factors such as age, size and ownership of the university. The obtained results showed that the research efficiency of selected HEIs was in the range between 0.548 and 1, with an average efficiency score of 0.898 and 56% of effective HEIs. The main problem for the inefficient HEIs was the low number of published professional articles or registered patents. The estimation of the beta regression model established that large and older universities tended to be more research efficient, and the effect of ownership status efficiency score did not play a significant role.

MATERIALS AND METHODS

This section will first deal with the description of the data used for data envelopment analysis and panel regression analysis. In the next part, the DEA methods and panel regression model estimation methods are described. In the field of data envelopment analysis, it will be both basic methods and methods that deal with an undesirable variable. The regression analysis is then focused on panel data.

Data for public Higher Education Institutions in the Czech Republic

All 26 public HEIs in the Czech Republic were chosen as production units under investigation. The list of these educational units and their other characteristics is given in Appendix 2. The essential characteristics of HEIs include identifier U1 to U26, name of the institution, region of jurisdiction according to NUTS2, the total physical number of students in all forms and levels of study (*stud*), the total average calculated number of educational employees at the institution (*empl*). The source of this information is the annual activity reports for individual universities. Furthermore, the indicator *st_empl* was calculated as the ratio of *stud/empl,* i.e., the number of students per university employee. As mentioned earlier, these indicators will be used to evaluate the "size" of HEIs according to the number of students, the number of employees or the number of students per employee of HEI.

In his article, Rychlík (2018) presented the classification of 26 public universities in the Czech Republic into four groups according to the assessment of quality and performance (indicator K). Group S1 includes four arts colleges, and group S2 includes two non-university colleges. The most numerous group is S3 with 15 smaller universities (smaller universities), and the last group S4 includes five universities that are strong in research (Charles University, Masaryk University, Palacký University Olomouc, Czech Technical University in Prague and Brno University of Technology). The division of these universities into the mentioned groups is considered when distributing financial resources by the Czech Ministry of Education, Youth and Sports.

Descriptive statistics of the number of students (*stud*) in all forms of study in bachelor's, master's and doctoral studies are presented in Table 1 for the years 2020 and 2021.

Group	Year / Statis.	2020 *stud*	2021 *stud*	2020 *empl*	2021 *empl*	2020 *st_empl*	2021 *st_empl*
S1	Mean	726.25	745.50	285.07	282.36	2.49	2.61
	Std. Dev.	499.46	515.04	166.98	168.44	0.36	0.48
S2	Mean	2,711.50	2,617.50	190.48	200.20	14.10	13.03
	Std. Dev.	779.94	685.19	36.18	46.61	1.42	0.39
S4	Mean	8,718.53	8,850.07	1,219.82	1,208.58	7.36	7.55
	Std. Dev.	4,549.81	4,702.17	476.57	480.41	3.20	3.36
S5	Mean	28,001.60	28,474.80	4,819.39	4,756.09	5.95	6.06
	Std. Dev.	13,338.87	13,952.28	2,492.72	2,305.57	1.18	1.20

Table 1: Descriptive statistics of HEIs data, 2020-2021 (source: own calculation, annual reports of universities)

Table 1 shows that group S4 has the most prominent university, with an average number of students of 28,002 in 2020, increasing to an average of 28,475 in 2021. Group S3 includes universities with an average number of students from 8,720 (in 2020) to 8,850 (in 2021), i.e., with slightly lower growth than the S4 group. It can, therefore, be expected that not only research activity but also education efficiency will be higher for group S4 compared to group S3, which also supports the average number of students per employee, which in the group of large universities (S4) is on average 5.95 or 6.06 in 2020 or 2021 and in the group of smaller universities (S3) shows an average of 7.36 or 7.55 in 2020 or 2021.

Data for Data Envelopment Analysis

In order to determine and analyse beta efficiency in educational activity, the input and output variables used in empirical studies were listed in the literature review section. Based on this analysis and given the data availability, the input and output variables of the educational (production) system at universities in the Czech Republic were determined. Two input variables were selected for entry: the number of first-time enrolled students in a bachelor's, master's or doctoral program (*NSTUD*) and the average full-time number of academic staff (*STAFFA*) for each university. At the output of the education system, there were two variables for each HEI: the desirable variable expressed the number of completed and employed graduates of bachelor's, master's or doctoral studies (*ABS*), and the undesirable output was the variable expressing the number of unemployed graduates (*UNABS*) who, as job seekers, are registered at the employment office and successfully graduated from school no more than two years ago. The number of two inputs and two outputs satisfies the rule in relation (4) for 26 universities.

The source of *NSTUD* and *STAFFA* data are annual reports on the activities of individual universities, which are obliged to publish these reports on their websites. The data source for *ABS* and *UNABS* is the database of the Educational Policy Center at the Faculty of Education, Charles University in Prague (Education Policy Center, 2022). The data selected from this database are only for public universities in the Czech Republic for bachelor's, master's and doctoral studies. The data used for DEA are characterised in Table 2, and the values of these indicators are given in Appendix 1.

Item	Variable	Title	Measurement
Inputs	*NSTUD*	Students enrolled in the course for the first time	number
	STAFFA	Average calculated number of academic staff	number
Desirable Output	*ABS*	Number of graduates	number
Undesirable Output	*UNABS*	Number of unemployed graduates	number

Table 2: Description of inputs and desirable and undesirable outputs (source: own processing)

Panel Data for Estimating The Effects of Factors on Education Efficiency

A panel regression analysis explains changes in education efficiency due to changes in economic, social, regional, and institutional factors. In the *economic area*, indicators of gross domestic product, unemployment rate, work intensity, the availability of broadband (i.e., the percentage of households that are connectable to the internet), poverty (i.e., the persons with an equivalised disposable income below the risk-of-poverty threshold, which is set at 60% of the national median equivalised disposable income), the share of university-educated people in the total number of people over 15 years of age. Demographic indicators such as age distribution, population growth, migration and population density were considered *social factors*. The *regional factor* was the NUTS2 variable, expressed by assignment to a region at the CZ01 to CZ08 level (with a value of 1, 2,…, 8): CZ01 (Prague), CZ02 (Central Bohemia), CZ03 (Southwest), CZ04 (Northwest), CZ05 (Northeast), CZ06 (Southeast), CZ07 (Central Moravia) and CZ08 (Moravian Silesia). The largest number of HEIs was in Prague (8), followed by the Southeast (6) (see Appendix 2). The last group is the *institutional factors* of the university. This is, for example, the total number of students (*stud*), the number of all physically calculated employees of the institution (*empl*), or their ratio *st_empl*, i.e., the number of students per employee of the monitored university. The first two institutional indicators represent the university's size, and *st_empl* is one of the indicators of the quality of the educational process). The values of these institutional indicators are presented in Appendix 2 and are based on the annual reports of individual universities.

For the panel regression analysis and explanation of changes in education efficiency, factors representing one of the areas mentioned above (economic, social, regional, institutional), were selected where, the data sets were publicly available, and the factors were not strongly dependent. Table 3 describes the list of these factors and their characteristics.

A group of factors	Variable	Title (data source, data code)	Measurement
economic	*poverty*	at-risk-of-poverty rate by NUTS 2 (Eurostat 2023b, TGS00103)	percentage of total population
	ur	unemployment rate by NUTS2 (Eurostat, 2023b, TGS00010)	percentage
social	*pop_den*	population density by NUTS2 (Eurostat (2023b, TGS00024)	thousand persons per square kilometre
regional	*NUTS2*	basic regions for the application of regional policies	CZ01 – CZ08
institutional	*st_empl*	the number of students per one university employee (Appendix 1)	number

Table 3: Description of the data source of factors for explaining beta education efficiency (source: own processing)

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a non-parametric data-driven methodology widely used to evaluate decision-making units' relative efficiency (DMUs). The literature review focuses on three primary DEA models: CCR, BCC and SBM. The CCR (Charnes-Cooper-Rhodes) model (Charnes et al., 1978) is an original DEA model that assumes a constant return to scale (CRS) for the production function. It measures the relative efficiency of decision-making units by comparing their input-output ratios.

The BCC (Banker-Charnes-Cooper) model (Banker et al., 1984) is an extension of the CCR model that relaxes the assumption of constant return to scale and allows for variable return to scale (VRS). The CCR and BCC models are models where the distance from the efficient boundary is measured radially with the possibility of reducing all inputs or maximizing all outputs. The SBM (Slack-Based Measure) model extends the CCR model by considering the potential for improving efficiency by eliminating input or output slacks. The SBM model was proposed by Tone (2001). The SBM model also incorporates both desirable and undesirable outputs.

Navas et al. (2020) used an extended classical DEA model of Charnes et al. (1978) to evaluate the efficiency of Colombian HEIs by including flexible measures that allow the status of input or output variables to be classified.

To evaluate the efficiency of public HEIs, the classic output-oriented DEA model was modified by introducing:

- non-radial distance measure (DDF - directional distance function),
- non-proportional DDF (i.e., individual desirable outputs can be increased with different intensities, and similarly undesirable outputs can be reduced non-proportionally),
- undesirable outputs.

This model was also used and modified in the publication of Toloo and Hanclova (2021). Let us assume that we have a system of n *DMU*s, i.e., HEIs, where DMU_j (j = 1, 2,…, n), which has m inputs $\boldsymbol{x}_j = \left(\boldsymbol{x}_{ij}\right)$ (i = 1, 2,…, m), desirable outputs $\boldsymbol{y}_j = \left(\boldsymbol{y}_{rj}\right)$ (r = 1, 2,…, s) and undesirable outputs $\boldsymbol{b}_l = \left(\boldsymbol{b}_{lj}\right)$ (l = 1, 2,…, k).

To increase the desirable outputs and reduce the undesirable outputs under a given level of inputs, Chung et al. (1997) introduced a directional output distance function as the joint production of desirable output $\boldsymbol{y}$ and undesirable output $\boldsymbol{b}$:

$$\vec{D}_T\left(x,y,b,g^y,g^b\right) = \sup\left\{\beta \mid (y,b) + \beta\left(g^y,g^b\right) \in T(x)\right\}, \quad (1)$$

where the nonzero vector $g = \left(g^y, g^b\right)'$ is the *direction vector*, and the vector $\beta = \left(\beta^y, \beta^b\right)'$ expresses the *non-proportional intensity* of the increase in desired production y and, simultaneously, the decrease in undesired production $\boldsymbol{b}$. Our DEA model $\left(g^y, g^b\right) = \left(y_o, -b_o\right)$. $T(x)$ is the permissible production technology. To evaluate the education efficiency of each HEI_j, we will look for the joint production (y, b) using the DDF with the following optimisation model:

$$\begin{aligned}
& z_{max} = \left\{w^{y}{}' \cdot \beta^y + w^{b}{}' \cdot \beta^b\right\} = \beta^* \\
s.t.\ & \textstyle\sum_{i=1}^{n} \lambda_j x_{ij} \le x_{io} && i = 1,\dots,m \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \ge \left(1+\beta_r^y\right) y_{ro} && r = 1,\dots,s \\
& \textstyle\sum_{j=1}^{n} \lambda_j b_{lj} \le \left(1-\beta_l^b\right) b_{lo} && l = 1,\dots,k \\
& VRS: \textstyle\sum_{j=1}^{n} \lambda_j = 1 \qquad \lambda_j \ge 0 && j = 1,\dots,n \\
& \beta_r^y, \beta_l^b \ge 0 && \forall\, r,l
\end{aligned} \quad (2)$$

where the vector $w' = \left(w^y, w^b\right)$ is the normalized weight vector, and we assume we have one desirable output and one undesirable output $w' = (0.5, 0.5)'$ for our output-oriented extended DEA model. DMU_j is efficient if corresponding $\beta_j^* = 0$, i.e., $\beta^{*y}_j = 0$ and $\beta^{*b}_j = 0$, otherwise, the monitored unit is inefficient.

Furthermore, a *y-b performance index* (*YBPI*) is introduced for each HEI according to the article by Zhou et al. (2012):

$$YBPI_j = \left(1-\beta_j^{b*}\right)/\left(1+\beta_j^{y*}\right) \tag{3}$$

This index $YBPI_j$ is a proportion where the numerator expresses the average proportion by which the undesirable output can be reduced. At the same time, the denominator measures the degree to which the desirable output can be increased.

To have a reliable result, Cooper et al. (2007, p. 116) claimed that the number of performance measures (inputs and outputs) should satisfy the rule:

$$n \geq \max\left[3(m+s+k), m\cdot(s+k)\right] \tag{4}$$

In conclusion, applying DEA with undesirable output in higher education can explore educational quality and efficiency.

Panel regression analysis

To explain the influence of economic, social, regional, and institutional factors on the education efficiency of HEIs, a panel regression model will be estimated in the second step for a low number of years and 26 cross-sectional units (HEIs). Two estimation methods can be applied to estimate the regression coefficients of such a panel model and other statistics. The first group represents panel estimators with fixed effects (*FE*) or random effects (*RE*), with the Hausman statistical test to help with the selection (Baltagi, 2008). The second group is represented by estimates of the panel regression model using the generalized least squares method (Generalized Least Squares, GLS), where problems in the error term are usually solved, especially for Feasible GLS (FGLS) panel models.

The panel regression model can be formulated as follows:

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + u_{it} = x_{it}' \cdot \beta + \mu_i + \varepsilon_{it} \quad u_{it} = \mu_i + \varepsilon_{it} \tag{5}$$

where $\beta = (\beta_1, \beta_2, \cdots, \beta_k)'$ are the regression parameters, $x_{it} = (x_{it1}, x_{it2}, \cdots, x_{itk})$ are the regressors, μ_i is the fixed or random effect of the i-th unit (HEI) and ε_{it} is the error term with the assumption $\varepsilon_{it} \sim iid(0;\sigma_\varepsilon^2), i = 1,2,\cdots,N \rightarrow and\ t = 1,2,\cdots T$.

For one-way *FE models* μ_i represents a cross-section fixed effect and is the unknown intercept for each *i-th* unit (HEI). Furthermore, within the framework of the *FE model*, it is assumed that with a cross-section fixed effect is designed to study the cases of changes within an entity (HEI). This model assumes that the mean value of the error term is zero and that there is no problem with serial correlation and heteroscedasticity of the error term:

$$\begin{aligned} &E(\varepsilon_{it}) = 0 \\ &E\left(\varepsilon_{it}\varepsilon_{js}\right) = \sigma_\varepsilon^2 > 0 \ for\ i = j, t = s \\ &= 0 \ \text{otherwise.} \end{aligned} \tag{6}$$

In the *RE model*, the error term u_{it} is decomposed into *between-unit error* (μ_i) and *within-unit error* (ε_{it}). The *RE model* assumes that the unit's error term is not correlated with the predictor's regressors:

$$corr\left(\mu_i, x_{itj}\right) = 0 \tag{7}$$

which allows for time-invariant variables to play a role as explanatory variables. The *RE model* is based on the following assumptions:

$$\begin{aligned} &\mu_i \sim iid(0,\sigma_\mu^2 > 0) \quad and \quad \varepsilon_{it} \sim iid(0,\sigma_\varepsilon^2 > 0) \\ &E\left(\mu_i \cdot \mu_j\right) = 0 \ for\ i \neq j \quad and \quad E\left(\varepsilon_{it} \cdot \mu_j\right) = 0 \\ &corr\left(u_{it}, u_{js}\right) = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2} = rho \quad for\ i = j, t \neq s \\ &= 1 \qquad for\ i = j, t = s \\ &= 0 \qquad \text{otherwise.} \end{aligned} \tag{8}$$

Furthermore, for all i and t are μ_i and ε_{it} independent random variables, and the regressors are uncorrelated with x_{itj}. For a RE model, the significance of random effects can be performed using the Breusch-Pagan Langrangian multiplier (LM) test (Breusch and Pagan, 1980), which relies on the null hypothesis $H_0 : \sigma_\mu^2 = 0$ and the alternative hypothesis $H_A : \sigma_\mu^2 > 0$ assuming normality $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$.

To recommend whether to use the *FE* or *RE model*, we use the Hausman specification test, where the null hypothesis supports the *RE model* and the alternative does not support the *RE model*, i.e., the *FE model*.

To estimate the influence of economic, social, regional, and institutional factors on beta efficiency, the second group can also use the estimation through the Feasible Generalized Least Squares (FGLS) approach, which allows the presence of heteroskedasticity or serial and cross-sectional correlation (Bai et al., 2021).

The general panel regression model described in Equation (9) will be specified for further research purposes:

$$beta_{it} = \beta_1 poverty_{it} + \beta_2 ur_{it} + \beta_3 pop\_den_{it} + \beta_4 st\_empl_{it} + \beta_5 NUTS2_i + u_{it}. \tag{9}$$

In order to estimate the panel regression model, the fixed and random effects method will be applied first, then the Hausman test will be used to verify which of the two approaches is more appropriate, and then we will focus on diagnostics. In the second stage, we will make an estimate using the FGLS method. We will verify and analyze the obtained estimation results in the context of this article.

RESULTS

In this section, we will first pay attention to analysis of the beta efficiency of the education process at selected public universities in the Czech Republic for 2020 and 2021. In the second part, we will explain the changes in the beta efficiency of education using selected economic, social, regional, and institutional factors.

Results of Data Envelopment Analysis

The optimization using the DEA model in the system of equations (2) took place first for 2020 and then for 2021 in the GAMS Distribution 41.5.0 software. The results of the DEA analysis for all universities are presented in Table 4.

Regarding the 1st part of the analysis, efficient public universities in education were 54% (i.e., 14 out of 26) in 2020 and 39% (i.e., 10 out of 26) in 2021. Thus, there was a reduction in the number of efficient public universities between the analyzed periods. From the point of view of the average efficiency in education (*beta*) shown in Table 5, this deterioration meant an increase in the average beta value from 0.172 to 0.217 in 2021. By analyzing the efficiency for desirable and undesirable output (*beta_ABS*, *beta_UNABS*), a slight decrease in the average value can be seen in Table 5 from 0.154 to 0.135, including a reduction in standard deviation. This means that there has been an improvement in efficiency from the point of view of increasing the number of completed studies and the employment of these graduates of all levels of study (i.e., bachelor's, master's and doctoral degrees in total) and the differences between public universities have also decreased.

We must, therefore, look for the cause of the deterioration of the average efficiency beta in the deterioration (increase) of the average efficiency *beta_UNABS* from 0.189 to 0.299, i.e., insufficient reduction of unemployed public university graduates. On the other hand, the average *YBPI* index (see Table 5), which was calculated according to equation (3), shows an average decrease from 0.772 to 0.649 in 2021, which documents that the average proportion of reducing the number of unemployed graduates to the level of increasing the number successfully of graduated and employed graduates improved in 2021.

year	2020				2021			
ID_HEI	*beta*	*beta_ABS*	*betaUNABS*	*YBPI*	*beta*	*beta_ABS*	*betaUNABS*	*YBPI*
U1	0	0	0	1	0	0	0	1
U2	0	0	0	1	0	0	0	1
U3	0	0	0	1	0	0	0	1
U4	0	0	0	1	0	0	0	1
U5	0	0	0	1	0.505	0.528	0.482	0.339
U6	0	0	0	1	0.300	0.010	0.589	0.407
U7	0	0	0	1	0	0	0	1
U8	0.389	0.201	0.577	0.352	0.451	0.219	0.684	0.259
U9	0.248	0.050	0.445	0.529	0.291	0.045	0.536	0.444
U10	0.283	0.566	0.000	0.639	0.359	0.382	0.336	0.480
U11	0.144	0	0.289	0.711	0.412	0.414	0.409	0.418
U12	0	0	0	1	0.112	0	0.224	0.776
U13	0	0	0	1	0.215	0.431	0	0.699
U14	0	0	0	1	0	0	0	1
U15	0.153	0	0.307	0.693	0	0	0	1
U16	0.336	0.343	0.330	0.499	0.453	0.222	0.683	0.259
U17	0.245	0.073	0.417	0.543	0.441	0.193	0.689	0.261
U18	1.613	2.516	0.711	0.082	0.662	0.611	0.713	0.178
U19	0.282	0.075	0.489	0.475	0.323	0.051	0.595	0.385
U20	0	0	0	1	0	0	0	1
U21	0.230	0.057	0.403	0.565	0.277	0.093	0.462	0.492
U22	0	0	0	1	0.290	0.112	0.467	0.479
U23	0	0	0	1	0	0	0	1
U24	0	0	0	1	0	0	0	1
U25	0.271	0	0.543	0.457	0.254	0	0.508	0.492
U26	0.267	0.125	0.409	0.525	0.287	0.186	0.387	0.517

Table 4: The HEIs with beta education efficiency and YBPI (source: own calculation in GAMS)

Variable	2020		2021	
	Mean	Std. Deviation	Mean	Std. Deviation
beta	0.172	0.324	0.217	0.202
beta_ABS	0.154	0.499	0.135	0.188
beta_UNABS	0.189	0.239	0.299	0.282
YBPI	0.772	0.275	0.649	0.308

Table 5: Comparison of descriptive statistics of education efficiency according to the years 2020 and 2021 (source: own calculation in GAMS)

Furthermore, Table 6 presents the results of the education efficiency according to groups of universities. At the same time, we will focus mainly on large universities in group S4 and universities in group S3. By comparing the education efficiency (*beta*), it is interesting to observe the deterioration of that efficiency in education for the S3 group (increasing *beta* from 0.269 to 0.306 in 2021), while the S4 group of large universities shows an improvement in education efficiency (decrease in *beta* from 0.085 to 0.051) and also the average *beta* level is lower (i.e., HEIs are efficient or close to the efficient frontier). A more detailed analysis of individual universities in the group of large universities (S4) confirms that the Czech Technical University in Prague (U3), Masaryk University (U7), Charles University (U14) and only in 2021 the Palacký University Olomouc (UP, U15). The Brno University of Technology (BUT, U25) is close to the efficient boundary in both years, where there was also a slight improvement in education efficiency (*beta* decreased from 0.271 to 0.254 in 2021).

The reason for the inefficiency of the education system is the insufficient reduction in the number of graduates registered at the employment offices. At the same time, there was an improvement for the UP in Olomouc and BUT in Brno in 2021 compared to 2020. The *YBPI* index for the latter universities shows an increase for both universities' *YBPI*, which expresses an improvement in the ratio of the increase of employed graduates to the decrease of unemployed graduates. The analysis of the results in the group of 15 smaller universities (S3) shows that the leading cause of the deterioration of the average education efficiency (*beta*) in 2020 and 2021 is the deterioration of efficiency in the reduction of unemployed graduates (i.e., *beta_UNABS* increased from 0.271 to 0.421 in 2021). On the other hand, there was an improvement in education efficiency in increasing successful and employed graduates (i.e., *beta_ABS* decreased on average from 0.267 to 0.191 in 2021). Still, the verage *YBPI* index for the S3 group shows that the ratio of the increase in the efficiency of employed graduates relative to the decrease in the efficiency of unemployed graduates has slightly worsened (i.e., the *YBPI* has decreased from 0.661 to 0.505 in 2021).

Group	Variable	Year 2020 Mean	Year 2020 Std. Deviation	Year 2021 Mean	Year 2021 Std. Deviation
S3	*beta*	0.269	0.397	0.306	0.177
	beta_ABS	0.267	0.642	0.190	0.192
	beta_UNABS	0.271	0.249	0.420	0.260
	YBPI	0.661	0.284	0.505	0.257
S4	*beta*	0.085	0.123	0.051	0.114
	beta_ABS	0	0	0	0
	beta_UNABS	0.170	0.247	0.102	0.227
	YBPI	0.830	0.247	0.898	0.227

Table 6: Descriptive statistics of education efficiency by a group of HEIs, 2020-2021 (source: own calculation in GAMS)

After the DEA analysis, the analysis of education efficiency and its causes in terms of strengthening the employment of graduates and the reduction of unemployed graduates can be examined for individual educational institutions based on the results in Table 4.

Estimating The Effects of Factors on Education Efficiency

In the next part, the specific panel regression model (9) is estimated by using fixed effects, random effects, and feasible generalized least squares methods.

Given the possible heterogeneity in public educational institutions, we first choose the fixed effects method and then the random effects method to estimate the panel regression model. The presence of educational efficiency heterogeneity is documented in Figure 2, which presents the development of education efficiency (*beta*) for each university U1 to U26 in 2020, and 2021 and the average value of both years, whose values are connected by a line. A value of zero represents an efficient college in the education process. The biggest problem appears with U18, specific to the Veterinary and Pharmaceutical University of Brno.

It is clear from the table that the beta efficiency is statistically significantly and negatively affected by the population density indicator (-0.404) at the 1% level of significance and positively by the number of students per employee of the university (-0.233) at the 5% level. importance.

Due to the undesirable multicollinearity and the dependence of the factors (regressors) that will explain the *beta* changes, Table 7 shows the Pearson's paired correlation coefficients for measuring the strength of linear independence of two factors. Below, this value is recorded as the *p*-value to determine the statistical significance of the pairwise correlation. It is clear from the table that *beta* efficiency is statistically significantly and negatively affected by the population density indicator (-0.404) at 1% significance level, and positively by the number of students per one employee of the university (-0.233) at the 5% level of significance.

The results of estimating the panel regression model from equation (9) using the fixed effects method is statistically insignificant because the *p*-value of the F statistic is 0.899, i.e., greater than 0.05. Therefore, we do not reject the null hypothesis that all regression parameters are equal to zero.

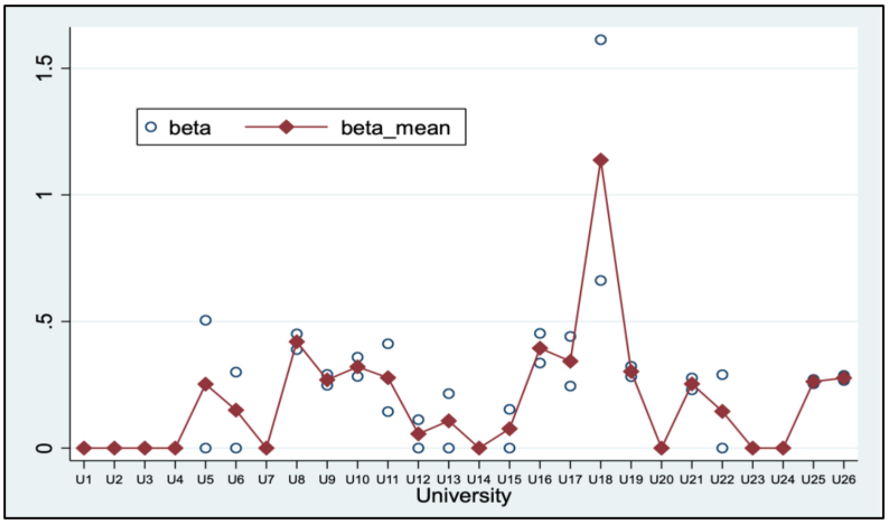

Figure 2: Beta efficiency of HEIs 2020-2021 (source: own calculation, in STATA)

	beta	*poverty*	*ur*	*pop_den*	*st_empl*
beta	1				
poverty	0.224	1			
	0.111				
ur	0.122	0.750	1		
	0.388	0.000			
pop_den	-0.404	-0.612	-0.259	1	
	0.003	0.000	0.064		
st_empl	-0.233	0.133	0.079	-0.152	1
	0.097	0.347	0.580	0.282	

Table 7: Pairwise correlation matrix of factors for beta panel regression, 2020-2021 (source: own calculation in STATA)

Also, *Rsquares(between)* = 0.186, which documents a low level of explanation of changes in *beta* education efficiency.

The estimate of the model with random effect (RE) summarizes the following equations:

$$\hat{\beta}_{it} = 0.334 - 0.0027\, poverty_{it} + 0.039 ur_{it} - 0.050\, pop\_den_{it} - 0.021^{*}\, st\_empl_{it} + 0.043 NUTS2_{it}.$$

The results of the Wald test for p-value (chi^2) = 0.023 confirm that the estimate of the *RE model* is ok, i.e., we reject the null hypothesis that all the coefficients in the *RE model* are different from zero. Statistics $R^2_{between} = 0.371$ shows that only 37% of changes in education efficiency are explained by selected factors. Testing the statistical significance of individual regression coefficients confirms that only the estimated regression coefficient $\hat{\beta}_4 = -0.021$ for the *st_empl* factor is statistically significant at the 10% significance level. The estimate documents that, on average, beta education efficiency improves as the ratio of students per employee in a college increases. The preference of the *RE model* estimate over the *FE model* was also verified using a Hausman test (i.e., HEIs error (μ_i) is not correlated with any of the factors). Considering that the estimate of the regression *RE model* was not statistically significant and did not bring the expected explanation by the mentioned factors, we proceeded to estimate the panel regression model (9) using the feasible generalized feast square method, which allows for heteroskedasticity or serial and cross-sectional correlation. The results of the estimated model are summarized by the following equation (11):

$$\hat{\beta}_{it} = 0.335 - 0.039^{***}\, poverty_{it} + 0.060^{**}\, ur_{it} - 0.069^{***}\, pop\_den_{it} - 0.018^{***}\, st\_empl_{it} + 0.042^{***}\, NUTS2_{it}. \quad (11)$$

where the statistical significance of the regression coefficient is **5% and ***1%. The result of the Wald test confirm that for statistics Wald chi^2(5) = 135.42 and the p-value (chi^2) < 0.001 we reject the null hypothesis and support the conclusion that all regression coefficients in the model are different from zero. At the same time, all the estimated regression coefficients are statistically significant at the 5% significance level, and we can proceed to interpret the results.

The estimate $\hat{\beta}_1 = -0.039$ means that for the economic factor of poverty with a higher risk of low disposable income (below the monitored threshold of 60% of the national median), there is a slight improvement in the average education efficiency at universities under ceteris paribus conditions. The regression coefficient $\hat{\beta}_2 = 0.060$, which as an economic factor expresses the needs of the labour market, documents that with an increase in the unemployment rate by 1%, there is an increase in the average beta by 0.060, i.e., a deterioration in education efficiency at universities. The demographic factor of population density was included in the group of social factors. The estimate $\hat{\beta}_3 = -0.069$ suggests a lower average beta can be expected in areas with higher population density, representing a better average education efficiency in public universities. The regression coefficient for the institutional factor *st_empl* was estimated $\hat{\beta}_4 = -0.018$, which confirms that with a higher number of students per employee of the university, there is an increase in the average education efficiency. The last estimated regression coefficient $\hat{\beta}_5 = 0.042$ testifies that if we move away from Prague to the peripheral regions and towards the east, the average beta increases and the inefficiency in education at universities increases.

The estimated panel regression model using the FGLS method documents the influence of selected economic, social, regional and institutional factors on education efficiency at public universities.

DISCUSSION

The conducted research pointed to three critical results for the assessment and analysis of the education efficiency of Czech public universities in 2020-2021. The following discussion will be divided into three parts:

- the level and development of education efficiency (*beta*) at public universities and the causes on the side of the number of employees or unemployed graduates of bachelor's, master and doctoral studies,
- the effect of the division of public universities into more homogeneous groups on education efficiency,
- Higher education institutions' efficiency changes based on economic, social, regional and institutional factors.

A comparison of the number of efficient public universities in 2020 and 2021 shows a decrease from 54% to 39%, confirming the level of average inefficiency by increasing the average beta from 0.171 to 0.217 in 2021. Let us look at the reasons for the deviations in the educational system outputs for the output-oriented DEA model from the efficient frontier. The main problem is the need for more unemployed graduates; while comparing the average *beta_UNABS* in 2020 (0.189) with 2021 (0.299), this problem has worsened. However, at some universities, the problem of fewer employed graduates than expected persisted. Comparing the average *beta_ABS* in 2020 (0.154) with 2021 (0.135) indicates a slight improvement in this situation due to the need to increase employed graduates to an efficient level.

These results can be compared with other professional literature that focuses on evaluating the efficiency of HEIs using output-oriented DEA models, considering that the analyses were performed in a different period. Abbott and Doucouliagos (2003) identified 66% of efficient universities regarding teaching and research efficiency under VRS conditions in Australian universities in 1995. This number is also influenced by the number of inputs and outputs and their content. Education efficiency was assessed in the Czech environment for the same set of 26 public schools in Mikušová (2017). The data from 2015 and the DEA model included three inputs and two outputs, as mentioned in the literature review section. The number of efficient HEIs was 50%, and the average education efficiency was 0.855 when using the classic DEA output-oriented model with VRS. However, this analysis did not include undesirable output, only all graduated students.

The division of the Czech HEIs into four groups S1-S4, proposed by Rychlík (2018), allowed us to examine the influence of education efficiency for large universities (S4) and smaller universities (S3), which leads to the classification of HEIs with higher homogeneity. The results support the research hypothesis that more prominent universities have a higher average education efficiency (*beta* is 0.085 and 0.05 in 2020 and 2021, respectively), which improved even more in 2021. It can be said that these universities in the S4 group are mostly efficient or have little problems with inefficiency that is improving, and the only problem is the insufficient reduction in the number of unemployed graduates (the average *beta_ABS* in the S4 group is 0.170 and 0.102 in 2020 and 2021 respectively).

On the other hand, in the group S3, which includes 15 smaller HEIs, the average education efficiency beta worsened in years (from 0.269 to 0.306). It is logical that both, *beta_ABS* (0.267 to 0.306 in 2021) and *beta_UNABS* (0.271 to 0.420 in 2021) have therefore deteriorated. However, for *beta_UNABS* this deterioration was greater than for *beta_ABS*.

In the S4 group with five large universities, the annual total number of students reached over 28,000, total full-time employees around 5,000 and the number of students per employee around 3.3. In the group of 15 smaller HEIs, the total number of students was around 8.8 thousand, the number of employees was 1200, and the number of students per employee was around 6. The share of the S4 group is enormous in the group of universities, and the share of the number of students per employee points to the better teaching efficiency of larger universities.

The conclusion that more prominent universities and a group of more homogeneous HEIs record higher education efficiency is also confirmed by the publication of Mikušová (2017), who divided the same set of HEIs into three groups according to the coefficient of economic difficulty with an average teaching efficiency for individual groups of 0.989, 0.982 and 0.996, while teaching efficiency for the whole set it was 0.885 with a more significant standard deviation. Similarly, Navas et al. (2020) also observed higher teaching efficiency of the group of large universities compared to the medium and small size HEIs, in a sample of 157 Colombian HEIs between 2010 and 2015.

Several factors affecting public higher education institutions' education efficiency (*beta*) in the Czech Republic in 2020-2021 were investigated by estimating a panel regression model using the FGLS method. The results for selected economic, social, regional and institutional confirm that strong and statistically significant factors include population density, unemployment rate and location of HEIs in the NUTS2 region. A weaker but statistically significant institutional factor is the number of students per employee of HEI. Higher regional population density increases education efficiency for HEIs from that region. The unemployment rate as an economic factor shows the influence of the situation on the regional labor market. With higher unemployment, the education efficiency of HEIs from this region also deteriorates. The numbering of regions according to NUTS 2, in turn, documents that HEIs located in regions further from Prague (peripheral) and towards the east of the Czech Republic have worse education efficiency.

Pedro et al. (2022) also investigated the efficiency of HEIs in Portugal in 2018-2019 in their study. They concluded that HEIs with better efficiency of social responsibility are in large urban centers, and teaching efficiency is positively related to regional gross domestic product. The main contribution of our article is the analysis of the unemployment problem. In the data envelopment model, the undesirable output of the educational process is the number of unemployed public university graduates. In a panel regression, one of the economic factors selected is the unemployment rate in the region where the college is located. This factor expresses the situation in the regional labor market and plays an essential role in the job search of university graduates. Unemployment among university graduates is critical in many countries, including the Czech Republic. The unemployment rate of graduates of all universities, which was at 11.8% in 2013, gradually decreased and, as of 2019, is in the range of 4.2 – 4.9% (see Figure 1). The reason for this unemployment of graduates can be skills mismatch and lack of work experience, which is based on insufficient cooperation of universities with practice.

The results of the panel regression estimation also confirmed that with a higher number of university students per employee, the education efficiency *beta* improves for the observed public universities. This conclusion supports the already mentioned that for more prominent universities in the S4 group, where the *st_empl* indicator is 5.95 and 6.06 in 2020 and 2021, respectively, the education efficiency *beta* is significantly better (0.085 and 0.05 in 2020 and 2021, respectively) compared to the group S3, where the number of students per employee *st_smpl* is 3.20 and 3.36 in 2020 and 2021 respectively, and education efficiency decreases by 0.269 and.306 in 2020 and 2021 respectively. This is consistent with Mikušová (2017) and Navas et al. (2020) findings.

Limitations of The Analysis

The research in this paper also has its limitations. The proposed modified DEA model was based on aggregate indicators of the number of enrolled students and the number of employed or unemployed students for all levels of study (bachelor's, master's and doctoral). The DEA model focused only on evaluating education (teaching) efficiency and part abstracted from research and other activities universities implement for sustainability. The findings of this study are associated with public colleges, and results may differ for private colleges. Attention needs to be paid not only to the quantity but also to the quality of all university activities and their inclusion in the models.

Therefore, future research can extend the proposed DEA model to a DEA network model for individual degrees of study. Similarly, other possibilities are to stop into the evaluation of the effectiveness of the assessment, research activities and international cooperation. To improve the quality of the investigation of the influence of economic, social, regional and institutional factors, it is more appropriate to expand the set of these factors, which will be significantly correlated with effective education, but on the other hand, these factors will not be correlated with each other. It is also appropriate to extend the time horizon of the investigation, given that the situation of HEIs is changing now, at least in terms of the number of students - more students from the Czech Republic and more students from abroad (war in Ukraine), greater possibilities of using private universities and also the specialization of tudents - the trend of humanitarian fields and the use of artificial intelligence.

CONCLUSION

The article was devoted to evaluating the educational process at public universities and explaining the effectiveness of education by other selected economic, social, regional, and institutional factors.

A modified DEA model was proposed for determining education efficiency, which was based on the inputs of the number of newly enrolled students and the recalculated number of academic staff and the desirable output of the number of employed graduates and the undesirable output of the number of unemployed graduates of bachelor's, master's and doctoral study programs. The proposed output-oriented DEA model used the DDF distance from the efficient frontier, the possibility of a disproportionate increase in the number of employed graduates or reducing the number of unemployed graduates. The conclusions of the analysis for the 26 public universities in the Czech Republic showed that the number of effective public universities is decreasing in 2020-2021. The average education efficiency *beta* worsened in the mentioned period, mainly due to an insufficient reduction in the number of unemployed graduates. Therefore, public universities cooperating with employers in the labor market should pay attention to this issue and improve this situation through cooperation. The division of public universities into groups showed that large universities were almost all efficient, and the number of unemployed graduates was only a minor problem. These universities generally determine the best practice in the educational process. In the group of secondary and minor universities, education efficiency deteriorated due to the insufficient increase in the number of employed graduates and mainly due to the reduction of unemployed graduates.

The conclusions of the analysis of the influence of factors on changes in the education efficiency of public high schools in the monitored period showed that a vital positive factor is the demographic indicator population density, and the institutional factor, the number of students per employee of HEI, i.e., the size of the university. On the other hand, unemployment hurts education efficiency, i.e., problems in the regional labor market and the university's location in peripheral regions or towards the east of the Czech Republic.

The summary of these results shows the necessary cooperation measures between universities and employers of graduates, namely in creating study programs with adequate skills and knowledge needed in the future, as well as internships in companies in the corresponding institutions. Also, cooperation with labor offices in solving problems in the labor market and additional retraining can contribute to solving this situation.

University managers, in turn, must consider the size and structure of the academic body and choose adequate limits and structure for students admitted to bachelor's, master's and doctoral study programs. The Czech Ministry of Education, Youth and Sport should also help the development of peripheral public universities through subsidy programs.

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APPENDIX 1 INPUT DATA FOR DEA

year	2020				2021			
ID_HEI	*NSTUD*	*STAFFA*	*ABS*	*UNABS*	*NSTUD*	*STAFFA*	*ABS*	*UNABS*
U1	167	259.35	152	2	146	256.58	258	3
U2	38	63.76	1	1	30	67.07	39	1
U3	5,138	743.36	1710	81	4686	772.34	3,367	72
U4	3,527	1,604.30	1729	61	3471	1,605.00	3,266	38
U5	120	161.17	91	2	116	165.55	151	7
U6	1,903	635.34	1198	39	1981	628.94	1,806	50
U7	5,587	1,806.80	2648	156	5863	1,874.00	5,415	135
U8	2,068	540.60	963	89	2133	556.80	1,582	68
U9	1,656	532.58	945	57	1894	561.31	1,662	42
U10	1,496	261.17	432	23	1390	255.74	825	21
U11	1,338	517.59	664	26	1366	526.40	923	25
U12	1,225	349.80	722	30	1256	342.59	1,172	17
U13	1,744	439.38	814	23	1795	445.39	1,074	17
U14	7,763	3,887.44	2521	100	7989	3,971.18	6,541	92
U15	4,007	1,395.56	1863	118	3734	1,368.93	3,544	101
U16	1,825	544.60	794	51	1627	545.00	1,243	54
U17	2,217	466.70	1039	61	2425	483.09	1,797	76
U18	449	235.16	82	31	317	208.210	257	22
U19	2,285	814.46	1215	85	2359	826.28	2,072	61
U20	2,427	487.95	1214	39	2576	492.34	2,267	25
U21	734	690.39	369	16	884	703.70	847	20
U22	784	84.53	335	14	684	85.56	322	12
U23	879	76.74	241	10	807	88.11	399	7
U24	51	80.50	1	1	60	74.20	182	4
U25	4,277	1,128.17	1744	165	3997	1,169.42	3,382	110
U26	2,586	752.27	1176	74	2584	759.19	1,974	43

APPENDIX 2 LIST OF UNIVERSITIES AND THEIR CHARACTERISTICS

HEI	HEI name	Group	Address	NUTS2	ID_NUTS2	*stud_20*	*epl_20*	*stud_21*	*epl_21*	*st_ empl_20*	*st_ empl_21*
U1	Akademie múzických umění v Praze	S1	Praha 1	Praha	CZ01	1,438	500.4	1,485	498.6	2.87	2.98
U2	Akademie výtvarných umění v Praze	S1	Praha 7	Praha	CZ01	306	129.9	314	132.7	2.36	2.37
U3	Česká zemědělská univerzita v Praze	S3	Praha 6	Praha	CZ01	21,164	1,596.7	21,591	1,607.6	13.25	13.43
U4	České vysoké učení technické v Praze	S4	Praha 6	Praha	CZ01	17,442	4,137.9	17,550	4,177.2	4.22	4.20
U5	Janáčkova akademie múzických umění v Brně	S1	Brno-město	Jihovýchod	CZ06	687	330.5	679	332.0	2.08	2.05
U6	Jihočeská univerzita v Českých Budějovicích	S3	České Budějovice	Jihozápad	CZ03	8,895	1,472.0	8,847	1,470.7	6.04	6.02
U7	Masarykova univerzita	S4	Brno-město	Jihovýchod	CZ06	32,190	4,703.3	32,786	4,882.3	6.84	6.72
U8	Mendelova univerzita v Brně	S3	Brno-město	Jihovýchod	CZ06	8,886	1,604.7	9,019	1,606.2	5.54	5.62
U9	Ostravská univerzita	S3	Ostrava-město	Moravskoslezsko	CZ08	8,526	1,072.8	8,779	1,081.9	7.95	8.11
U10	Slezská univerzita v Opavě	S3	Opava	Moravskoslezsko	CZ08	5,282	601.1	5,337	582.4	8.79	9.16
U11	Technická univerzita v Liberci	S3	Liberec	Severovýchod	CZ05	5,948	1,178.9	6,166	1,159.7	5.05	5.32
U12	Univerzita Hradec Králové	S3	Hradec Králové	Severovýchod	CZ05	6,390	726.4	6,334	713.2	8.80	8.88
U13	Univerzita J. E. Purkyně v Ústí nad Labem	S3	Ústí n/L	Severozápad	CZ04	7,966	943.5	7,887	914.7	8.44	8.62
U14	Univerzita Karlova	S4	Praha 1	Praha	CZ01	49,508	9,098.9	50,918	8,634.3	5.44	5.90
U15	Univerzita Palackého v Olomouci	S4	Olomouc	Střední Morava	CZ07	22,106	3,087.2	22,983	3,089.2	7.16	7.44
U16	Univerzita Pardubice	S3	Pardubice	Severovýchod	CZ05	7,062	1,136.6	6,869	1,117.7	6.21	6.15
U17	Univerzita Tomáše Bati ve Zlíně	S3	Zlín	Střední Morava	CZ07	9,138	934.8	9,565	955.0	9.78	10.02
U18	Veterinární a farmaceutická univerzita Brno	S3	Brno-město	Jihovýchod	CZ06	1,884	605.1	1,792	537.8	3.11	3.33
U19	VŠB-Technická univerzity Ostrava	S3	Ostrava-město	Moravskoslezsko	CZ08	11,087	2,213.7	11,390	2,191.4	5.01	5.20
U20	Vysoká škola ekonomická v Praze	S3	Praha 3	Praha	CZ01	13,700	996.7	14,306	973.0	13.75	14.70
U21	Vysoká škola chemicko-technologická v Praze	S3	Praha 6	Praha	CZ01	3,823	1,222.6	3,836	1,263.4	3.13	3.04
U22	Vysoká škola polytechnická Jihlava	S2	Jihlava	Jihovýchod	CZ06	2,160	164.9	2,133	167.2	13.10	12.75
U23	Vysoká škola technická a ekonomická v ČB	S2	České Budějovice	Jihozápad	CZ03	3,263	216.1	3,102	233.2	15.10	13.30
U24	Vysoká škola uměleckoprůmyslová v Praze	S1	Praha 1	Praha	CZ01	474	179.5	504	166.2	2.64	3.03
U25	Vysoké učení technické v Brně	S4	Brno-město	Jihovýchod	CZ06	18,762	3,069.6	18,137	2,997.5	6.11	6.05
U26	Západočeská univerzita v Plzni	S3	Plzeň-město	Jihozápad	CZ03	11,027	1,992.0	11,033	1,954.1	5.54	5.65

Full research paper

MEASURING THE EFFICIENCY OF TURKISH RESEARCH UNIVERSITIES VIA TWO-STAGE NETWORK DEA WITH SHARED INPUTS MODEL

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ABSTRACT

The efficiency of universities, which have a network structure of production process, is an essential component of performance measurement in education. However, most previous studies use traditional Data Envelopment Analysis (DEA), which disregards the network structure of the production process in universities. This study adopts a two-stage Network Data Envelopment Analysis (NDEA) with shared inputs model to assess the overall, teaching and research efficiencies of Turkish research universities. The findings show that only 6 out of 23 research universities are efficient, and some universities with lower world rankings are more efficient than those with higher rankings. On the other hand, no significant difference was found between the efficiency levels of regions with a high level of socio-economic development and regions with a relatively low level of socio-economic development. The study also evaluates the effects of different priority scenarios on efficiency and the optimal allocation of shared inputs between sub-processes. This study provides guidance for universities seeking to improve their performance and for the Council of Higher Education (CHE) in determining incentives for research universities. It also promotes the use of multi-stage NDEA with shared inputs model over traditional DEA for accurate efficiency assessment in the field of education.

KEYWORDS

Network DEA, research efficiency, regional development, shared inputs, Turkish research universities, teaching efficiency

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Highlights

- *The study applies a two-stage NDEA with shared inputs model to measure the efficiency of Turkish research universities in teaching and research activities.*
- *The study reveals that 6 out of 23 research universities are efficient in both teaching and research processes.*
- *The study finds that some universities ranked lower in the world rankings are more efficient than those ranked higher.*
- *The level of regional socio-economic development does not affect the efficiency of research universities.*

INTRODUCTION

Universities are multifaceted organizations that fulfill numerous functions and tasks in society. Teaching and research are the foremost and vital pursuits, as they enhance the development of a highly skilled workforce, generate knowledge, and provide social benefits (Erdem, 2013). It is essential to note, however, that universities vary in their objectives, aims, and capacity to undertake these activities. Some universities prioritize teaching and learning, while others prioritize scholarly research and innovation. Additionally, certain universities aim to excel in both areas and are commonly known as research universities. These institutions distinguish themselves through their pursuit of cutting-edge research, research-focused culture, and significant contributions to science and technology fields (Altbach, 2011). Research universities play a crucial role in advancing the knowledge economy and society through training researchers who push the frontiers of knowledge, generate innovative ideas and solutions for global challenges, and collaborate with diverse stakeholders to transfer knowledge and innovations. Research universities offer top-notch education to both undergraduate and graduate students, who gain invaluable experience through access to pioneering research and opportunities to participate in research projects. In addition, research universities are pioneering community service and outreach programs aimed at addressing regional and local issues and needs (Altbach and Salmi, 2011; TAÜG, 2016).

The Turkish government and higher education authorities have initiated a program to support and promote research activities and establish a culture of scientific inquiry in the country by recognizing the significance of research universities. In 2017, 10 universities were designated as research universities based on their research potential and performance indicators, and the number of research universities has since increased to 23 as of 2021. These universities are incentivized by the state to improve their research infrastructure, human resources, and overall quality. The Council of Higher Education (CHE) conducts regular monitoring and evaluation to assess their performance based on 33 indicators related to publications, citations, patents, and projects, etc. (CHE, 2020, 2021).

However, becoming a research university requires more than just achieving high levels of research output and impact. Using available resources efficiently to achieve desired outcomes in research and teaching is crucial. Efficiency refers to an organization's ability to utilize its inputs, including human capital and physical infrastructure, to produce outputs such as graduates or publications (Daft, 2015; Lindsay, 1982). Effectiveness is a crucial aspect of organizational performance, indicating the degree to which an entity meets its goals and achieves its purpose (Lindsay, 1982). Both efficiency and effectiveness are crucial for evaluating the performance of research universities.

Several techniques can be utilized to measure the efficiency of higher education institutions. One of the most prevalent approaches is using Data Envelopment Analysis (DEA), which is a non-parametric technique for comparing the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs (Cooper et al., 2007). It helps in determining the efficiency of the DMUs in producing multiple outputs with multiple resources. DEA calculates the efficiency score of each DMU based on its proximity to an efficient frontier that represents the best practice among the DMUs. Additionally, DEA identifies the sources of inefficiency for each DMU and proposes potential enhancements (Charnes et al., 1978).

Nonetheless, the standard DEA has some restrictions when utilized for complex establishments such as universities that contain several activities or stages within their system. For instance, universities engage in teaching and research, which involve varying inputs and outputs, intermediate products, and interrelationships. Standard DEA models often treat the system as a black box, disregarding these aspects when transforming inputs into outputs, which can lead to imprecise or deceptive efficiency measurements (Färe and Grosskopf, 1996, 2000). To overcome this issue, researchers have developed network DEA (NDEA) models that consider the system's internal structure and processes. NDEA models disaggregate the system into multiple stages or subprocesses, each with its inputs and outputs. The transfer of products or services between the stages is indicated by intermediate flows. NDEA models can measure the system efficiency and the efficiency of individual stages and subprocesses (Färe et al., 2007; Yang et al., 2018).

NDEA models are superior to standard DEA models in evaluating research universities' efficiency as they can consider the complex and varied operations. Research universities have a two-stage system dedicated to teaching and research, with each stage having its own inputs and outputs. Staff who teach and engage in research are referred to as shared inputs. NDEA models can assess the comprehensive efficiency of research universities, as well as their individual teaching and research efficiencies. Additionally, the NDEA with shared inputs model can analyze how various strategies or scenarios impact research university efficiency (Chen et al., 2010). For instance, what would occur if research universities prioritized teaching over research or vice versa? How should a research university allocate its faculty members between teaching and research activities to achieve optimal efficiency?

Universities not only generate general economic impacts through local expenditures (such as salaries and services), but also create local knowledge spillovers through university research, which in turn lead to regional innovation processes. That is, universities generate knowledge; and this knowledge is used or developed by local firms, entrepreneurs, public institutions, and other stakeholders. This improves the economic performance, competitiveness, and welfare of the region (Arbo and Benneworth 2007; Geuna and Musico, 2009; Goldstein and Renault 2004). Numerous studies have suggested that research universities have a beneficial impact on their regions, as validated by the positive socio-economic outcomes (Chankseliani et al., 2021; Cui and Li, 2022; Findler et al., 2019; Parilla and Haskins, 2023; Smith and Bagchi-Sen, 2012). When examined in the context of Türkiye, there are also studies that show that universities in Türkiye have a high demographic, economic, spatial, social, and cultural influence on their regions (Erdoğan and Karagöl, 2018; Işık and Başaran, 2021; Yavuzçehre, 2016). However, research is currently insufficient regarding how varying levels of regional socio-economic development shape the efficiency of research universities. Regional development has the potential to affect research universities' resources, research, and competitiveness. Universities situated in wealthier regions are likely to have certain advantages, while those in poor regions may face distinct challenges. It is crucial to examine whether the regional socio-economic development level impacts the overall efficiency of research universities.

This research assesses and compares the overall efficiency, along with the teaching and research efficiency, of Turkish research universities by applying the two-stage NDEA with shared inputs method. The study investigates the impact of prioritizing activities and the optimal distribution of academic workforce between teaching and research. Moreover, it assesses the influence of regional socio-economic development on research university efficiency. The research questions addressed in this study are:

- RQ1: What is the current level of overall efficiency of research universities in Türkiye?
- RQ2: What level of research and teaching efficiency could Turkish research universities achieve by prioritizing teaching activities?
- RQ3: What level of research and teaching efficiency could Turkish research universities achieve by prioritizing research activities?

- RQ4: What academic workforce ratio between teaching and research activities would establish efficiency for Turkish research universities?
- RQ5: Does regional socio-economic development impact the overall efficiency of research universities in Türkiye?

LITERATURE REVIEW

One of the most frequently published areas in the DEA literature is education (Liu et al., 2013). However, most of these studies used the standard DEA method, thus neglecting the sub-processes of decision units (Abbott and Doucouliagos, 2003; Avkiran, 2001; Doğan, 2018; Flégl et al., 2013; Halásková et al., 2022; Johnes and Johnes, 1995; Nazarko and Šaparauskas, 2014; Özel, 2014; Tomkins and Green, 1988). Due to the drawbacks of this single-stage model, the NDEA is recommended for efficiency measurement (Chen et al., 2010; Cook et al., 2010; Färe and Grosskopf, 1996, 2000; Färe et al., 2007). In NDEA, the overall efficiency of universities is calculated by considering the activities of sub-processes.

It can be observed that in recent years, more studies have been conducted using the two-stage NDEA to measure efficiency in universities. Lu (2012) measured the cost-effective teaching-research efficiency of Taiwanese universities using a two-stage NDEA. In a study comparing the efficiency of 9 faculties at Iran's Al-Zahra University, Saniee Monfared and Safi (2013), examined the overall efficiency of faculties as well as their teaching and research efficiency using a two-stage NDEA. They assumed that faculty members spend one-third of their time on teaching and two-thirds on research. Chodakowska (2015), calculated the teaching and research efficiency of Polish universities using both the standard DEA method and the two-stage NDEA method and compared the results obtained using both methods. Lee and Worthington (2016) measured the efficiency of Australian universities' research processes using a two-stage DEA. Shamohammadi and Oh (2019), assessed the teaching and research efficiency of Korean private universities and their overall efficiency using a two-stage DEA. Yang et al. (2018), measured the efficiency of 64 Chinese research universities using two-stage DEA: teaching-research efficiency and science-technology transformation efficiency.

Tavares et al. (2021), studied the efficiency of 45 Brazilian federal universities in three stages with NDEA. Ding et al. (2021), divided the research processes of Chinese universities into faculty research process and student research process and measured the research efficiency of universities with two-stage DEA. Chen et al. (2021), used the two-stage NDEA to measure and compare the teaching and research efficiency of 52 Chinese universities for two different situations in which these universities prioritized the research and teaching process. Koçak and Örkçü (2021), studied and compared the overall efficiency of Turkish state universities using both the single stage DEA and the two-stage NDEA. To identify the factors that cause inefficiency, they evaluated and compared the efficiency of graduate education and technological-scientific research processes, which they separated for the NDEA, under both the independent model (single-stage DEA) and the dependent model (two-stage NDEA).

With the increasing importance of research university initiatives in Türkiye, there is a need for more scientific research to be conducted in this field. One of the main issues in this regard is the performance and therefore efficiency analysis of research universities. The studies by Çağlar and Gürler (2020) and Mammadov and Aypay (2020) are pioneering works on efficiency analysis of Turkish research universities. However, these studies also use the traditional DEA for efficiency measurement, which has the disadvantages mentioned above. There has been no study in the literature that analyzes the overall efficiency levels of Turkish research universities together with their teaching and research components using two-stage NDEA with shared inputs model. This research is important in terms of contributing to filling this gap in the literature and encouraging more work in this field.

MATERIALS AND METHOD

Two-Stage NDEA with Shared Inputs Model

The NDEA methodology is an extension of the traditional DEA approach that evaluates the efficiency of interconnected units or sub-technologies in a network. Essentially, the aim of NDEA is to pinpoint the most efficient units or sub-technologies within the network and provide valuable insights that can be used to enhance the overall efficiency of the network (Färe and Grosskopf, 2000; Kao, 2014; Lewis and Sexton, 2004). Various NDEA models have been developed and continue to be developed over time based on the number of activities and stages in the organization and the differences in the relationship structure of these stages with each other. In this section, we describe the two-stage NDEA with shared inputs model of Chen et al. (2010) and how we have adapted it and applied it to our data.

The generic of the two-stage NDEA process in which inputs are shared between the stages is shown in Figure 1. The n decision units subjected to analysis are represented by $DMU_j\left(j=1,2,\ldots,n\right)$, and the total m inputs used by these decision units in both the first and second stages are represented by $X_{ij}\left(i=1,2,\ldots,m\right)$. Suppose these common inputs are assigned to the first and second stages as $a_i X_{ij}$ and $\left(1-a_i\right)X_{ij}\left(0\le a_i\le 1\right)$, respectively. The decision units receive two types of outputs from the inputs they use in the first stage. One of these types of outputs is not final outputs, but intermediate outputs that are used as inputs to the second stage and are labelled $Z_{dj}\left(d=1,2,\ldots,t\right)$. Other first stage outputs are final outputs and can be represented as $Y^1_{r_1 j}\ \left(r_1\in O_1\right)$. The final outputs at the end of the second stage can be represented as $Y^2_{r_2 j}\ \left(r_2\in O_2\right)$.

The overall efficiency of the two-stage process for any decision unit can be calculated using the linear programming Model 1. Although the overall efficiency of the two-stage network process calculated according to Model 1 is unique, the efficiency values of the individual subprocesses are not since they may be an alternative optimal solution of the model in question. Keeping the overall efficiency of the whole process, the maximum efficiency values of the first stage can be calculated using Model 2 and the maximum efficiency values of the second stage can be calculated using Model 3 (Chen et al., 2009; Chen et al., 2010; Chen et al., 2021; Kao and Hwang, 2008). In all models $\beta_i^1 = \omega_i^1 a_{ik}; \beta_i^2 = \omega_i^2 a_{ik}$ for linearity and it is assumed that $\mu_{r_1}^1 = \mu_{r_2}^2$, $\pi_d^1 = \pi_d^2$, $\omega_i^1 = \omega_i^2$, $\beta_i^1 = \beta_i^2$, like the assumptions of Kao and Hwang (2008) and Liang et al. (2008).

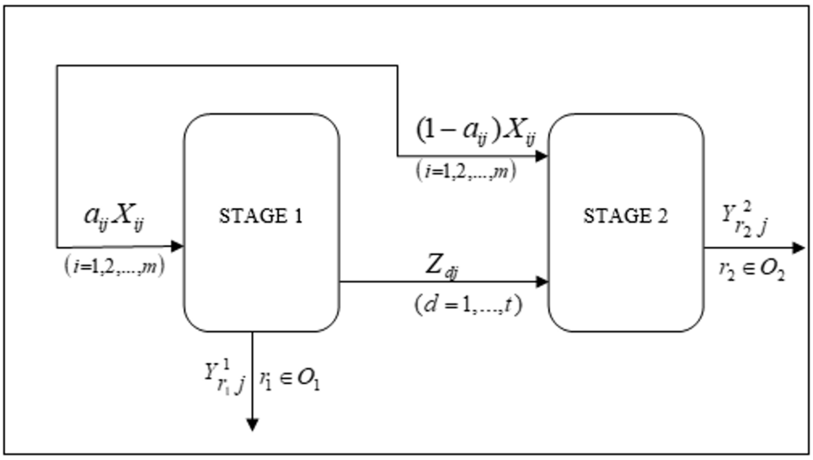

Figure 1: Two-stage network process with shared inputs (source: own elaboration based on Chen et al., 2010: 341)

$$
\begin{aligned}
&\theta_k^* = Max \sum_{r_1 \in O_1} \mu_{r_1}^1 Y_{r_1 k}^1 + \sum_{d=1}^{t} \pi_d^1 Z_{dk} + \sum_{r_2 \in O_2} \mu_{r_2}^2 Y_{r_2 k}^2 + U^1 + U^2 \\
&s.t. \sum_{i=1}^{m} \beta_i^1 X_{ik} + \sum_{i=1}^{m} \omega_i^2 X_{ik} - \sum_{i=1}^{m} \beta_i^2 X_{ik} + \sum_{d=1}^{t} \pi_d^2 Z_{dk} = 1 \\
&\sum_{r_1 \in O_1} \mu_{r_1}^1 Y_{r_1 j}^1 + \sum_{d=1}^{t} \pi_d^1 Z_{dj} + U^1 - \sum_{i=1}^{m} \beta_i^1 X_{ij} \le 0 \\
&\sum_{r_2 \in O_2} \mu_{r_2}^2 Y_{r_2 j}^2 + U^2 - \left[\sum_{i=1}^{m} \omega_i^2 X_{ij} - \sum_{i=1}^{m} \beta_i^2 X_{ij} + \sum_{d=1}^{t} \pi_d^2 Z_{dj} \right] \le 0 \\
&\beta_i^1 \le \omega_i^1; \beta_i^2 \le \omega_i^2 \\
&\mu_{r_1}^1, \pi_d^1, \omega_i^1, \beta_i^1, \mu_{r_2}^2, \pi_d^2, \omega_i^2, \beta_i^2 \ge \varepsilon; U^1, U^2 \ free \\
&j = 1,\ldots,n; i = 1,\ldots,m; d = 1,\ldots,t; r_1 \in O_1; r_2 \in O_2
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&\theta_k^{1*} = Max \sum_{r_1 \in O_1} \mu_{r_1}^1 Y_{r_1 k}^1 + \sum_{d=1}^{t} \pi_d^1 Z_{dk} + U^1 \\
&s.t. \sum_{i=1}^{m} \beta_i^1 X_{ik} = 1 \\
&\sum_{r_1 \in O_1} \mu_{r_1}^1 Y_{r_1 j}^1 + \sum_{d=1}^{t} \pi_d^1 Z_{dj} + U^1 - \sum_{i=1}^{m} \beta_i^1 X_{ij} \le 0 \\
&\sum_{r_2 \in O_2} \mu_{r_2}^2 Y_{r_2 j}^2 + U^2 - \left[\sum_{i=1}^{m} \omega_i^2 X_{ij} - \sum_{i=1}^{m} \beta_i^2 X_{ij} + \sum_{d=1}^{t} \pi_d^2 Z_{dj} \right] \le 0 \\
&\sum_{r_1 \in O_1} \mu_{r_1}^1 Y_{r_1 k}^1 + \sum_{d=1}^{t} \pi_d^1 Z_{dk} + \sum_{r_2 \in O_2} \mu_{r_2}^2 Y_{r_2 k}^2 + U^1 + U^2 \\
&-\theta_k^* \left[\sum_{i=1}^{m} \beta_i^1 X_{ik} + \sum_{i=1}^{m} \omega_i^2 X_{ik} - \beta_i^2 X_{ik} + \sum_{d=1}^{t} \pi_d^2 Z_{dk} \right] = 0 \\
&w_1^* . \left[\sum_{r_1 \in O_1} u_{r_1}^1 Y_{r_1 k}^1 + \sum_{d=1}^{t} \eta_d^1 Z_{dk} + U^1 \right] - \theta_k^* \le 0 \\
&\beta_i^1 \le \omega_i^1; \beta_i^2 \le \omega_i^2 \\
&\mu_{r_1}^1, \pi_d^1, \omega_i^1, \beta_i^1, \mu_{r_2}^2, \pi_d^2, \omega_i^2, \beta_i^2 \ge \varepsilon; U^1, U^2 \ free \\
&j = 1,\ldots,n; i = 1,\ldots,m; d = 1,\ldots,t; r_1 \in O_1; r_2 \in O_2
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
&\theta_k^{2*} = Max\sum\nolimits_{r_2\in O_2}\mu_{r_2}^2 Y_{r_2k}^2 + U^2\\
&\sum\nolimits_{i=1}^{m}\omega_i^2 X_{ik} - \beta_i^2 X_{ik} + \sum\nolimits_{d=1}^{t}\pi_d^2 Z_{dk} = 1\\
&\sum\nolimits_{r_1\in O_1}\mu_{r_1}^1 Y_{r_1j}^1 + \sum\nolimits_{d=1}^{t}\pi_d^1 Z_{dj} + U^1 - \sum\nolimits_{i=1}^{m}\beta_i^1 X_{ij} \le 0\\
&\sum\nolimits_{r_2\in O_2}\mu_{r_2}^2 Y_{r_2j}^2 + U^2 - \left[\sum\nolimits_{i=1}^{m}\omega_i^2 X_{ij} - \sum\nolimits_{i=1}^{m}\beta_i^2 X_{ij} + \sum\nolimits_{d=1}^{t}\pi_d^2 Z_{dj}\right] \le 0\\
&\sum\nolimits_{r_1\in O_1}\mu_{r_1}^1 Y_{r_1k}^1 + \sum\nolimits_{d=1}^{t}\pi_d^1 Z_{dk} + \sum\nolimits_{r_2\in O_2}\mu_{r_2}^2 Y_{r_2k}^2 + U^1 + U^2\\
&-\theta_k^*\left[\sum\nolimits_{i=1}^{m}\beta_i^1 X_{ik} + \sum\nolimits_{i=1}^{m}\omega_i^2 X_{ik} - \beta_i^2 X_{ik} + \sum\nolimits_{d=1}^{t}\pi_d^2 Z_{dk}\right] = 0\\
&w_2^*.\left[\sum\nolimits_{r_2\in O_2}\mu_{r_2}^2 Y_{r_2k}^2 + U^2\right] - \theta_k^* \le 0\\
&\beta_i^1 \le \omega_i^1; \beta_i^2 \le \omega_i^2\\
&\mu_{r_1}^1, \pi_d^1, \omega_i^1, \beta_i^1, \mu_{r_2}^2, \pi_d^2, \omega_i^2, \beta_i^2 \ge \varepsilon; U^1, U^2\ free\\
&j = 1,\ldots,n; i = 1,\ldots,m; d = 1,\ldots,t; r_1 \in O_1; r_2 \in O_2
\end{aligned}
\tag{3}
$$

Data Sources and Empirical Application

The efficiency score is sensitive to the choice of inputs and outputs (Mikušová, 2017). Therefore, the choice of input and output indicators is very important in assessing the efficiency of universities. Previous studies in this field show that different types and numbers of input and output variables are used (Avkiran, 2001). The input and output variables used in this study were selected from the input and output variables used in previous studies in this field (Avkiran, 2001; Chen et al., 2021; Chodakowska, 2015; Saniee Monfared and Safi, 2013), considering data availability, and reflecting the teaching and research processes of Turkish research universities as best as possible and shown in Figure 1. The dataset of the study consists of data from 23 research universities in the academic year 2020-2021. The names of these universities and their abbreviations in our study are given in Table 1 (in the Appendix). Three of these universities (IDBU, KU, SU) are private and the rest are public universities. The data on these universities comes from the Higher Education Information Management System (CHE, 2022) and University Ranking by Academic Performance (URAP) Research Center, which measures their academic performance by the quality and quantity of their scholarly publications (URAP, 2021). The data set used in the study is given in Table 2 (in the Appendix).

Research universities in Türkiye have two basic processes, one for teaching and one for research. To measure the overall, teaching and research efficiency of the research universities in Türkiye, a two-stage NDEA with shared inputs model shown in Figure 2 was used in this study. The first stage of this model defines teaching activities while the second stage defines research activities. The number of professors (X_1), associate professors (X_2), assistant professors (X_3), lecturers (X_4), and research assistants (X_5) is the same for both teaching and research processes. Academic staffs devote part of their time to teaching (α) and another part to research (1-α). The outputs of the teaching process are the number of undergraduate students (Y_1), master's students (Z_1), and doctoral students (Z_2). Among these variables, the number of master's students (Z1) and doctoral students (Z_2) are also the inputs of the research process. The output of the research process is the URAP score[1, 2] (Y_2), which is calculated based on the university's research performance indicators. URAP score provides important information about the research output performance of universities. Descriptive statistics of the variables are presented in Table 3.

1 URAP is a ranking system for the world's universities based on their academic performance as measured by six indicators: Articles, citations, total documents, total article impact, total citation impact, and international collaboration. The scores from these indicators are weighted to determine the final rankings of the institutions. The weights are assigned by a group of experts using the Delphi method. The ranking covers 3000 institutions with the highest number of publications, and the data are processed and cleaned to ensure reliability (URAP, 2021).

2 The URAP score does not have any limits or normalization. It is simply the sum of the weighted scores of each indicator. Therefore, it can vary depending on the number and quality of publications and citations of each institution.

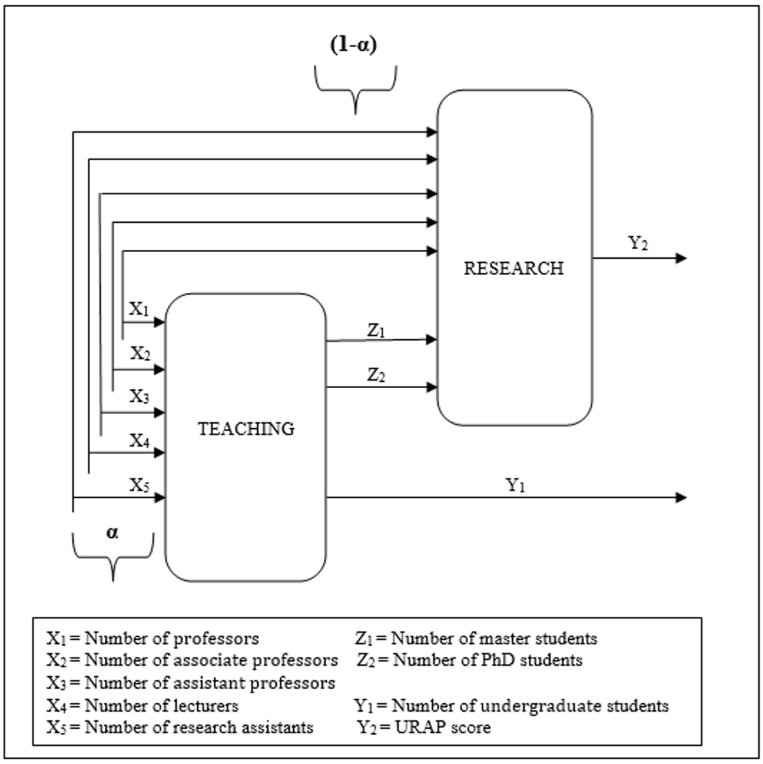

Figure 2: Two-stage NDEA model for teaching and research activities of universities (source: own elaboration)

Variable	Min	Max	Mean	Median	Std. dev.
X_1	81	1,160	515	523	310.37
X_2	47	427	228	230	119.31
X_3	61	649	332	334	171.42
X_4	104	707	386	375	188.01
X_5	8	1,520	730	821	417.04
Z_1	777	9,703	4,480	5,207	2,716.40
Z_2	381	6,207	2,439	2,255	1,678.47
Y_1	4,156	382,226	46,560	28,321	77,854.61
Y_2	158.29	332.02	241.98	238.73	37.71

Table 3: Descriptive statistics of the variables (source: own elaboration based on values shown in Table 2)

Data Analysis

Two-stage NDEA is based on linear programming models, and therefore programs such as MATLAB, GAMS, LINDO, and MICROSOFT EXCEL, which provide solutions for linear programming models, are commonly used in the analysis. Due to the legal obligation for faculty members in Turkish research universities to allocate a certain portion of their time to teaching activities in addition to research activities, lower and upper limits $(0.3 \le \boldsymbol{a}_i \le 0.7)$ have been determined for the proportional time allocated for teaching activities. Therefore, constraints similar to those of Cook and Hababou (2001), Saniee Monfared and Safi (2013) and Cinar (2016) were added to the linear programming models shown in Models 1, 2, and 3 by adding $0.3\boldsymbol{\beta}_i^1 \le \boldsymbol{\omega}_i^1 \le 0.7\boldsymbol{\beta}_i^1; 0.3\boldsymbol{\beta}_i^2 \le \boldsymbol{\omega}_i^2 \le 0.7\boldsymbol{\beta}_i^2$, and the MICROSOFT EXCEL SOLVER add-in was used to solve these models. A total of 69 linear programming models were created and solved since the efficiency of 23 decision units was compared, and three different models were created for each decision unit.

The 23 universities were grouped into three terciles by their region's socio-economic development index (SEDI) using the Socio-Economic Development Ranking of Provinces and Regions Report (SEGE, 2019) in this study. The SEDI measures the socio-economic region's (SER)[3] socio-economic development level (L), with higher values indicating more development. The groups are:

- L1: (8 universities, $\textbf{SEDI} > 3$)
- L2: (8 universities, $1.5 \le \textbf{SEDI} \le 3$)
- L3: (7 universities, $\textbf{SEDI} < 1.5$)

The distribution of research universities according to the level of socio-economic development of the regions in which they are located is shown in Figure 3 (in the Appendix). Using IBM SPSS Statistics software version 21 and the Kruskal-Wallis test, we compared the efficiency scores of the three development level groups.

3 We refer to NUTS II regions because they are an appropriate territorial scale for national and regional analysis and are designated as the basic development planning units in the context of regional policies (Development Agencies, 2023).

RESULTS

Table 4 (in the Appendix) shows the overall efficiency scores of research universities (θ_k^*) when *the teaching stage is maximized* under the assumption of VRS (Banker et al., 1984), and the teaching efficiency scores (θ_k^{1*}) and research efficiency scores (θ_k^2) that are its components. Table 5 (in the Appendix), on the other hand, shows the overall efficiency scores of research universities (θ_k^*) when *the research stage is maximized* under the assumption of VRS, and the teaching efficiency scores (θ_k^1) and research efficiency scores (θ_k^{2*}) that are its components.

The first column of the Table 4 and Table 5 (in the Appendix) shows the abbreviated names of research universities analyzed, the second column shows the codes of socio-economic regions (SER) where universities are located, the third column shows the level of development of the group to which the region belongs (L), the fourth column shows the overall score of the efficiency of the two-stage process (θ_k^*). The fifth and sixth columns of the tables show teaching and research efficiency, respectively, with different priorities (θ_k^{1*} and θ_k^2 for teaching, θ_k^1 and θ_k^{2*} for research). On the other hand, the optimal weighting of teaching stage (w_1^*) is shown in the seventh column and the optimal weighting of research stage (w_2^*) is shown in the eighth column. The optimal distribution ratios of the five shared inputs used in both stages between stages ($\alpha_1^*, \alpha_2^*, \alpha_3^*, \alpha_4^*, \alpha_5^*$) are given between the ninth and thirteenth columns.

We find that the overall efficiency scores of the universities vary from 0.344 to 1.000, and the overall efficiency average is 0.739. While the first 6 universities in the Table 4 and Table 5, IDBU, SU, IIT, KU, GTU, and IU are efficient in both teaching and research processes, the remaining 17 universities are not efficient in at least one of these processes. It can be said that efficient universities efficiently allocate their resources to teaching and research activities and maximize their outputs.

It may be that universities focus more on some activities than others, in other words, they assign different priorities to teaching and research activities. Although the overall efficiency values of universities calculated according to Model 1 are unique with respect to the two-stage network process, there are alternative solutions for the teaching and research efficiency values. When the teaching phase is given priority, Model 2 is used to maximize this phase. As seen in Table 4, when the teaching stage is prioritized, 6 of 17 inefficient universities METU, IUC, ITU, AU, GU and YTU are efficient at the teaching stage, but inefficient at the research stage. As is well known, research universities focus more on research activities and give priority to these activities. When priority is given to the research phase, Model 3 is used to maximize this phase. As seen in Table 5, when the research stage is prioritized, 4 of 17 inefficient universities METU, IUC, ITU and HU are efficient in the research stage, but inefficient in the teaching stage.

Another dimension of the study is to test whether there is a statistically significant difference between the efficiency of research universities according to the level of socio-economic development of the regions in which they are located. The average efficiency scores of the research universities, based on the level of socio-economic development of their regions, are shown in Figure 4 (in the Appendix). Since the data did not fulfil the condition of normal distribution, the Kruskal-Wallis test, a non-parametric test, was used to compare the efficiency of three independent groups. There was no significant difference found in the efficiency scores between regions with high socio-economic development levels and those with relatively low socio-economic development levels regarding overall ($\chi^2 = 3.48, p > 0.05$), teaching ($\chi^2 = 5.33, p > 0.05$), and research ($\chi^2 = 4.06, p > 0.05$).

DISCUSSION

This study evaluated the efficiency of 23 research universities in Türkiye. It used a two-stage NDEA with shared inputs model. The main objective of this study is to compare the efficiency of research universities in Türkiye and to identify inefficient processes and take measures. The findings showed that only six universities, three public and three privates, are overall efficient. This suggests that 100 of private universities and 15 of public universities in the research university program are overall efficient. This efficiency rate is quite low and requires the relevant administrators to take measures in this regard.

Interestingly, some of the big and famous universities in Türkiye were inefficient; these include HU, BU, METU, ITU and AU. On the other hand, some of the relatively smaller and less famous universities, such as IIT and GTU, were overall efficient. This finding supports Altbach's (2015) view that the rankings made by ranking organizations may be problematic because they mainly focus on the effectiveness dimension of organizational performance, which is the outputs or outcomes of the institutions, rather than the efficiency dimension, which is the inputs and processes of the institutions (Lindsay, 1982). For example, according to the URAP World University Rankings (URAP, 2021), at the time of this study, HU ranked 500th in the world and 1st in Türkiye, while IIT ranked 1926th in the world and 44th in Türkiye. However, our analysis shows that HU is not efficient, IIT is efficient. This implies that HU uses more input resources than IIT to achieve the same level of output. Ranking organizations may overlook the efficiency of small universities, which use their limited input resources efficiently, because they only use output-oriented indicators and do not consider the inputs of the universities. Erdoğmuş and Esen (2016) observed that small universities could perform better than medium and big universities in rankings where both output and input indicators were taken into account. Similarly, Chen et al. (2021), using the two-stage NDEA method to evaluate the efficiency of Chinese universities, found that the world-renowned Peking and Tsinghua Universities are not efficient, while some lower ranked universities in China are efficient.

The efficiency analysis results offer valuable insight to higher education administrators, facilitating comparative evaluations of their institutions' development potential, strengths, and weaknesses. This information also assists in identifying areas within higher education institutions requiring attention (Jauhar et al., 2018; Nazarko and Šaparauskas, 2014). Therefore, thepotential managerial and practical implications of the findings are anticipated to be considerable. The two-stage NDEA with shared inputs model used to measure efficiency in this study provides a unique solution for the overall efficiency score, while offering alternative solutions for the efficiency scores of the sub-processes of inefficient decision units. This allows decision units that focus more on one process than another to clearly see the efficiency levels of their sub-processes and the processes that cause inefficiency. In our study, we found that 6 out of 17 inefficient universities were efficient in the teaching stage in the first scenario where teaching activities were prioritized, and that these universities could not be overall efficient due to inefficiency in research stage. Therefore, managers need to develop strategies to increase their outputs in the research stage (number of publications, citations, patents, projects, etc.) for these universities to be overall efficient.

In the second scenario where research activities were prioritized, it was found that 4 out of 17 inefficient universities were efficient in the research stage and that these universities could not be overall efficient due to inefficiency in the teaching stage. The managers of these universities must develop strategies to increase their output in the teaching stage (number of undergraduate, master, and doctoral students) for these universities to be overall efficient. On the other hand, CHE can evaluate and take necessary measures for 13 research universities that are inefficient in the research stage despite prioritizing research activities.

One objective of this study was to measure the efficiency of Turkish research universities in various socio-economic regions with a two-stage NDEA method. The results indicate that there is no significant difference in efficiency scores between regions of varying development, suggesting that the efficiency of research universities in Türkiye is independent of the socio-economic status or features of their respective regions. This indicates that the efficiency of research universities hinges on their internal management and governance rather than their regional circumstance. The result corroborates earlier research that identified no substantial dissimilarities in university efficacy based on geographical location (Agasisti et al., 2011; Chen et al., 2021). However, unlike previous studies, we classified regions using an index of socio-economic development calculated by the relevant government agency. The index includes various indicators including income, education, health, and innovation. By doing so, we can closely examine how regional development impacts the efficiency of research universities.

The finding that the efficiency scores of research universities did not vary significantly across regions implies that, regardless of the socio-economic conditions, these universities managed their resources and operations in a manner that led to comparable levels of efficiency. This consistency suggests a certain resilience or adaptability within these institutions, allowing them to maintain efficiency regardless of the external context. By emphasizing the role of internal management and governance in university efficiency, this study agrees with other research in the field of higher education that internal factors, such as management, governance, staff quality, and research culture, are more important than external factors for university efficiency (Egorov and Serebrennikov, 2023; Kempkes and Pohl, 2010; Kupriyanova et al., 2018; Zinchenko and Egorov, 2019).

This study not only confirms previous findings that university efficiency is independent of geographical location (Agasisti et al., 2011; Chen et al., 2021), but also adds to the existing body of knowledge by providing a more comprehensive classification of regions based on an index of various socio-economic indicators. By emphasizing the importance of internal factors such as the quality of academic staff, the research culture, the management and governance, and the incentive mechanisms rather than regional conditions, this approach provides valuable insights for policymakers and university administrators seeking to improve the efficiency of research universities.

Our findings carry implications for higher education policies and practices in Türkiye. This study may suggest that research universities located in less developed regions do not face efficiency-related disadvantages when compared to their peers located in more developed regions. Therefore, these universities have the potential to enhance their teaching and research activities, improve their performance, and contribute to the development of their respective regions. However, there is potential for enhancement in the efficiency of research universities across all regions, as only a small number of them attained complete efficiency scores. Research universities must optimize their resource allocation and utilization to attain superior outcomes. Conversely, our findings indicate that regional development policies should focus on enhancing the effectiveness and impact of research universities in addressing regional needs and challenges, instead of improving their efficiency. Policy makers should encourage research universities to collaborate with local stakeholders, including businesses, NGOs, and public institutions, to address regional issues and opportunities. Additionally, university managers can adopt best practices from other institutions in different regions to enhance quality and innovation.

Study Limitations

This study possesses certain limitations that warrant acknowledgement. The availability of data from CHE and private research universities was limited, thus influencing the selection of input and output variables. Financial variables were not included in the analysis due to lack of access to financial data.

Another limitation of this study was the unavailability of detailed data on sub-components of the socio-economic development index of the regions where the universities are located. These sub-components include education, health, and innovation. This limitation hindered the identification of targeted improvement areas by preventing a nuanced analysis of how particular socio-economic factors may impact university performance.

If the data for these sub-components were available, the study could potentially bring into focus certain socio-economic factors that may have a significant association with university performance. The information could play a crucial role for university administrators in forming strategic decisions concerning resource allocation, program development, and policy implementation.

CONCLUSIONS

The purpose of this research was to evaluate the efficiency of 23 Turkish research universities utilizing a shared inputs model in a two-stage NDEA and to explore the influence of regional socio-economic status on research university efficiency. The research indicated that only 25 of the research universities demonstrated efficiency on all dimensions and that their overall efficiency scores were affected by the prioritization of teaching or research activities. The efficiency level of research universities remained unaffected by the socio-economic status of regions, according to the study. Additionally, the validity of rankings based on output or outcome measures was questioned. The study recommended incorporating efficiency indicators for a more objective and equitable comparison between universities. The study asserted that utilizing the two-stage NDEA with shared inputs model provided a more complete and practical approach to gauge efficiency in higher education systems characterized by complex network structures.

Based on these findings, the study had several implications for higher education managers, policy makers and ranking organizations. First, higher education managers were recommended to identify the sub-processes that caused inefficiency and develop strategies to improve them. For example, some universities might have needed to balance their outputs in teaching and research processes, while others might have needed to allocate their resources more efficiently. Second, policy makers were suggested to reconsider their policies and incentives for research universities that were inefficient in research despite prioritizing research activities. Furthermore, regional development policies were encouraged to focus not only on increasing the efficiency of universities, but also their effectiveness and impact in addressing regional needs and challenges. Third, ranking organizations were urged to include efficiency indicators in their ranking criteria that reflected how well universities used their input resources to produce outputs in their teaching and research processes.

This study has used a two-stage DEA approach to examine the relationship between university performance and socio-economic development. However, this study could be improved by future research in two ways. First, future research could use more input and output components and include more processes besides teaching and research to evaluate university efficiency more comprehensively and realistically. Second, future research should use data on the sub-components of the socio-economic development index, such as income, health, and education. This would help understand the performance of universities in different socio-economic contexts better. It would also help develop improvement strategies and policy decisions and provide a benchmark for universities. Therefore, future research in this area should use more data and variables to understand the relationship between university performance and socio-economic development better.

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APPENDIX

Abbreviation	Name of Research University	Abbreviation	Name of Research University
ATAU	Atatürk University	IIT	İzmir Institute of Technology
AU	Ankara University	ITU	İstanbul Technical University
BU	Boğaziçi University	IU	İstanbul University
CU	Çukurova University	IUC	İstanbul University-Cerrahpaşa
DEU	Dokuz Eylül University	KTU	Karadeniz Technical University
EGEU	Ege University	KU	Koç University
ERCU	Erciyes University	METU	Middle East Technical University
FU	Fırat University	MU	Marmara University
GTU	Gebze Technical University	SU	Sabancı University
GU	Gazi University	UU	Uludağ University
HU	Hacettepe University	YTU	Yıldız Technical University
IDBU	İhsan Doğramacı Bilkent University		

Table 1: Definition of abbreviations of Turkish Research Universities (source: own elaboration)

DMUs	X_1	X_2	X_3	X_4	X_5	Z_1	Z_2	Y_1	Y_2
ATAU	602	299	649	319	893	5,650	2,325	134,744	240.32
AU	1,160	318	284	707	1,239	6,770	6,207	46,540	271.72
BU	200	117	163	225	312	2,168	1,045	12,766	235.75
CU	537	182	327	443	763	3,237	1,615	32,494	212.53
DEU	741	356	513	707	986	5,207	2,317	46,348	249.64
EGEU	886	386	379	567	997	5,210	3,003	35,820	257.29
ERCU	469	218	427	318	851	6,174	2,218	41,543	235.06
FU	410	174	386	260	732	3,196	981	29,048	224.24
GTU	113	67	111	104	274	2,097	746	5,418	192.16
GU	912	352	221	564	1,172	6,141	3,606	28,321	255.66
HU	926	356	567	642	1,520	5,960	4,292	37,004	332.02
IDBU	106	64	192	381	8	813	438	10,655	250.63
IIT	85	62	61	129	259	967	449	4,795	158.29
ITU	523	247	334	463	720	8,082	3,881	25,645	286.40
IU	906	427	594	473	1,168	9,703	5,908	382,226	303.76
IUC	580	230	352	155	801	2,218	2,255	20,177	222.36
KTU	424	159	386	279	944	2,010	1,275	24,989	225.53
KU	210	77	128	192	19	851	753	7,305	243.87
METU	390	175	264	558	821	5,255	3,281	22,203	282.72
MU	710	365	604	375	1,021	9,290	4,340	50,520	238.73
SU	81	47	84	125	16	777	381	4,156	197.28
UU	582	309	262	547	838	4,614	2,164	41,358	213.03
YTU	294	254	345	340	447	6,654	2,626	26,804	236.46

Note: X1: No. of profs, X2: No. of assoc. profs, X3: No. of asst. profs, X4: No. of lecturers, X5: No. of research assts, Z1: No. of master students, Z2: No. of PhD students, Y1: No. of undergraduate students, Y2: URAP score

Table 2: The data set used in this study (source: own elaboration based on CHE, 2022 and URAP, 2021)

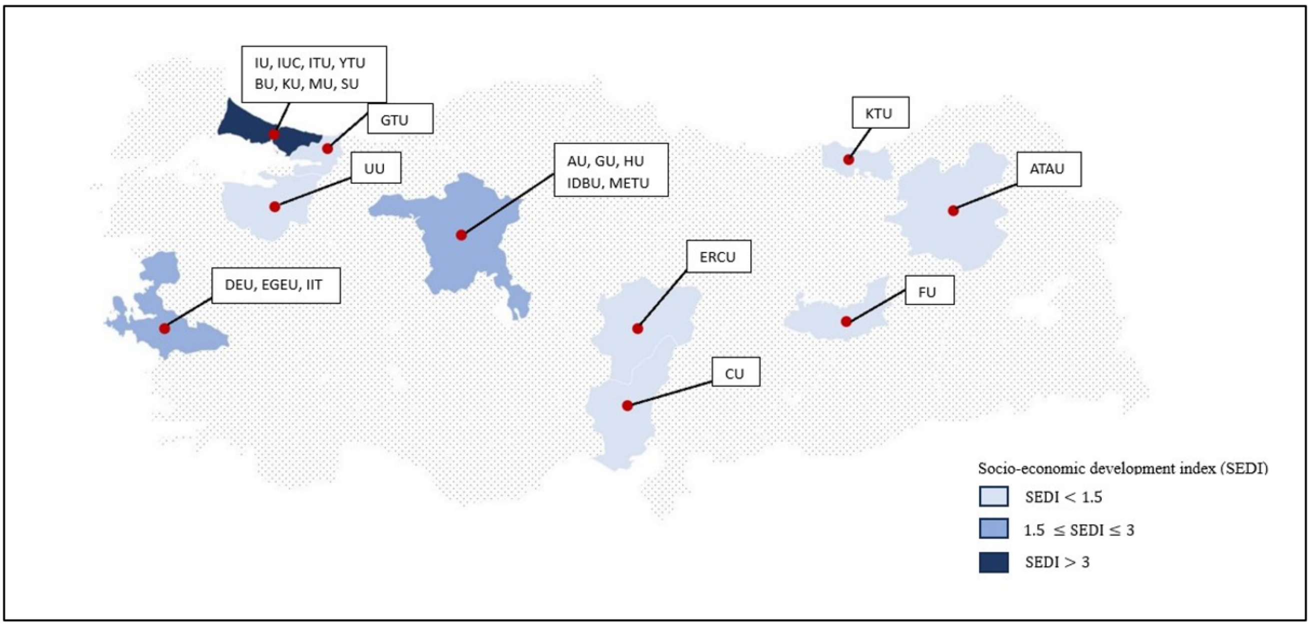


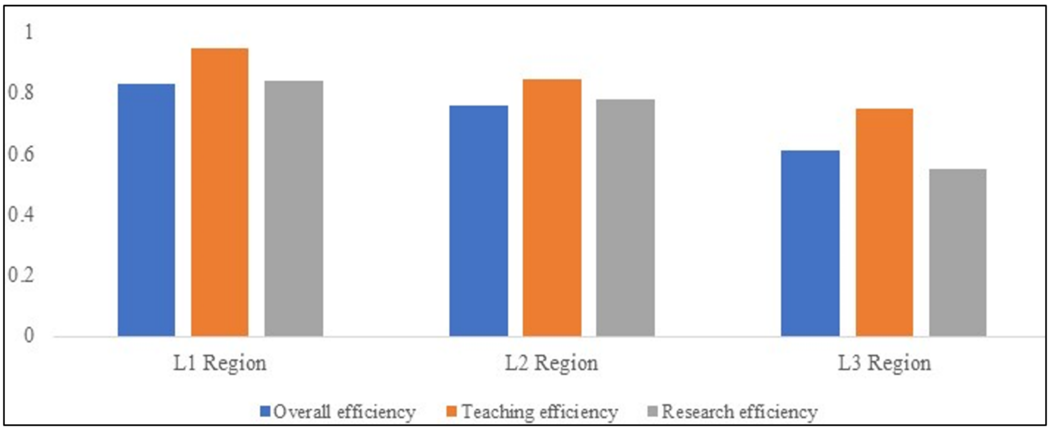
Figure 3: Distribution of research universities according to the level of socio-economic development of the regions in which they are located (source: own elaboration based on SEDI data of NUTS II regions in SEGE, 2019 using map chart in Microsoft Excel)

DMUs	SER	L	θ_k^*	θ_k^{1*}	θ_k^2	w_1^*	w_2^*	α_1^*	α_2^*	α_3^*	α_4^*	α_5^*
IDBU	TR51	2	1.000	1.000	1.000	0.300	0.700	0.700	0.700	0.700	0.300	0.700
SU	TR10	1	1.000	1.000	1.000	0.573	0.427	0.700	0.700	0.700	0.300	0.700
IIT	TR31	2	1.000	1.000	1.000	0.699	0.301	0.700	0.700	0.517	0.700	0.700
KU	TR10	1	1.000	1.000	1.000	0.253	0.747	0.700	0.700	0.700	0.498	0.700
GTU	TR42	3	1.000	1.000	1.000	0.299	0.701	0.700	0.700	0.700	0.700	0.700
IU	TR10	1	1.000	1.000	1.000	0.689	0.311	0.700	0.700	0.700	0.700	0.700
METU	TR51	2	0.957	1.000	0.932	0.365	0.635	0.300	0.300	0.300	0.700	0.700
IUC	TR10	1	0.928	1.000	0.904	0.300	0.700	0.700	0.700	0.700	0.300	0.700
ITU	TR10	1	0.815	1.000	0.740	0.288	0.712	0.700	0.700	0.300	0.700	0.300
AU	TR51	2	0.792	1.000	0.669	0.371	0.629	0.700	0.700	0.481	0.700	0.700
BU	TR10	1	0.788	0.686	0.827	0.275	0.725	0.300	0.700	0.300	0.300	0.700
GU	TR51	2	0.748	1.000	0.645	0.290	0.710	0.700	0.700	0.390	0.700	0.700
HU	TR51	2	0.722	0.641	0.769	0.369	0.631	0.700	0.700	0.700	0.700	0.700
ATAU	TRA1	3	0.677	0.724	0.570	0.694	0.306	0.700	0.700	0.700	0.700	0.700
YTU	TR10	1	0.632	1.000	0.393	0.394	0.606	0.700	0.700	0.700	0.300	0.700
FU	TRB1	3	0.574	0.559	0.580	0.298	0.702	0.700	0.700	0.700	0.300	0.700
KTU	TR90	3	0.545	0.598	0.515	0.358	0.642	0.700	0.700	0.700	0.300	0.700
ERCU	TR72	3	0.521	0.956	0.197	0.427	0.573	0.700	0.700	0.300	0.700	0.300
UU	TR41	3	0.508	0.781	0.245	0.490	0.510	0.700	0.700	0.700	0.700	0.700
MU	TR10	1	0.495	0.890	0.000	0.556	0.444	0.700	0.700	0.700	0.700	0.300
EGEU	TR31	2	0.494	0.624	0.341	0.541	0.459	0.700	0.700	0.700	0.466	0.700
CU	TR62	3	0.459	0.619	0.266	0.549	0.451	0.700	0.700	0.700	0.700	0.443
DEU	TR31	2	0.344	0.496	0.117	0.599	0.401	0.700	0.700	0.300	0.300	0.700

Table 4: The efficiency of research universities giving priority to the teaching stage (source: own elaboration)

DMUs	SER	L	θ_k^*	θ_k^1	θ_k^{2*}	w_1^*	w_2^*	α_1^*	α_2^*	α_3^*	α_4^*	α_5^*
IDBU	TR51	2	1.000	1.000	1.000	0.300	0.700	0.300	0.300	0.300	0.300	0.700
SU	TR10	1	1.000	1.000	1.000	0.573	0.427	0.700	0.700	0.700	0.300	0.700
IIT	TR31	2	1.000	1.000	1.000	0.699	0.301	0.300	0.300	0.300	0.300	0.473
KU	TR10	1	1.000	1.000	1.000	0.253	0.747	0.700	0.700	0.300	0.300	0.700
GTU	TR42	3	1.000	1.000	1.000	0.299	0.701	0.700	0.700	0.608	0.300	0.700
IU	TR10	1	1.000	1.000	1.000	0.689	0.311	0.700	0.700	0.300	0.300	0.300
METU	TR51	2	0.957	0.882	1.000	0.365	0.635	0.700	0.700	0.300	0.300	0.327
IUC	TR10	1	0.928	0.762	1.000	0.300	0.700	0.700	0.700	0.700	0.300	0.700
ITU	TR10	1	0.815	0.376	1.000	0.288	0.712	0.300	0.700	0.300	0.300	0.300
AU	TR51	2	0.792	0.916	0.719	0.371	0.629	0.700	0.700	0.339	0.700	0.700
BU	TR10	1	0.788	0.603	0.858	0.275	0.725	0.300	0.700	0.700	0.300	0.700
GU	TR51	2	0.748	0.924	0.676	0.290	0.710	0.700	0.700	0.300	0.700	0.700
HU	TR51	2	0.722	0.245	1.000	0.369	0.631	0.700	0.700	0.700	0.308	0.700
ATAU	TRA1	3	0.677	0.720	0.580	0.694	0.306	0.700	0.700	0.700	0.682	0.700
YTU	TR10	1	0.632	0.922	0.444	0.394	0.606	0.612	0.700	0.700	0.300	0.700
FU	TRB1	3	0.574	0.474	0.617	0.298	0.702	0.700	0.700	0.700	0.323	0.700
KTU	TR90	3	0.545	0.491	0.575	0.358	0.642	0.700	0.700	0.700	0.300	0.700
ERCU	TR72	3	0.521	0.477	0.553	0.427	0.573	0.700	0.700	0.700	0.310	0.700
UU	TR41	3	0.508	0.776	0.250	0.490	0.510	0.700	0.700	0.700	0.700	0.700
MU	TR10	1	0.495	0.545	0.431	0.556	0.444	0.700	0.700	0.700	0.420	0.700
EGEU	TR31	2	0.494	0.496	0.490	0.541	0.459	0.700	0.700	0.401	0.438	0.700
CU	TR62	3	0.459	0.616	0.269	0.549	0.451	0.700	0.700	0.700	0.300	0.700
DEU	TR31	2	0.344	0.340	0.350	0.599	0.401	0.700	0.700	0.700	0.700	0.700

Table 5: The efficiency of research universities giving priority to the research stage (source: own elaboration)



Note: Average teaching efficiency score: mean of the teaching efficiency scores (θ_k^{1*}) in Table 4.

Average research efficiency score: mean of the research efficiency scores (θ_k^{2*}) in Table 5.

Figure 4: Average efficiency scores of research universities based on the socioeconomic development level in their respective regions (source: own elaboration)