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ARTICLES

A COMPLEMENTARY APPROACH BASED ON DATA ENVELOPMENT ANALYSIS TO ASSESS INDUSTRIAL ENGINEERING HIGHER EDUCATION UNDERGRADUATE PROGRAMS IN BRAZIL

Renata Oliveira[1*], Andreia Zanella[2], Vitor Martins[3] and Nathalia Monteiro[4]

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ABSTRACT. This paper proposes a complementary approach to assess the performance of Industrial Engineering undergraduate programs within the Brazilian Higher Education System. This approach presents an alternative Composite Indicator formulation derived from a Data Envelopment Analysis (DEA) model and the Benefit-of-Doubt (BoD) approach. This method enhances comparability among programs across diverse Higher Education Institutions (HEIs) by optimizing weights and incorporating weight restrictions. The application of the novel approach was conducted with the analysis of 73 undergraduate programs within the Brazilian Federal Public System in 2019, the study identified both programs with suboptimal performance levels and benchmark programs showcasing best practices. This feature of the BoD model can support the HEIs assessed as suboptimal in pursuing improvement opportunities in a benchmarking exercise. The incorporation of Weight Restrictions (WRs) enables a more comprehensive consideration of key performance indicators (KPIs) within the Preliminary Program Grade (CPC) framework, thereby revealing additional improvement opportunities. This research contributes to the field by integrating DEA and BoD into the official STEM performance criteria framework for the first time, offering insights into evaluating undergraduate Industrial Engineering programs within Brazilian HEIs.

Keywords: Performance assessment, data envelopment analysis, composite indicator, higher education, industrial engineering, preliminary program grade.

1 INTRODUCTION

The performance assessment of higher education institutions (HEIs) is essential in academic and managerial decision-making, serving as a key mechanism for policy formulation and insti-

*Corresponding author
[1]Universidade do Estado do Pará (UEPA), NOMADE, Campus V. Tv. Dr. Enéas Pinheiro, 2626, Marco, Belém, PA, Brazil – E-mail: renata.oliveira@uepa.br – http://orcid.org/0000-0002-1904-7533
[2]Universidade Federal de Santa Catarina (UFSC), NOMADE, R. Eng. Agronômico Andrei Cristian Ferreira, s/n, Trindade, Florianópolis, SC, Brazil – E-mail: andreia.zanella@ufsc.br – http://orcid.org/0000-0002-0651-0349
[3]Universidade do Estado do Pará (UEPA), NOMADE, PPGTEC Campus V. Tv. Dr. Enéas Pinheiro, 2626, Marco, Belém, PA, Brazil – E-mail: vitor.martins@uepa.br – http://orcid.org/0000-0003-4891-8630
[3]Universidade do Estado do Pará (UEPA), NOMADE, Campus VIII, Av. Hiléia, s/n, Amapá, Marabá, PA, Brazil – E-mail: nathalia.monteiro@uepa.br – http://orcid.org/0000-0002-2619-2667

tutional improvement. In the Brazilian context, the National Higher Education Evaluation System (SINAES) provides the primary framework for evaluating HEIs, undergraduate programs (i.e., bachelor programs), and student performance Brasil (2004). Since 2008, two key indicators—the Preliminary Program Grade (CPC) and the General Program Index (IGP)—have been used to quantify educational quality, streamlining assessments and reducing the need for on-site evaluations (Brasil, 2008; Verhine & Dantas, 2009). Although widely adopted, the methodologies behind these indicators remain a subject of debate, particularly regarding their capacity to accurately reflect institutional diversity and educational quality (Schwartzman, 2008).

The assessment of HEIs has gained increasing relevance in the wake of Sustainable Development Goal 4 (SDG 4) within the 2030 Agenda (UN, 2015). This global initiative emphasizes inclusive, equitable, and quality education as a fundamental pillar of sustainable development. In this context, the SINAES framework becomes a crucial instrument for promoting educational quality in alignment with international standards. The CPC, considered the primary Quality Indicator of Higher Education in Brazil (Ikuta, 2016), provides a broad view of the educational landscape, offering insights into the strengths and weaknesses of Brazilian higher education (Griboski & Fernandes, 2016). However, despite its relevance, the formulation of the CPC has been a subject of ongoing debate and criticism within the academic community (Schwartzman, 2008).

A key point of discussion concerns the exogenous weighting system assigned to different CPC components. Even minor alterations in these weights can significantly impact the final performance measurements of undergraduate programs (Bittencourt et al., 2010), potentially influencing the strategic decisions of educational institutions. The lack of consensus regarding the allocation of weight is further complicated by the standardization of these weights across all programs and HEIs, disregarding institutional specificities and disciplinary differences. This issue is particularly critical in the comparison of public and private HEIs under identical performance criteria (Lacerda & Ferri, 2017). Furthermore, the substantial reliance on student-related components, reaching 70% of the CPC, raises concerns about subjectivity in student responses, necessitating a more contextualized approach to evaluation (Griboski & Fernandes, 2016; Ikuta, 2016).

Given these challenges, this study proposes a complementary procedure to assess the performance of Brazilian undergraduate programs based on Data Envelopment Analysis. Specifically, the research seeks answers to the following research question (RQ)

RQ. How an alternative CPC formulation, based on Data Envelopment Analysis (DEA), can provide a more flexible and institutionally tailored assessment of undergraduate program performance?

To address this question, two hypotheses were formulated as follows.

(i) By allowing for endogenous weight determination, DEA-based model, enables institutions to value their unique strengths;

(ii) Introducing weight restrictions in the CPC calculation fosters a balanced trade-off between complete flexibility and standardization, leading to a more equitable assessment framework.

To test these hypotheses, the study explores two distinct scenarios: (1) exploring assessment results of a DEA formulation allowing full flexibility in the selection of weights; (2) Exploring results enforcing weight restrictions in the DEA model to balance flexibility with standardization. By adopting this approach, the study refines the CPC alternative composite indicator, enhancing its utility as a complementary tool for performance analysis. The proposed formulation has the potential to support managerial decisions, identify critical areas for continuous improvement, and highlight best practices among suboptimal programs.

Given the complexities inherent in higher education assessments, multiple theoretical perspectives can deepen the performance analysis of the programs (Andriola, 2004; Andriola & Araújo, 2018). Tehrefore, this alternative CPC formulation represents a methodological innovation towards a more nuanced assessment of undergraduate programs.

This paper is structured as follows. Section 2 reviews the literature on HEI performance assessment with special focus on DEA-based assessments of undergraduate programs and graduate programs. Section 3 provides an in-depth discussion of the official dimensions and components of the CPC index. Section 4 details the Benefit of the Doubt (BoD) approach, including the DEA composite indicator (CI) model and complementary CPC assessment. Section 5 presents and discusses the results, while Section 6 offers concluding remarks, highlighting the implications of the proposed method and suggesting directions for future research.

2 LITERATURE REVIEW ON THE ASSESSMENT OF HIGHER EDUCATION PROGRAMS USING DEA

This section reports a literature review of DEA-based assessments of higher education Institutions (HEIs). It is organized into two subsections. The first subsection focuses on assessments of undergraduate programs, while the second one addresses graduate programs, particularly at Brazilian master's and doctoral levels.

2.1 DEA-based studies assessing Undergraduate Programs

This subsection examines studies that applied DEA to assess the efficiency of undergraduate programs in HEIS. Papers published between 1988 and 2025 were searched, and as a result, 19 peer-reviewed papers released up to the year 2022 were found. Also, it is noteworthy that studies of HEI's administration efficiency were disregarded due to their scope (e.g., Di Leo et al., 2024; Almeida et al., 2024)

All papers reviewed in this subsection are indexed in the following bases: Scopus, spanning the period. Note that the papers discussed in this subsection focused particularly on applied studies of Data Envelopment Analysis (DEA) models. The papers analyzed include network DEA, directional distance function (DDF), and bootstrap analysis. The thematic scope of these studies covers efficiency evaluations at the institutional, departmental, and program levels, taking into consideration different hierarchical levels of HEIs. Furthermore, the inclusion of studies from diverse educational contexts, such as Chinese, Polish, Greek, Taiwanese, and Brazilian HEIs, enhanced the global perspective of this review. By synthesizing efficiency assessments across various contexts, this study identifies key research gaps, particularly concerning the Benefit of Doubt (BoD) approach and the application of DEA in the efficiency evaluation of Brazilian HEIs, highlighting the contribution of this paper to advancing knowledge in the field.

On the assessments of HEIs, Johnes & Yu (2008) assessed the research efficiency of a set of Chinese universities. Similarly, Nazarko & Šaparauskas (2014) assessed the efficiency of Polish technology universities and their strategies for financial resource allocation. The work of Zhang & Shi (2019) assessed the teaching performance of Chinese colleges and universities from the perspective of network DEA. Xiong et al. (2022) analyzed resource allocation problems according to the teaching and research performance of universities. Ding et al. (2021) proposed a three-stage DEA model to measure the performance of higher education institutions across Chinese provinces. Chen & Chang (2021) developed a novel two-stage DEA method for evaluating the operating efficiency of multiple Chinese university departments. Finally, Yang et al. (2018) introduced a two-stage DEA model specified with a directional distance function to quantify inefficiencies in terms of inputs and outputs in Chinese universities. The use of DDF makes this work methodologically distinct from the previous ones analyzed.

Regarding departmental-level assessments, Beasley (1990) is considered a pioneer in terms of using DEA to evaluate the efficiency of departments in the U.K., Beasley (1990) introduced an enhanced methodology to quantify both teaching and research efficiencies. This approach was extended by Kounetas et al. (2011), who studied the research efficiency of academic departments at a Greek university. Chang et al. (2012) applied a two-stage DEA model to assess the efficiency of tourism and leisure departments in Taiwanese universities, offering valuable managerial insights. Soon after, Barra & Zotti (2016) brought innovative perspectives with their works focusing on assessing relatively heterogeneous units within disciplinary departments. These authors adopted the combination of bootstrap and DEA, while Ding et al. (2021) selected a set of nonhomogeneous network DEA models for assessing faculty departments. Also, Ghasemi et al. (2020) explored the performance of a few campuses whilst assessing departmental efficiency in HEIs with strong hierarchical vocation. Chen & Chang (2021) formulated weight restrictions for assessing departmental efficiency, supported by judgment values.

In terms of the efficiency assessment of Brazilian programs, the use of the DEA technique has gained attention since the 2000s. Despite the popularity, the assessment of programs in HEIs, specifically considering the CPC-related topics, has been identified in only three recent papers within the recent literature (e.g., Zanella & Oliveira, 2021).They are discussed in the next paragraphs.

The first paper is the work of Borges Carnielli (2006), who evaluated 181 programs based on the 2003 National Program Exam database. This research reported a comprehensive evaluation using the criteria set by the National Higher Education System (SINAES, in Portuguese, Sistema Nacional de Educação Superior). The second paper is the paper of Soliman et al. (2017), who applied a DEA model to assess the efficiency of a set of 1229 Engineering programs in both private and public institutions using data from the year 2009. These authors addressed components related to faculty qualification, working hours, and student perception of the formative process offered by the program as inputs (resources), and components such as students' scores in the National Student Performance Exam (ENADE, in Portuguese: Exame Nacional do Desempenho de Estudantes), and the value-added by the formative process as outputs (results) of the process. The last one is the paper of Rodrigues & Gontijo (2019), which addressed the KPIs of the CPC as inputs and outputs of the process to assess the efficiency of Public Administration Programs. They also incorporated expert opinions on the importance of the components through weight restrictions in the DEA model.

Note that the three papers identified addressed the assessment of HEIs and higher education programs from the perspective of efficiency analysis, and the variables considered were rather inputs and outputs. Nevertheless, works using the Benefit of Doubt (BoD) approach to construct a composite indicator were not identified during the literature review stage, meaning that to the best of our knowledge, this is the first research paper proposing the construction of an alternative composite indicator to CPC to assess undergraduate Industrial Engineering programs in the context of Brazilian Higher Education Institutions (HEIs).

2.2 DEA-based studies assessing Brazilian Master's and Doctoral Graduate Programs.

This subsection presents a body of literature on the assessment of graduate programs in Brazil published between 2015 and 2025. Particular focus was dedicated to studies based on Data Envelopment Analysis (DEA). The use of DEA in multi-method frameworks was taken into account as well (e.g., Network DEA, MCDM/A-DEA). Although this paper does not assess graduate programs, exploring the literature on Brazilian DEA applications in the context of graduate education offers valuable methodological and conceptual insights that enrich this investigation. As a result, a set of 13 papers published between 2015 and 2023 in Brazilian journals is discussed broadly and in more depth in the next paragraphs. One should note that papers assessing graduate programs using different operations research techniques rather than DEA are not covered in this subsection (e.g., Tavares et al., 2022).

Since the 2010s, a range of studies has emerged in Brazil exploring the application of DEA to evaluate the performance and efficiency of *stricto sensu* graduate programs. Particularly, in the period analyzed, Brazilian literature has contributed to this field, reinforcing DEA's role in assessing graduate programs across several disciplines.

Among these contributions, the paper of Vasconcelos et al. (2016) is considered a pioneer work in efficiency assessment of Brazilian engineering graduate programs according to the data and criteria of the Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES) - in Portuguese, *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior*. These authors emphasize the methodological rigor required in selecting appropriate input-output variables for DEA models, underscoring DEA's potential as a tool to support evidence-based decision-making in educational policy. Similarly, Gontijo et al. (2018) demonstrated the adaptability of DEA in the public sector by applying it to assess educational efficiency in public organizations. Their methodological framework aligns closely with the evaluation of graduate programs, bridging institutional performance and educational outputs.

Another advanced application of DEA is presented by Angulo-Meza et al. (2018), employing a Network DEA model to evaluate the efficiency of Brazilian graduate programs within the "Engineering III" subarea. This approach allows for a stage-wise decomposition of the academic production process, distinguishing between inputs and outputs across sub-processes such as student supervision, scientific publication, and intellectual production. Their findings contribute to a more nuanced understanding of how graduate programs transform academic resources into scientific outcomes.

Tavares et al. (2021) proposed an efficiency evaluation approach for HEIs based on the Network DEA model. The objective was to reflect the complexity of universities by considering multiple activities and sub processes within a three-stage evaluation focused on different perspectives: financial, teaching, research, and innovation. The approach was applied to 45 Brazilian federal universities using data from 2016 and 11 variables distributed across the three stages. The results reveal significant variations in performance among the HEIs and identify those with higher relative efficiency at each stage. The approach also enables the identification of efficient HEIs that may serve as benchmarks for others. This methodological approach aligns with and extends previous work by Angulo-Meza et al. (2018) on network DEA applications in graduate program evaluation.

Felicetti & Cabrera (2022) focused on students' experiences within graduate programs. Although their study does not directly implement DEA, it reveals how students' perceptions, particularly regarding engagement and collaborative learning, can serve as meaningful inputs in DEA-based evaluations. This perspective adds nuance to the broader understanding of educational outputs and their subjective dimensions.

In parallel, Azevedo et al. (2021) examined the evolution of graduate education in Brazil, advocating for adaptive methodologies in program assessment. Their findings support the integration of structured models like DEA to sustain continuous improvement efforts in professional doctoral programs.

In addition to these national contributions, Guimarães et al. (2019) provided insights into Internationalization at Home (IaH), highlighting how internationalization strategies intersect with educational quality, an important aspect in performance frameworks such as DEA. While not explicitly framed within DEA, the study underlines the strategic role of global engagement in improving academic outcomes. Complementing this perspective, Hammes et al. (2020) and Filho et al. (2023) employ DEA to analyze public spending in federal universities, linking budgetary efficiency to academic performance. These studies underscore how fiscal responsibility and performance metrics are intertwined in Brazilian higher education.

Furthermore, Villano & Tran (2019) conducted a meta-regression analysis that reflects the increasing reliance on heterogeneous DEA models to accommodate varied institutional contexts. Their results affirm DEA's growing legitimacy as a preferred tool in educational evaluation.

On a related front, Daú et al. (2023) explored the integration of sustainability indicators aligned with the UN 2030 Sustainable Development Goals into higher education assessments. Their innovative approach opens new avenues for combining DEA with broader social responsibility frameworks, enabling the evaluation of how graduate programs contribute to both education quality and the achievement of global sustainability goals.

Internationally, methodologies such as those proposed by Fisher et al. (2017) and Popović et al. (2020) have expanded DEA's application scope by linking student quality and academic performance, or incorporating multi-criteria decision-making methods to assess teaching effectiveness. These models, although not exclusive to the Brazilian context, illustrate transferable techniques that can enrich domestic evaluations.

The literature review presented in this subsection highlights the relevance of DEA methodology in the assessment of Brazilian master's and doctoral graduate programs. By encompassing perspectives from fiscal efficiency, sustainability, student engagement, and program quality, these studies can enrich both performance and efficiency assessments.

2.3 Discussion of literature review findings

The literature reviewed in this paper reveals a methodologically diverse field of research using DEA to evaluate higher education programs. The adoption of DEA models, along with variations such as network DEA, directional distance functions (DDF), and bootstrapped models, demonstrates a growing effort to refine efficiency assessments and account for the multifaceted nature of academic performance. Notably, the broad geographical scope of the review, spanning Asia, Europe, and Latin America, provided a wide and in depth outlook of the research body released since the 2000s. It also surfaces research opportunities in country-specific applications, particularly within the Brazilian context.

Regarding assessing undergraduate program assessments, the majority of studies focus on resource utilization and academic outcomes, typically measured through student performance, faculty characteristics, and institutional productivity. However, few studies integrate the perspective of student satisfaction, program infrastructure, and graduate performance as recommended by the CPC framework. This finding suggests that while international literature is robust in methodological experimentation, there is limited contextual calibration to national performance frameworks such as those established by Brazil's Ministry of Education (MEC).

At the departmental level, research has demonstrated the capacity of DEA to analyze multidisciplinary academic units. This is particularly useful in multidisciplinary fields like Industrial Engineering, where departments may vary significantly in size, focus, and output. Studies employing multi-stage and hierarchical DEA have addressed this challenge, yet Brazilian departmental-level applications remain sparse. Furthermore, the frequent omission of stakeholder perceptions, such as student evaluations or expert judgments, as part of the input-output configuration presents an opportunity for future research to bridge quantitative assessment with qualitative insights.

Graduate-level assessments in Brazil incorporated multi-method approaches, including MCDM/A-DEA hybrids and sustainability KPIs. These developments reflect an awareness of the broader mission of higher education beyond academic outputs, encompassing institutional accountability, internationalization, and social responsibility. However, this complexity also increases the need for transparent, reproducible, and policy-aligned assessment models. DEA's flexibility makes it a strong candidate for such evaluations, though its application must be aligned with policy objectives like CAPES' framework.

Another key observation is the limited use of composite indicators models specified in the reviewed DEA literature. Most studies use DEA purely as a benchmarking tool rather than as a basis for constructing performance indexes. The Benefit of the Doubt (BoD) methodology, which allows endogenous weighting of indicators, is rarely used in the HEI context, despite its compatibility with the composite nature of policy-oriented indices like CPC. As a result, there is a significant gap in research bridging DEA and BoD for the purpose of institutional evaluation in Brazil.

Despite the abundance of DEA literature applied to institutional and departmental analyses, only a handful of studies have explicitly explored DEA's alignment with Brazil's Preliminary Program Grade (CPC) framework. Borges & Carnielli (2006), Soliman et al. (2017), and Rodrigues & Gontijo (2019) provided foundational contributions by evaluating higher education programs using CPC-related indicators. However, none of these studies employed the Benefit of the Doubt (BoD) approach to construct a composite indicator, reinforcing the originality of the present research in proposing a DEA-BoD framework tailored to assess Industrial Engineering undergraduate programs.

3 THE OFFICIAL CPC CALCULATION PROCEDURE

The Preliminary Program Grade (CPC) can be considered a composite indicator that combines various Key Performance Indicators (KPIs) reflecting the performance criteria of undergraduate programs into an overall performance measure. Established in 2008, CPC has evolved through a sequence of updates over time to accommodate alterations to the National Student Performance Exam (ENADE) and also to respond to the needs of the academic community. The main modifications have primarily focused on the inclusion of assessment components and the corresponding set of weights (Barreyro & Rothen, 2014). Table 1 reports dimensions (criteria) and components (or KPIs) of the CPC, along with the weight system integral to its calculation.

Table 1 – Official dimensions, components, and weights of CPC.

Dimension	Official Components	Output (Y_r)
Graduate Performance	ENADE Grade (20%)	Y_1
Program value-added	Difference Between Observed and Expected Performance Indicator Score (35%)	Y_2
Student's Perception	Didactic-Pedagogical Organization (7.5%)	Y_3
	Infrastructure and Physical Installations (5%)	Y_4
	Opportunities for Expanding Academic and Professional Training (2.5%)	Y_5
Faculty	Faculty members holding Master's Degree (7.5%)	Y_6
	Faculty member holding PhD Degree (15%)	Y_7
	Faculty Work Journey (7.5%)	Y_8

Source: Brasil (2019)

The assessment framework reported in Table 1 is based on Technical Note No. 45/2019 (Brasil, 2019). It defines a four-dimensional set of criteria; each one is assigned a specific weight based on its relative importance. These dimensions encompass various quantifiable components to assess particular aspects of the overall performance of the undergraduate programs. The first dimension is Graduate Performance. It is quantified by the KPI entitled "ENADE Grade" (Y_1). It reflects the academic achievements of the graduates. The second dimension is the "Program Value-Added", which is reflected by the KPI "Difference Between Observed and Expected Performance Indicator Score" (Y_2). This KPI quantifies the program's effectiveness in adding value to students' career outcomes. The third dimension is "Student's Perception" and it is represented by three KPIs ("Didactic-Pedagogical Organization" (Y_3); "Infrastructure and Physical Installations" (Y_4), and "Opportunities for Expanding Academic and Professional Training" (Y_5)). The KPIs associated with these components collectively measure the students' perspectives on the educational environment, infrastructure, and growth opportunities. The fourth and last dimension is "Faculty", which is composed of KPIs reflecting the faculty education level and working regime (e.g., full-time, part-time). The KPIs are the following: "Faculty members holding a master's degree" (Y_6), "Faculty members holding a PhD" (Y_7), and "Faculty Work Journey" (Y_8). These KPIs collectively gauge the qualifications, expertise, and commitment of the faculty, providing a comprehensive evaluation of the faculty's role in the program.

All CPC KPIs undergo standardization and rescaling, assuming continuous values comprised between zero and five. Based on the standardized component values, the CPC Continuous Grade for each program j (NC_j) is given by weighting the scores for each KPI as reported in formulation 1.

$$NC_j = 0,2Y_1j + 0,35Y_2j + 0,075Y_3j + 0,05Y_4j + 0,025Y_5j + 0,075Y_6j + 0,15Y_7j + 0,075Y_8j \quad (1)$$

4 METHODOLOGY

This section presents the Composite Indicator (CI) DEA model specified for quantifying the performance of undergraduate programs within the Brazilian public Federal System. DEA was introduced by Charnes et al. (1978) as a linear programming-based technique designed to quantify the relative efficiency of a homogeneous set of Decision-Making Units (DMUs) (Cooper et al., 2006).

DEA-based models enable the estimation of one aggregate efficiency measure for each DMU by making direct comparisons with other DMUs within a sample. While initially proposed to assess the technical efficiency of homogeneous DMUs using multiple inputs to generate multiple outputs, DEA can also be applied in the context of constructing composite indicators

A CI aggregates a specific set of individual KPIs into a global performance measure. The resulting CI can capture multidimensional concepts that a single individual indicator might overlook. Advantages of using CIs include the ability to summarize information and supporting interpreting results compared t a set of indicators, as outlined in the guidelines by the Organization for Economic Cooperation and Development (OECD) (Nardo et al., 2008).

The use of DEA for constructing CIs was initially proposed by Cook & Kress (1990). But, Cherchye et al. (2007) further popularized the use of CIs based on DEA by introducing a mathematically straightforward model known as the ”Benefit-of-the-doubt (BoD) Composite Indicator”. This approach assigns endogenous weights to each indicator for each DMU under evaluation through optimization. Consequently, each DMU is evaluated with weights that maximize its advantage in the assessment, mitigating the use of a singular weight system that could disadvantage other DMUs.

The linear programming model for estimating the performance of Brazilian Industrial Engineering undergraduate programs is expressed in formulation (2). As noted by Cherchye et al. (2007), this model is analogous to the original input-oriented DEA model proposed by Charnes et al. (1978), wherein all process indicators are treated as outcomes (outputs), and a dummy variable equal to ”1” is considered as a singular input for all DMUs.

$$\begin{aligned} & IC_{j_o}^{CPC} = \max \sum_{r=1}^{s} u_r y_{rj_o} & \\ & \text{s.t.} \sum_{r=1}^{s} u_r y_{rj} \leq 1 & j = 1, \ldots, n \\ & u_r \geq \varepsilon, & r = 1, \ldots, s \end{aligned} \tag{2}$$

In formulation (2), y_{rj} represents the value observed in indicator r for DMU j. The subscript “o” in j_o, represents the DMU under evaluation, note that (2) is solved n times. u_{rj} represents the weight of the i-th KPI of DMU j. Thus, u_{rj} reflects every decision variable of this optimization model. The letter ε is an infinitesimal value that guarantees strictly positive weights. The study conducted in this article uses the model of formulation (2) to quantify the performance of undergraduate programs considering the KPIs of the CPC. Therefore, the DMUs represent the “undergraduate programs” and the individual indicators (y_{rj}) represent the “KPIs of the CPC”. $CI_{j_o}^{CPC}$ can assume values ranging between 0 and 1. $CI_{j_o}^{CPC} = 1$ outlines the frontier of efficiency and indicates the highest performances in the Production Possibility Set (PPS), while $CI_{j_o}^{CPC} \leq 1$

indicates potential for improvement. To facilitate the interpretation of results estimated using formulation (2), a small illustrative example is depicted in Figure 1. This small example illustrates the performance assessment of five DMUs (A, B, C, D, and E). They were assessed using two desirable outputs KPIs (Y_1 and Y_2). DMUs A, B, and C had the best performances in the set, so they are outlining the frontier of efficiency, against which the other DMUs D and E were compared and evaluated. Taking as reference DMU D to illustrate the estimation of scores, CI_D^{CPC} is given by the ratio between $O'D/O'D^*$ (Figure1), where O' is the origin coordinate $(0,0)$; D^* is the projection of the DMU D on the performance frontier, meaning the reference point representing the desirable output levels for D to be considered efficient. Therefore, CI_D^{CPC} can also be interpreted as a radial improvement potential for DMU D.

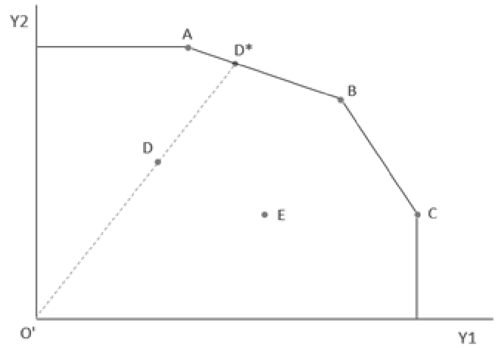

Figure 1 – Small Example of a Production Possibility Set (PPS).

One advantage of a DEA-based CI model lies in allowing each DMU to select its own set of weights, therefore emphasizing their specialties or vocations through optimization, whilst the performance score is still a relative measure. While advantageous, this flexibility in choosing weights may also represent a weakness when a DMU performs poorly in a specific KPI. In such cases, nearly zero weight may be allocated to this KPI, leading to its overlook in the performance analysis. Since this model exclusively requires weights to be positive, assessments where there is interest in avoiding the assignment of very low weights may benefit from incorporating value judgments through the imposition of weight restrictions.

In this paper, the undergraduate programs under assessment were initially evaluated under total flexibility of positive weights. Subsequently, partial weight restrictions (WRs) were imposed on the weights of KPIs to reflect their relative importance to all evaluated KPIs. There is a body of research addressing procedures to add restrictions to weights in DEA-based models, and this line of work can be traced back to the works of Dyson & Thanassoulis (1988) and Wong & Beasley (1990). Since then, the issue of WRs on DEA-based models has attracted considerable attention in the literature, and different approaches have been proposed. Some noteworthy contributions to WR literature include the works of Thompson et al. (1990), Sarrico & Dyson (2004), Estellita Lins et al. (2007), and Zanella et al. (2015).

In this research, weight restrictions were applied to the DMU under assessment (j_o), as shown in formulation (3). These WRs limit the virtual weights associated with KPI r $(u_r y_{rj_o})$ relative to the virtual weight allocated to all KPIs $(\sum_{i=1}^{m} u_r y_{rj_o})$. Each virtual weight can be interpreted as the product between the absolute weight and the value of the KPI associated with it. It can also be interpreted as the relative "importance" of a KPI in the framework.

The restrictions to the virtual weights (3) were first proposed by Wong & Beasley (1990) and have been extensively used in applications when the objective is to limit the weight of a KPI of the composite indicator in percentage terms.

$$w_r(1-k) \geq \frac{u_r y_{rj_o}}{\sum_{i=1}^{m} u_r y_{rj_o}} \geq w_r(1+k) \tag{3}$$

In formulation (3), w is the weight of KPI r. $1 \pm k$ reflects the degree of flexibility allowed for the KPI weight. The higher the value of k, the greater the degree of flexibility allowed. For instance, $k = 0$ specifies lower and upper limits equal to the value defined in the original CPC weighting system (see reference values in Table 1). However, when $k = 0.2$, the assessment allows a margin of more or less 20% in the reference value of the weights.

4.1 Sample description

The performance assessment reported in this paper was conducted using a sample collected from the National Institute of Educational Studies and Research Anísio Teixeira (INEP) open database. The database refers to the base year of 2019, the most recent year of evaluation for engineering programs available in INEP's open databases at the time of this research. Regarding industrial engineering programs, INEP reported 654 industrial engineering programs, including in-person, hybrid, and digital programs. The HEIs composing the population include colleges, university centers, and universities. Only in-person programs from public federal HEIs were considered for the sample, as these are the programs required to participate in the National Student Performance Exam (ENADE) in Brazil. Nevertheless, public state and private programs whose participation in ENADE is optional were not included in this sample. Also, to enhance the reliability of the assessment results, programs with less than 10 students enrolled were excluded from the sample. Consequently, the final sample comprised 73 undergraduate programs of Industrial Engineering. All programs included in this sample are listed in Appendix A.

5 RESULTS AND DISCUSSION

5.1 Exploratory analysis of CPC KPIs

Figure 2 illustrates the histograms depicting the distribution of the eight CPC KPIs, while Table 1 presents the primary descriptive measures. Notable asymmetries are observed in the data distributions, particularly in KPIs associated with Faculty Work Journey (Y_8) and Faculty members holding a Master's degree (Y_6). Regarding KPI Y_8, a few programs received a grade different from 5, indicating high performance in this criterion. This level of performance was expected, as the sample consists of HEIs where the full-time work journey is the standard. The histogram of KPI Y_6 reveals that 75% of the programs within the sample excel in this criterion. The grades attained are mostly higher than 4.38, as shown in Table 2.

Table 2 – Descriptive statistics for the KPIs.

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
Average	3.520	2.570	2.258	2.392	2.943	4.512	3.579	4.991
Standard D.	0.796	0.553	0.648	0.767	0.637	0.611	0.950	0.043
Minimum	1.788	0.776	0.785	0.635	0.877	1.818	1.029	4.717
Quartile 1	2.974	2.269	1.903	1.903	2.578	4.383	3.109	5.000
Median	3.587	2.497	2.211	2.434	2.985	4.670	3.750	5.000
Quartile 3	4.103	2.792	2.581	2.895	3.393	5.000	4.278	5.000
Maximum	5.000	4.728	3.851	4.263	4.312	5.000	5.000	5.000

Another histogram showing a pronounced concentration of programs with similar grades refers to KPI Y_2, which exhibits one of the lowest standard deviations in the sample. In contrast, the most significant discrepancy in the sample is associated with the KPI linked to faculty members holding PhD degrees (Y_7), characterized by the highest standard deviation in the sample.

Several programs exhibit very low or zero values for some KPIs. As clarified in Technical Note No. 38, programs lacking higher educators with a master's degree (Y_6) or PhD degree (Y_7), or those with partial or full-time Faculty Work Journey (Y_8), have their grades computed as zero. Additionally, concerning the KPIs within the Student Perception dimension (Y_3, Y_4, and Y_5), if no student responds to at least one item in each KPI, the program receives a computed value of zero.

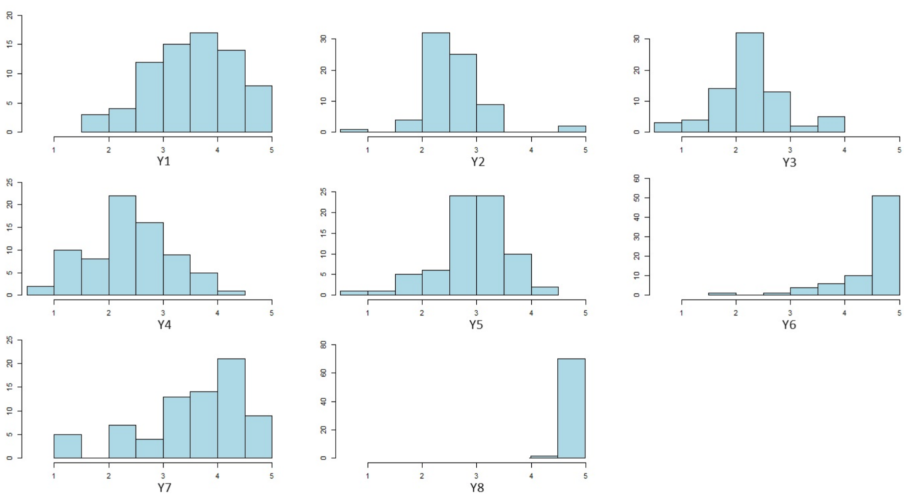

Figure 2 – Histograms of individual KPIs.

Figure 3 depicts the Pearson correlation coefficients between the KPIs, providing insights into the relationships among KPIs.

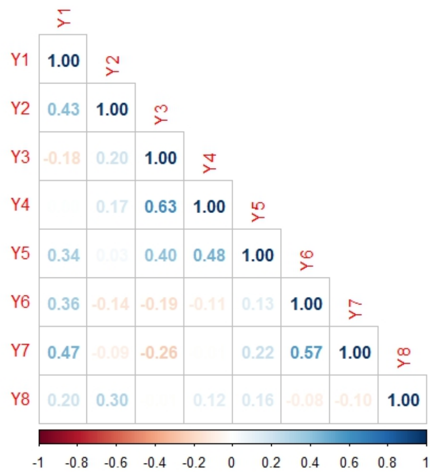

Figure 3 – Correlations between KPIs.

The highest correlation coefficients in Figure 3 highlight the relationships among the KPIs within the dimension of Student Perception of the Training Process. Despite the distinct objectives of the three KPIs - Didactic-Pedagogical Organization (Y_3), Infrastructure and Physical Installations (Y_4), and Opportunities for Expanding Academic and Professional Training (Y_5) - students' responses consistently align, indicating a propensity among students to evaluate various aspects similarly. Another noteworthy correlation is evident between the KPIs reflecting the proportion of "Faculty members with a master's degree" (Y_6) and "Faculty members with a PhD" (Y_7). This correlation aligns with expectations, given that the Y_6 KPI includes professors with doctoral degrees in its calculation. Furthermore, a significant correlation exists between the KPIs "Faculty members with a PhD" (Y_7) and "ENADE Grade" (Y_1). Despite these KPIs aiming to capture distinct aspects of programs, the coefficient suggests that programs with high grades in one KPI tend to perform well in the other.

As outlined in the OECD handbook (Nardo et al., 2008) on constructing composite indicators, assessing statistical correlations between individual indicators is crucial. Correlated indicators included with weights w_1 and w_2 essentially represent a combined weight of $w_1 + w_2$. In such cases, it is imperative to determine whether the correlated indicators measure the same aspect. In the present research, the high correlation between Y_6 and Y_7 reveals that these two KPIs seek to reflect a common aspect of "higher educator qualification". In contrast, the correlations observed in the Student Perception dimension, despite being high, indicate that the KPIs aim to capture different aspects, as discussed in the earlier sections of this work.

5.2 Performance assessment allowing flexibility to weights

In this subsection, results estimated using formulation (2) are discussed. The set of optimized weights was calculated with full flexibility. For depicting the application of the method, Table 3 reports the 10 programs that attained $CI_{j_o}^{CPC*} = 1$, reflecting the Industrial Engineering programs (DMUs) considered relatively efficient in the PPS, along with the number of occurrences when each DMU was selected as a benchmark for other units.

The undergraduate programs of the Federal University Rio de Janeiro (UFRJ - Macaé), the Federal University of Ceará (UFC - Russas), the Celso Suckow da Fonseca Federal Center for Technological Education (CEFET-RJ Nova Iguaçu), and the Federal Technological University of Paraná (UTFPR - Apucarana) are the ones most frequently selected as examples of best practices. They were selected as peers 61, 22, 11, and 10 times, respectively.

These DMUs benchmarks were identified using the dual envelopment model of formulation 2. The envelopment model is given by the expression $CI_{j_o}^{CPC} = \min\left(\delta - \varepsilon \sum_{r=1}^{s} s_r\right)$ subject to: $y_{ij_o} - \sum_{j=1}^{n} y_{rj}\lambda_j + s_r = 0, \quad r = 1,\ldots,s$; and $\lambda_j \geq 0, \quad \forall j$, and it gives the same optimization results for $CI_{j_o}^{CPC*}$ under Constant Returns to Scale.

Table 3 – Programs operating on the Frontier using formulation 2.

Program HEI (city)	Program code	$CI(j_o)^C PC$	Benchmark Frequency
UFRJ (Macaé)	112610	1	61
UFC (Russas)	1299935	1	22
CEFET-RJ(Nova Iguaçu)	92895	1	11
UTFPR (Apucarana)	1114930	1	10
UFABC (S. B. do Campo)	1102530	1	4
UFRGS (Porto Alegre)	45020	1	2
UFF (Niterói)	12727	1	1
UFMG (Belo Horizonte)	50478	1	1
UFRJ (Rio de Janeiro)	14352	1	1
UFSC (Florianópolis)	31945	1	1

To illustrate the discussion of the results, we consider the program of the Federal University of Pelotas (UFPEL, Pelotas), also named DMU 42, located in the Brazilian state of Rio Grande do Sul. UFPEL selected two peers: UFABC (São Bernardo do Campo) and UTFPR (Apucarana), whose KPI levels are shown in Table 4. Note that λ_j can be interpreted as the intensity variable comparing the DMU under assessment to its peers. Each KPI value of the peers (benchmark) represents a learning opportunity for UFPEL to reach higher levels of performance.

Table 4 – Benchmarking exercise example at UFPEL.

	Program (City)	Program Code	DMU	λ_j	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
jo	UFPEL (Pelotas)	1102178	U42	-	2.833	2.433	2.714	3.303	2.905	4.761	4.5	4.862
Peer	UFABC (S. B. Campo)	1102530	U09	0.586	4.12	2.452	2.393	2.82	3.45	5	5	5
Peer	UTFPR (Apucarana)	1114930	U71	0.387	2.705	2.778	3.741	4.263	3.681	5	4.056	5

To exemplify the benchmarking exercises between UFPEL and its peers, Figure 4 illustrates the KPI levels of UFPEL, UFBAC, and UTFPR.

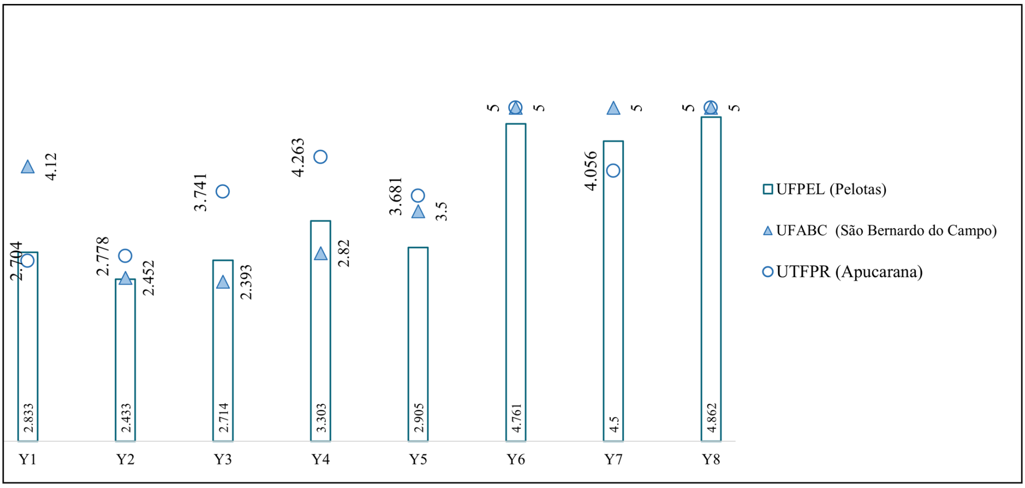

Figure 4 – Comparison of KPI levels between the UFPEL program and its peers.

The UFPEL program can learn from UFABC examples best practices of KPI "ENADE Grade" (Y_1), Program value-added, represented by KPI "Difference Between Observed", "Opportunities for Expanding Academic and Professional Training" (Y_5), and "Faculty member holding PhD Degree" (Y_7). From peer UFTPR, the DMU under assessment can acquire insights regarding KPIs "Expected Performance Indicator Score" (Y_2), the "Student's Perception", represented by KPIs "Didactic-Pedagogical Organization" (Y_3), and the "Infrastructure and Physical Installations" (Y_4). UFPEL can learn from both peers some managerial practices in terms of "Faculty members holding a master's degree" (Y_6) and the "journey of work of the faculty" (Y_8).

5.3 Performance assessment under weight restrictions

With the incorporation of formulation (3) into formulation (2), a few changes were observed. When k=0.5, it means that 50% of the virtual weights were restricted in the assessment. In practical terms, a 50% bound ensures that the assessment remains anchored to the official CPC policy framework while allowing programs to express some institutional specificity. For instance, for KPI Y2, the weight is constrained between 17.5% and 52.5% , which reflects a balance between respecting the official 35% weight and acknowledging variability in institutional performance drivers.

Therefore, the DMUs also had 50% freedom to select the weights that maximize their performance score in the optimization. Table 6 shows the lower and upper bounds of the virtual WRs for each KPI considered in the assessment. As a result, the composite indicator scores estimated ranged between 0.4455 and 1.

The histogram depicted in Figure 5 shows the distribution of the CI scores under WRs. One can observe that most of the programs achieved scores between 0.7 and 0.9, indicating that most of the programs still have room for improvement.

Table 5 – Lower and upper bounds of the WRs.

KPI	Lower bound $w_i(1-k)$	Official CPC Weights w_i	Upper bound $w_i(1+k)$
Y_1	0.1	0.2	0.3
Y_2	0.175	0.35	0.525
Y_3, Y_6 and Y_8	0.0375	0.075	0.1125
Y_4	0.025	0.05	0.075
Y_5	0.0125	0.025	0.0375
Y_7	0.075	0.15	0.225

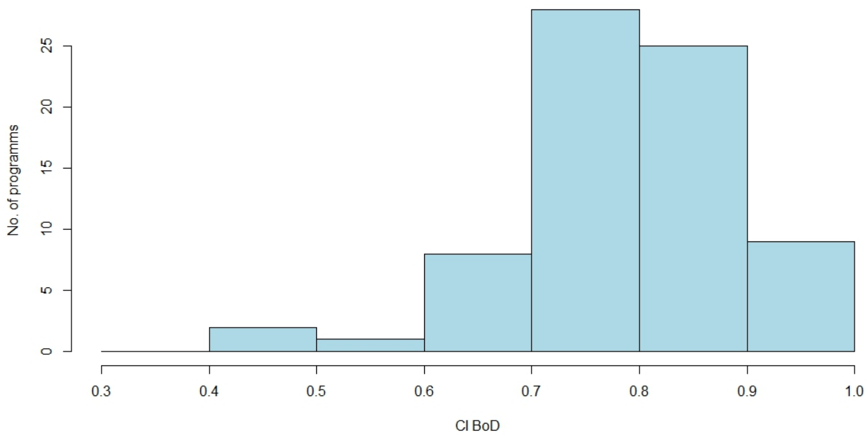

Figure 5 – Histogram of 73 programs evaluated with the CI model.

Regarding the descriptive statistics of the 73 DMUs within the Production Possibility Set (PPS), the mean and standard deviation of the scores were 0.7895 and 0.1042, respectively. Based on the quartile values, the Industrial Engineering programs were classified as follows: bottom performance programs (Q4), where $0.4455 \leq CI_{j_o}^{CPC*} \leq 0.7366$; moderate performance programs (Q3), where $0.7366 < CI_{j_o}^{CPC*} \leq 0.7909$; high-performance programs (Q2), where $0.7909 < CI_{j_o}^{CPC*} \leq 0.8585$; and shining stars performance programs (Q1), where $0.8585 < CI_{j_o}^{CPC*} \leq 1$. Table 6 presents the *CI* values of the Industrial Engineering programs evaluated under Weight Restrictions (WRs).

Two Industrial Engineering programs - UFRJ (Rio de Janeiro) and UFC (Russas) - maintained their top positions as benchmarks under WRs.

Table 6 shows that in the presence of WRs, three programs lost benchmark status when WRs were added (e.g., UFRJ-Macaé, CEFET-Nova Iguaçu, UTFPR-Apucarana). One should note that the change in benchmark programs under weight restrictions indicates that WRs help filter out DMUs that were efficient only due to extremely flexible weighting. The revised set of benchmarks can reflect more realistically the public policies and support deepening institutional learning.

Table 6 – Industrial Engineering programs assessed under WRs.

Program HEI (city)	CI BoD	Program HEI (city)	CI BoD	Program HEI (city)	CI BoD
UFRJ (Rio de Janeiro)	1	UTFPR (Ponta Grossa)	0.822	UFS (São Cristóvão)	0.755
UFC (Russas)	1	UFMS (Campo Grande)	0.821	UFPB (João Pessoa) ○	0.754
UFSC (Florianópolis) □	0.958	UFPEL (Pelotas)	0.815	UFAL (Penedo)	0.75
UFF (Niterói)	0.952	UFPR (Jandaia do Sul)	0.814	IFES (Cariacica)	0.741
UFRGS (Porto Alegre)	0.936	CEFET (B. Horizonte)	0.811	UFCA (J. do Norte)	0.74
UFSM (Santa Maria)	0.935	UFRJ (Macaé)	0.811	UFERSA (Mossoró)	0.738
UFV (Viçosa)	0.929	UFPE (Caruaru)	0.808	UFBA (Salvador)	0.735
UFSC (Florianópolis) △	0.915	UFF (Volta Redonda)	0.803	UFPI (Teresina)	0.728
UFMG (Belo Horizonte)	0.911	UFSCAR (Sorocaba)	0.801	UFCG (C. Grande)	0.726
UFABC (S. B. Campo)	0.9	UFV (Rio Paranaíba)	0.799	UNIFEI (Itabira)	0.724
UFSC (Florianópolis) ○	0.882	UFSCAR (São Carlos)	0.792	UFGD (Dourados)	0.708
UNIFEI (Itajubá)	0.88	UNIVASF (Juazeiro)	0.791	UFMS (Três Lagoas)	0.705
UTFPR (Apucarana)	0.878	UFPB (João Pessoa)	0.79	UFAM (Manaus)	0.702
UFF (Rio das Ostras)	0.874	UNIPAMPA (Bagé)	0.789	UFCG (Sumé)	0.696
UFG (A. de Goiânia)	0.873	UFPR (Curitiba)	0.788	UFES (São Mateus)	0.683
UFOP (João Monlevade)	0.869	UFF (Volta Redonda)	0.787	UFERSA (Angicos)	0.68
UFOP (Ouro Preto)	0.867	UNIR (Cacoal)	0.786	IFMG (Congonhas)	0.664
UNB (Brasília)	0.86	UTFPR (Medianeira)	0.784	UFPA (Abaetetuba)	0.658
UFF (Petrópolis)	0.857	UFU (Ituiutaba)	0.78	IFMG (Bambuí)	0.656
CEFET (Nova Iguaçu)	0.854	UTFPR (Londrina)	0.778	IFSP (São Paulo)	0.628
UFRN (Natal)	0.846	UFG (Catalão)	0.77	UFAM (Itacoatiara)	0.612
UFSJ (São João del Rei)	0.844	UFVJM (Teófilo Otoni)	0.768	IFMG (G. Valadares)	0.578
UNIRIO (Rio de Janeiro)	0.841	UFPE (Recife)	0.762	UFAL (D. Gouveia)	0.478
CEFET (Rio de Janeiro)	0.831	UFES (Vitória)	0.757	UFPEL (Pelotas) ◇	0.445
UFTM (Uberaba)	0.829				

Caption: □ Program code 31945; △ Program code 35550; ○ Program code 23960; ◇ Program code 122366.

Three programs that had previously achieved the maximum performance score experienced a significant decrease in their performance when WRs were imposed on the evaluation, namely UFRJ - Macaé, CEFET - Nova Iguaçu, and UTFPR - Apucarana. This means that these programs have at least one of the eight components with very low values and when these components carry more weight in the assessment, they decrease the course's performance.

The assessments based on DEA and WRs were particularly useful to identify the programs' strengths and weaknesses. Taking the Program of the Federal University of Pelotas (UFPEL - program code 1102178) as an example, Figure 6 illustrates its distribution of virtual weights in the eight KPIs considered.

In the assessment using formulations (2) with WRs (3), the Pelotas Federal University Program (UFPEL) allocated the lowest weights (between the limits allowed) to the KPIs Y_1 and Y_2, indicating potential weaknesses in these components compared to the other programs in the sample. Similarly, the highest weights (between the allowed limits) were assigned to KPIs Y_3 to Y_8, representing a potential strength of this program. Appendix A provides information on weights selected by other programs for further analysis.

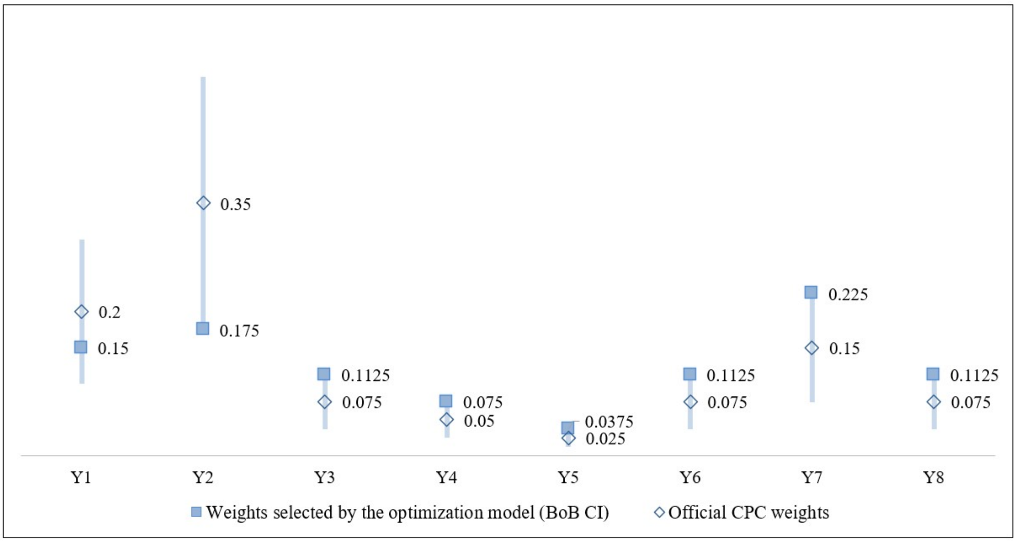

Figure 6 – Comparison of optimized weights for the UFPEL program and the official CPC set of weights.

5.4 Comparing the official CPC index and the DEA alternative formulation results

Figure 7 illustrates the correlation between the BoD-based composite indicator scores, ranging from 0 to 1, and the CPC Continuous Score values (INEP approach), ranging from 0 to 5. A Pearson correlation coefficient of 0.9247 indicates a strong positive correlation between the outcomes of the two assessment methods. Figure 7 also reports the 73 undergraduate Industrial Engineering programs categorized according to four performance levels. The dispersion pattern reveals that programs with both bottom and top performance scores are equivalent using both assessment approaches. Unlike the INEP approach, where each program's performance is independently calculated based on weighted averages of KPIs, the BoD approach involves direct comparisons among all programs. Moreover, the composite indicator approach can offer flexibility in the estimation of virtual weights for the KPIs. Appendix A reports further information and data regarding the CI values and the categorization of all DMUs in the sample used in this paper.

The alternative formulation of the composite indicator (CI_{jo}^{CPC}) proposed in formulation (2) can work as a complementary management tool to assess the performance of Higher Education Institutions (HEIs). Unlike traditional methods that rely exclusively on exogenous weighted averages, the BoD approach provides a more insightful assessment by allowing direct comparisons among programs within the sample. This feature can support a more accurate evaluation of the programs' relative strengths and weaknesses, while also empowering institutions with the flexibility to adapt and optimize their strategies. The support for benchmarking can also facilitate strategic decision-making, enabling HEIs to identify specific areas for improvement and allocate resources more effectively. Therefore, integrating the use of BoD with the official assessment method represents an asset to support decisions at the high administration level.

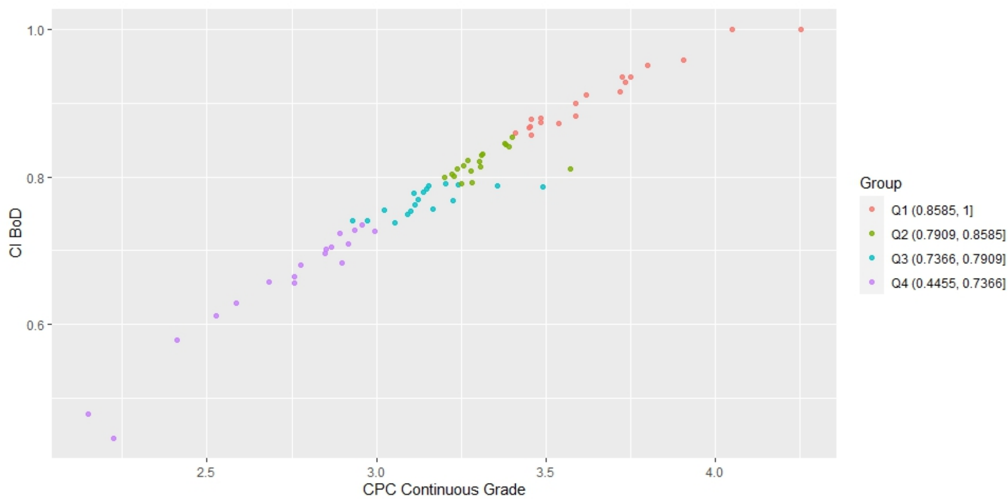

Figure 7 – Relationship between the CI BoD scores and the CPC scores.

6 CONCLUSIONS

This study proposed a complementary method to enhance the performance assessment of Brazilian undergraduate programs in Industrial Engineering. The approach relies on the Data Envelopment Analysis (DEA) Benefit of the Doubt (BoD) method to specify a composite indicator. Key Performance Indicators (KPIs) from the INEP official CPC framework were adopted. The application of the weight restrictions (expression 3) allowed for the incorporation of their relative importance within a flexible framework. By analyzing the weights assigned by each Industrial Engineering undergraduate program within the permitted limits, it was possible to identify further opportunities for performance improvement. The low or high weights assigned reveal the strengths and weaknesses of each program compared to others in the sample. Such insights would not be captured by INEP's rigid CPC calculation.

The analysis focused on Higher Education Institutions (HEIs) within the federal public system in Brazil, using data from 2019, which was the most recent data available at the time of collection.

The BoD DEA approach offered additional insights that can be combined with the official INEP assessment methodology. This DEA-based approach enabled the generation of performance scores with optimized weighting systems capable of addressing concerns highlighted by Bittencourt et al. (2010). These concerns relate to HEIs' vocational strengths being taken into account in the assessment. The results were explored within a benchmarking exercise amongst DMUs. Given that the BoD composite indicator is based on a DEA model, it naturally inherits its properties, including the ability to identify efficient units as benchmarks. In this context, the study takes advantage of this feature to identify high-performing Industrial Engineering programs — i.e., those with the highest performance scores and profiles similar to those of low-performing programs — thereby serving as relevant references for improvement.

Furthermore, two key insights emerge from this evaluation. First, identifying benchmark Industrial Engineering undergraduate programs within the sample provided valuable management guidelines of best practices for DMUs categorized as inefficient. Second, the exploration of weight restrictions specified in formulation (3) enabled exploring further opportunities for improving performance in the assessed programs.

In addition, this study identified significant correlations, particularly within the Student Perception dimension, which warrants further exploration to understand their influence on CPC results. Involving experts or regulators in an interactive modeling process to establish weight restrictions is also suggested. For future research, it is recommended to deepen the analysis of interrelationships among the CPC's KPIs. Overall, the BoD-based composite indicator, particularly when combined with WRs, also enhances performance assessments. By retaining the core components of the CPC and adding flexibility in their evaluation, this approach offers a meaningful complement to INEP's method, providing actionable insights for both policymakers and HEIs.

Finally, this collaborative approach would integrate stakeholder insights and preferences, enhancing the robustness and inclusivity of the evaluation framework.

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Authors' contributions

Renata Oliveira: Research design, methodology, literature reviews, data analysis, writing, and chart illustration. Andreia Zanella: Research design, data collection, data analysis, illustration, chart illustration, supervision. Vitor Martins: Literature review, validation. Nathalia Monteiro: Literature review, validation.

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Data Availability

The data analyzed in this study are publicly available in the INEP Open Data Repository under the title "Indicadores de Qualidade da Educação Superior." The data can be accessed at https://www.gov.br/inep/pt-br/acesso-a-informacao/dados-abertos/indicadores-educacionais/indicadores-de-qualidade-da-educacao-superior.

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APPENDIX A – CI VALUES AND WEIGHTS SELECTED BY THE PROGRAMS IN EACH KPI

Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
14352	UFRJ (Rio de Janeiro)	1	Q1	0.1	0.525	0.113	0.075	0.013	0.037	0.075	0.063
1299935	UFC (Russas)	1	Q1	0.3	0.211	0.038	0.025	0.012	0.112	0.189	0.112
31945	UFSC (Florianópolis)	0.958	Q1	0.26	0.215	0.037	0.025	0.013	0.112	0.225	0.112
12727	UFF (Niterói)	0.952	Q1	0.3	0.175	0.073	0.025	0.037	0.052	0.225	0.113
45020	UFRGS (Porto Alegre)	0.936	Q1	0.3	0.175	0.038	0.075	0.038	0.099	0.225	0.051
121626	UFSM (Santa Maria)	0.935	Q1	0.239	0.175	0.049	0.075	0.013	0.112	0.225	0.112
21585	UFV (Viçosa)	0.929	Q1	0.3	0.175	0.037	0.025	0.013	0.113	0.225	0.112
35550	UFSC (Florianópolis)	0.915	Q1	0.3	0.175	0.037	0.034	0.013	0.103	0.225	0.113
50478	UFMG (Belo Horizonte)	0.911	Q1	0.263	0.175	0.038	0.037	0.038	0.112	0.225	0.112
1102530	UFABC (S. B. do Campo)	0.9	Q1	0.262	0.175	0.037	0.038	0.037	0.113	0.225	0.113
23960	UFSC (Florianópolis)	0.882	Q1	0.3	0.175	0.037	0.025	0.037	0.112	0.225	0.087
18254	UNIFEI (Itajubá)	0.88	Q1	0.225	0.175	0.038	0.075	0.038	0.113	0.225	0.112
1114930	UTFPR (Apucarana)	0.878	Q1	0.15	0.175	0.112	0.075	0.037	0.112	0.225	0.112

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Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
82842	UFF (Rio das Ostras)	0.874	Q1	0.231	0.175	0.082	0.025	0.038	0.113	0.225	0.113
1300254	UFG (Aparecida de Goiânia)	0.873	Q1	0.3	0.217	0.037	0.025	0.037	0.113	0.158	0.113
61560	UFOP (João Monlevade)	0.869	Q1	0.217	0.175	0.045	0.075	0.037	0.113	0.225	0.113
18875	UFOP (Ouro Preto)	0.867	Q1	0.221	0.175	0.042	0.075	0.037	0.112	0.225	0.112
122206	UNB (Brasília)	0.86	Q1	0.3	0.175	0.038	0.025	0.012	0.112	0.225	0.113
1303882	UFF (Petrópolis)	0.857	Q1	0.3	0.198	0.113	0.025	0.037	0.112	0.102	0.113
92895	CEFET/RJ (Nova Iguaçu)	0.854	Q2	0.15	0.175	0.112	0.075	0.037	0.113	0.225	0.113
18853	UFRN (Natal)	0.846	Q2	0.271	0.175	0.037	0.075	0.038	0.113	0.179	0.112
122320	UFSJ (São João del Rei)	0.844	Q2	0.238	0.175	0.037	0.062	0.037	0.113	0.225	0.113
1101776	UNIRIO (Rio de Janeiro)	0.841	Q2	0.259	0.191	0.037	0.025	0.038	0.112	0.225	0.112
20137	CEFET/RJ (Rio de Janeiro)	0.831	Q2	0.238	0.175	0.037	0.062	0.038	0.112	0.225	0.112
1106042	UFTM (Uberaba)	0.829	Q2	0.291	0.175	0.046	0.025	0.012	0.112	0.225	0.112
1116535	UTFPR (Ponta Grossa)	0.822	Q2	0.207	0.175	0.056	0.075	0.037	0.113	0.225	0.113
1128349	UFMS (Campo Grande)	0.821	Q2	0.267	0.175	0.07	0.025	0.012	0.113	0.225	0.112

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Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
1102178	UFPEL (Pelotas)	0.815	Q2	0.15	0.175	0.112	0.075	0.037	0.112	0.225	0.113
1270224	UFPR (Jandaia do Sul)	0.814	Q2	0.215	0.175	0.097	0.025	0.037	0.113	0.225	0.113
5001281	CEFET/MG (B. Horizonte)	0.811	Q2	0.3	0.3	0.037	0.025	0.038	0.113	0.075	0.113
112610	UFRJ (Macaé)	0.811	Q2	0.205	0.175	0.057	0.075	0.037	0.113	0.225	0.113
118092	UFPE (Caruaru)	0.808	Q2	0.283	0.175	0.113	0.025	0.038	0.112	0.142	0.113
90471	UFF (Volta Redonda)	0.803	Q2	0.234	0.175	0.079	0.025	0.038	0.113	0.225	0.113
96407	UFSCAR (Sorocaba)	0.801	Q2	0.275	0.175	0.038	0.025	0.037	0.112	0.225	0.113
1112659	UFV (Rio Paranaíba)	0.799	Q2	0.263	0.175	0.074	0.075	0.037	0.038	0.225	0.112
87564	UFSCAR (São Carlos)	0.792	Q2	0.275	0.175	0.038	0.025	0.038	0.113	0.225	0.112
85584	UNIVASF (Juazeiro)	0.791	Q2	0.3	0.196	0.037	0.075	0.013	0.113	0.154	0.112
122934	UFPB (João Pessoa)	0.79	Q3	0.236	0.175	0.076	0.025	0.037	0.112	0.225	0.112
104266	UNIPAMPA (Bagé)	0.789	Q3	0.155	0.245	0.037	0.075	0.037	0.112	0.225	0.112
99630	UFPR (Curitiba)	0.788	Q3	0.3	0.175	0.037	0.025	0.037	0.112	0.225	0.087
44374	UFF (Volta Redonda)	0.787	Q3	0.275	0.175	0.037	0.025	0.037	0.112	0.225	0.113

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Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
1106843	UNIR (Cacoal)	0.786	Q3	0.292	0.408	0.037	0.025	0.012	0.038	0.075	0.112
1102417	UTFPR (Medianeira)	0.784	Q3	0.164	0.175	0.113	0.075	0.037	0.112	0.211	0.112
1109224	UFU (Ituiutaba)	0.78	Q3	0.218	0.175	0.045	0.075	0.038	0.113	0.225	0.112
1204220	UTFPR (Londrina)	0.778	Q3	0.218	0.175	0.044	0.075	0.038	0.112	0.225	0.112
107907	UFG (Catalão)	0.77	Q3	0.21	0.19	0.037	0.075	0.038	0.112	0.225	0.112
1103226	UFVJM (Teófilo Otoni)	0.768	Q3	0.106	0.344	0.037	0.025	0.038	0.113	0.225	0.113
21710	UFPE (Recife)	0.762	Q3	0.3	0.175	0.038	0.025	0.013	0.113	0.225	0.112
96020	UFES (Vitória)	0.757	Q3	0.3	0.175	0.038	0.025	0.013	0.113	0.225	0.112
99416	UFS (São Cristóvão)	0.755	Q3	0.243	0.175	0.069	0.025	0.037	0.112	0.225	0.113
19563	UFPB (João Pessoa)	0.754	Q3	0.241	0.209	0.037	0.025	0.037	0.113	0.225	0.113
1288845	UFAL (Penedo)	0.75	Q3	0.1	0.232	0.112	0.075	0.038	0.112	0.218	0.112
121880	IFES (Cariacica)	0.741	Q3	0.3	0.175	0.056	0.075	0.038	0.112	0.132	0.113
91284	UFCA (Juazeiro do Norte)	0.74	Q3	0.15	0.175	0.113	0.075	0.038	0.112	0.225	0.113
117042	UFERSA (Mossoró)	0.738	Q4	0.3	0.264	0.038	0.025	0.012	0.112	0.136	0.113

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Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
79570	UFBA (Salvador)	0.735	Q4	0.3	0.175	0.037	0.025	0.037	0.112	0.2	0.113
150098	UFPI (Teresina)	0.728	Q4	0.3	0.175	0.047	0.075	0.038	0.113	0.14	0.112
116406	UFCG (Campina Grande)	0.726	Q4	0.255	0.22	0.037	0.025	0.013	0.112	0.225	0.112
1102590	UNIFEI (Itabira)	0.724	Q4	0.203	0.175	0.06	0.075	0.038	0.112	0.225	0.113
95743	UFGD (Dourados)	0.708	Q4	0.228	0.197	0.038	0.075	0.013	0.113	0.225	0.113
122904	UFMS (Três Lagoas)	0.705	Q4	0.247	0.175	0.04	0.075	0.012	0.113	0.225	0.113
84526	UFAM (Manaus)	0.702	Q4	0.192	0.175	0.113	0.033	0.038	0.113	0.225	0.112
1106578	UFCG (Sumé)	0.696	Q4	0.15	0.175	0.113	0.075	0.038	0.113	0.225	0.113
99094	UFES (São Mateus)	0.683	Q4	0.3	0.175	0.038	0.025	0.012	0.113	0.225	0.112
1270673	UFERSA (Angicos)	0.68	Q4	0.1	0.3	0.113	0.075	0.038	0.038	0.225	0.112
1137741	IFMG (Congonhas)	0.664	Q4	0.285	0.19	0.112	0.075	0.038	0.113	0.075	0.113
1110447	UFPA (Abaetetuba)	0.658	Q4	0.15	0.175	0.113	0.075	0.037	0.112	0.225	0.112
1110412	IFMG (Bambuí)	0.656	Q4	0.245	0.23	0.113	0.075	0.037	0.112	0.075	0.112
1147844	IFSP (São Paulo)	0.628	Q4	0.3	0.175	0.112	0.025	0.037	0.113	0.125	0.113

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Program Code	HEI (City)	CI Score	Group	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
112088	UFAM (Itacoatiara)	0.612	Q4	0.1	0.225	0.112	0.075	0.038	0.113	0.225	0.113
5000576	IFMG (G. Valadares)	0.578	Q4	0.284	0.191	0.112	0.075	0.038	0.112	0.075	0.113
1151165	UFAL (Delmiro Gouveia)	0.478	Q4	0.3	0.268	0.038	0.025	0.038	0.113	0.107	0.112
122366	UFPEL (Pelotas)	0.445	Q4	0.2	0.175	0.112	0.025	0.037	0.112	0.225	0.113