Full research paper

MEASURING ACADEMIC EFFICIENCY IN HIGH-IMPACT SCHOLARSHIPS: A TWO-STAGE WINDOWS DEA AND GAUSSIAN MIXTURE MODEL APPROACH

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ABSTRACT

Evaluating the effectiveness of social support programs in higher education requires moving beyond homogeneous assessments of student performance. This study integrates intersectionality with dynamic efficiency analysis to examine how academic efficiency evolves across diverse student profiles within the Líderes del Mañana full-scholarship program in Mexico. Using a longitudinal dataset of 1,796 students (22,718 student–term observations), we apply a two-stage approach. First, Window Data Envelopment Analysis (DEA) estimates relative academic efficiency over time. Second, Gaussian Mixture Modeling identifies intersectional student profiles based on efficiency trajectories and contextual characteristics. Results reveal five distinct efficiency trajectories. While most students converge toward high-efficiency levels, one cluster exhibits a clear negative efficiency slope, greater variability, and limited institutional alignment, indicating it is a priority for intervention. Other clusters display stable high performance, continuous improvement, or moderate but non-accelerating trajectories. Findings demonstrate that efficiency differences are not explained by single demographic factors but by configurations of social background and institutional context. This study provides a scalable, data-driven framework for aligning equity and efficiency objectives in higher education policy and scholarship programs.

KEYWORDS

Educational efficiency, intersectionality, Data Envelopment Analysis (DEA), Gaussian Mixture Models (GMM), higher education, learning analytics

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Highlights

- *Combining Window DEA and Gaussian Mixture Modeling identifies five intersectional efficiency profiles, revealing academic trajectories hidden by conventional single-axis analyses.*
- *Academic efficiency is dynamic and cumulative: students converge toward the efficiency frontier in later semesters, but trajectories diverge significantly across intersectional profiles.*
- *Institutional context buffers or amplifies structural disadvantage: semi-urban students are the most vulnerable due to a policy blind spot in urban-rural support frameworks.*
- *Efficiency and equity are complementary objectives: differentiated, intersectionality-informed interventions outperform uniform or single-demographic targeting strategies.*

INTRODUCTION

Higher education institutions worldwide face the dual challenge of promoting access for underrepresented students while ensuring efficient use of limited resources to support their academic success. In Mexico, programs like Líderes del Mañana at Tecnológico de Monterrey exemplify efforts to address educational inequity by providing full scholarships to high-achieving youth who demonstrate exceptional academic performance, social leadership, and financial need. The program seeks not only to facilitate access to higher education but also to cultivate transformational leaders committed to social impact in their communities. Participants receive comprehensive support, including full tuition coverage, medical insurance, financial aid for materials, and access to mentoring networks, with the expectation that they will later contribute as agents of social transformation (*Programa LDM | Líderes Del Mañana, n.d.*).

Understanding how effectively educational resources translate into student outcomes is critical for both program sustainability and social equity. However, traditional approaches to evaluating educational efficiency often treat student populations as homogeneous or segment them by single characteristics such as socioeconomic status or geographic origin (Johnes, 2006; Borgonovi and Pokropek, 2019). This overlooks the reality that students navigate educational systems with multiple, intersecting identities, including gender, race, class, disability status, and geographic background, that interact to shape their experiences and outcomes in complex ways.

Intersectionality has become a key framework for analyzing how multiple social identities interact to produce differentiated experiences in educational contexts (Agosto and Roland, 2018; Nichols and Stahl, 2019). In higher education, studies show that gender remains the most examined axis, while other identities receive less attention (Harris and Patton, 2019; Nichols and Stahl, 2019). Moreover, in K–12 and teacher education, intersectionality is mostly applied at the micro-level, focusing on individual experiences with limited attention to systemic resource allocation (Agosto and Roland, 2018; Leckie and Buser De, 2020; Pugach et al., 2019).

Parallel to this theoretical development, Data Envelopment Analysis (DEA) and related efficiency measures have been widely applied to assess educational performance across schools, secondary education systems, and universities in multiple countries (Chiariello et al., 2022; Muniz et al., 2024; Sun et al., 2023; Taleb et al., 2023; Temoso et al., 2023; Tran et al., 2022; Ulkhaq et al., 2024; Zhou et al., 2024). These studies identify factors associated with higher efficiency, such as infrastructure, ICT integration, teacher qualifications, and institutional resources, while highlighting regional or systemic disparities in performance.

Despite these advances, a critical gap remains: existing efficiency studies treat student populations as homogeneous or segment them by single demographic characteristics. At the same time, intersectionality research has yet to be integrated with efficiency measurement. This disconnect limits our understanding of whether educational systems efficiently serve all students equally or whether resource utilization varies systematically across students with different combinations of intersecting identities. As postsecondary institutions become increasingly diverse, and as quantitative methods for intersectional analysis mature (Keller et al., 2023; Prior et al., 2025; Slominski et al., 2024), the need to bridge these research streams has never been more pressing. This study addresses the following research questions:

- How does educational efficiency vary across students with different intersectional profiles?
- Which combinations of social identities are associated with more or less efficient conversion of educational inputs into academic outcomes?
- What factors explain differences in efficiency across intersectional student groups over time?

This paper addresses these questions by integrating quantitative intersectional methods with dynamic efficiency analysis within the Líderes del Mañana program. We employ a multi-stage analytical framework that combines person-centered clustering techniques with DEA to examine how efficiently educational resources are utilized across intersectional student profiles.

Our approach unfolds as follows. First, we prepare and clean program data, defining relevant input and output variables. Second, we apply Gaussian Mixture Models (GMMs) to identify distinct intersectional student profiles across multiple identity dimensions and characteristics. And third, we employ dynamic DEA to evaluate efficiency over time for each identified cluster, assessing how effectively students convert program inputs (financial support, infrastructure, mentoring) into outputs (academic performance, persistence, leadership development).

This integrated approach makes three key contributions. Methodologically, it demonstrates how person-centered intersectional analysis can be combined with efficiency measurement to produce insights invisible to conventional approaches. Substantively, it reveals whether and how educational efficiency varies across multiply marginalized student groups, identifying potential inequities in resource utilization. In practice, it provides evidence-based guidance for designing targeted interventions that are responsive to students' complex, multidimensional identities.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundations of intersectionality and its application in educational research, discusses quantitative methods for intersectional analysis, and examines the literature on efficiency measurement in education. Section 3 describes the context of the Líderes del Mañana program, our data sources, and the five-stage analytical framework. Section 4 presents results from clustering analysis, dynamic DEA, and predictive modeling. Section 5 discusses the implications of our findings for educational equity and resource allocation. Section 6 concludes with policy recommendations and directions for future research.

LITERATURE REVIEW

This section presents a comprehensive literature review organized thematically by applications of intersectionality, quantitative methods for analyzing heterogeneity, and efficiency measurement in education. The literature review culminates with Table 1, which summarizes relevant studies since 2014. Additionally, each subsection identifies research gaps and outlines the contributions of this study.

Intersectionality in education research

Intersectionality has emerged as a critical framework for understanding how multiple social identities interact to shape educational experiences and outcomes. In higher education, Nichols and Stahl (2019) conducted a systematic review of 50 studies examining inclusion and exclusion through an intersectional lens, finding that gender dominates as the primary axis combined with other identities, and that most studies rely on qualitative case studies. Harris and Patton (2019) traced the application of intersectionality across 97 higher education articles, highlighting tensions between the framework's radical social justice origins and its increasingly academicized use.

Beyond higher education, intersectionality has been applied across educational contexts. Agosto and Roland (2018) reviewed 15 studies in K–12 educational leadership and found that intersectional analyses primarily focus on individual leaders' experiences rather than systemic inequities. In teacher education, Pugach et al. (2019) synthesized 25 years of research and found that identity is often treated unidimensionally, with limited attention to intersecting social markers. Leckie and Buser De (2020) demonstrated how intersectionality-informed professional development can integrate teachers' lived experiences of privilege and oppression into classroom practice. Macias and Stephens (2019) examined how race and gender intersect to create compounded challenges for women of color in education workplaces, particularly among Latina educators.

Intersectionality has also been adopted in specialized educational domains. Robert and Yu (2018) evaluated its use in transnational education policy research, arguing that its deployment in non-Western contexts yields new analytic insights. Maina-Okori et al. (2018) examined intersectionality in environmental and sustainability education, critiquing the field's limited engagement with overlapping systems of marginalization. Bešić (2020) advocated for an intersectional approach to inclusive education in Austria, arguing that recognizing multiple identity factors is essential to identifying discriminatory processes affecting diverse student groups.

Gap: While intersectionality is widely applied theoretically in education research, quantitative operationalization remains limited. Most studies employ qualitative methods and struggle to capture the complexity of intersecting identities through statistical approaches that move beyond examining single identity dimensions or simple two-way interactions.

Quantitative methods for intersectional analysis

Recent methodological advances have begun bridging the gap between intersectional theory and quantitative research. Latent class analysis (LCA) has emerged as a person-centered approach for identifying unobserved subpopulations. Slominski et al. (2024) introduced LCA to STEM education research as a mixture-modeling technique that can uncover heterogeneous student experiences obscured by variable-centered methods. Garnett et al. (2014) applied LCA to examine intersecting forms of discrimination and bullying among ethnically diverse adolescents, identifying four latent classes with differential mental health outcomes. Bauer et al. (2022) systematically reviewed 16 quantitative health studies that employed clustering methods aligned with intersectional theory, finding limited engagement with the intersectional methodology literature despite widespread theoretical citation.

Clustering techniques have also been applied to educational contexts. Hanauer et al. (2025) used hierarchical cluster analysis with data from 2,082 STEM students to identify four underlying identity orientations: heritage, health, self-expression, and career, revealing the complexity of student positionalities. Reinwald and Annen (2023) employed k-medoid clustering to create intersectional employee profiles and examine how professional development affects job satisfaction across groups over 5 years.

Multilevel modeling represents another quantitative approach for intersectional analysis. Byrd et al. (2015) used multilevel models with data from the Education Longitudinal Study to examine how adolescent school misconduct relates to social control across racial, ethnic, and gender groups in different contexts. Robson et al. (2014) applied multilevel multinomial logistic regression within an intersectionality framework to examine postsecondary trajectories of students with special education needs in Toronto.

The Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) has recently been introduced as a purpose-built quantitative intersectional method. Keller et al. (2023) demonstrated MAIHDA using German data on 5,451 students across 40 intersectional strata defined by gender, immigrant background, and parental characteristics, highlighting advantages including scalability, parsimony, and precision-weighted estimates for small strata. Prior et al. (2025) applied MAIHDA to examine sociodemographic inequalities in student achievement in London across 144 intersectional strata, finding that between-stratum variation is driven largely by additive rather than interactive effects.

Gap: Despite these methodological advances, no studies have combined intersectional analysis with efficiency measurement in education. Quantitative intersectional methods, such as clustering and MAIHDA, have been applied to examine outcomes and experiences but not to assess how efficiently educational resources are utilized across intersectional student groups or whether resource allocation varies by students' multiple, overlapping identities.

Efficiency analysis in education

DEA has become the predominant method for evaluating educational efficiency across multiple levels and contexts. At the K–12 level, Chiariello et al. (2022) used stochastic frontier analysis to evaluate regional efficiency in primary and secondary education in Italy from 2011–2018, revealing significant North–South disparities driven by contextual factors, including GDP, poverty, and institutional quality. Muniz et al. (2024) applied the Slacks-Based Measure (SBM) DEA model to Brazilian schools in Sobral, identifying libraries, computer labs, and sports courts as key infrastructure elements associated with student performance. Kounetas et al. (2023) examined 643 Greek secondary schools over 18 years, finding persistent inefficiencies across regions with limited reform impact and identifying school-level factors, such as science laboratories and class size, as determinants of efficiency.

In higher education, DEA applications have grown increasingly sophisticated. Taleb et al. (2023) applied super-efficiency SBM models to 41 Taiwanese universities, identifying 25 institutions as super-efficient. Tran et al. (2022) conducted one of Vietnam's most comprehensive efficiency assessments, covering 172 institutions and revealing that public universities are less efficient than private ones, while internationally engaged institutions are more efficient. Temoso et al. (2023) introduced a network-based DEA framework for South African universities that separates teaching and research processes, finding that research units lag substantially behind teaching units (efficiency of 0.782 vs. 0.942). Sun et al. (2023) developed a double-frontier parallel

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DEA model to jointly assess ordinary and vocational education subsystems across 30 Chinese provinces, incorporating both optimistic and pessimistic perspectives.

Cross-national efficiency studies have also emerged. Ulkhaq et al. (2024) evaluated schools across six South-East Asian countries using 2018 PISA data, combining super-efficiency DEA with bootstrapped quantile regression to examine ICT-related determinants. Zhou et al. (2024) assessed the efficiency of China's educational science and technology industry across 31 provinces using the DEA Malmquist index, identifying technological progress as the primary driver of efficiency change.

Gap: Existing efficiency studies in education treat student populations as homogeneous or segment them by single characteristics (e.g., public vs. private institutions, regional location). None of them examines efficiency through an intersectional lens that acknowledges how students' multiple, overlapping identities may relate to resource utilization and educational outcomes. This oversight limits understanding of whether educational systems efficiently serve all students or whether disparities exist across intersectional groups.

Research contributions

This paper addresses the identified gaps by integrating intersectionality with efficiency analysis in education, a combination absent from existing literature, as summarized in Table 1. Specifically, this study employs clustering methods to identify intersectional student profiles across multiple identity dimensions and then applies DEA to assess educational efficiency across these profiles. This approach contributes to three areas:

Methodological innovation: Demonstrates how quantitative intersectional methods (clustering) can be combined with efficiency measurement (DEA) to produce actionable insights about resource allocation and student outcomes across multiply marginalized groups.

Substantive understanding: Reveals whether educational efficiency varies across intersectional student profiles, identifies which combinations of identities are associated with efficient resource utilization, and highlights potential inequities invisible in traditional analyses.

Policy relevance: Provides evidence for targeted interventions by identifying specific intersectional groups that may require additional support or different resource configurations to achieve equitable outcomes, moving beyond one-size-fits-all approaches to educational improvement.

By bridging intersectionality and efficiency analysis, this study advances both the theoretical sophistication of educational equity research and the practical capacity to design interventions responsive to students' complex, multidimensional identities.

Paper	Scope	Intersection-ality	Latent class analysis	Multilevel modeling	Clusters	DEA	Efficiency in education
Leckie and Buser De (2020)	Teacher	X					
Slominski et al. (2024)	Students	X	X				
Byrd et al. (2015)	Students	X		X			
Prior et al. (2025)	Students	X		X			
Robson et al. (2014)	Students	X		X			
Garnett et al. (2014)	Students	X	X		X		
Hanauer et al. (2025)	Students	X			X		
Reinwald and Annen (2023)	Students	X			X		
Alvarez-Hernandez (2021)	Students	X				X	X
Zhou et al. (2024)	Students					X	X
Chiariello et al. (2022)	Students					X	X
Muniz et al. (2024)	Students					X	X
Taleb et al. (2023)	Universities					X	X
Tran et al. (2022)	Universities					X	X
Kounetas et al. (2023)	Secondary school					X	X
Temoso et al. (2023)	Universities					X	X
Sun et al. (2023)	Universities					X	X
Ulkhaq et al. (2024)	Schools					X	X
This paper	Students	X			X	X	X

Table 1: Literature review

MATERIALS AND METHODS

Dataset description

The dataset used in this study comes from the IFE Living Lab and Data Hub of Tecnológico de Monterrey, Mexico. This initiative was designed to support research on the academic progress and social commitment of students participating in the Líderes del Mañana program, a long-standing scholarship and leadership development effort that aims to expand access to higher education for academically talented young people with limited socioeconomic resources. The program's mission is to foster social mobility, prepare students to be positive agents of community change, and reduce educational inequality.

The dataset contains 22,718 observations and 47 variables, organized at the student–academic period level, which allows the same student to appear multiple times across different academic terms (Table 2). The dataset comprises information on undergraduate students enrolled in the Líderes del Mañana program from 2014 to 2023. These students represent multiple cohorts over nine academic cycles, and the data covers a broad range of categories relevant to both academic performance and contextual background. Sociodemographic variables include measures such as gender, age range, and type of residential environment; admission data include pre-university achievement indicators such as high school grade point average and standardized assessment scores; and academic records capture term- and program-level grades, credit load, and curricular status. Additionally, the dataset contains indicators of students' experiences in leadership and community projects, extracurricular involvement, and other measures linked to their engagement and retention in the university context.

The dataset includes three psychometric instruments collected at admission. The DISC assessment measures four personality dimensions: Dominance (decisiveness and leadership), Influence (communication and teamwork), Steadiness (empathy and stability), and Conscientiousness (analytical thinking and precision). The Values Index captures seven motivational drivers: Aesthetic, Economic, Individualistic, Political, Altruistic, Regulatory, and Theoretical. CV levels reflect pre-college participation intensity across eight domains (sports, cultural activities, student organizations, community service, leadership, work experience, academic achievements, and international experience). Finally, Full-Time Equivalent (FTE) is a continuous variable indicating the proportion of courses a student is enrolled in relative to the expected full load for their semester.

Category	Variable	Nature	Measurement Scale
Intersectional and Demographic	Gender	Categorical	Nominal (Female, Male)
	Age Group	Categorical	Ordinal (18 and below, 19-21, 22+)
	Zone Type	Categorical	Nominal (Urban, Rural, SemiUrban)
	First Generation	Categorical	Binary (Yes, No)
Prior Academic Background	High School GPA	Continuous	Ratio (90-100)
	Admission Test Score	Discrete	Interval (0-1600)
	Origin School	Categorical	Binary (0,1)
Psychometric and Leadership	DISC Scores	Continuous	Ratio (0-100)
	Values Index	Continuous	Ratio (0-100)
	CV Levels	Discrete	Ordinal (1,2,3,4)
Institutional and Performance	Term GPA	Continuous	Ratio (0-100)
	Term GPA Program	Continuous	Ratio (0-100)
	Graduation Status	Categorical	Binary (0,1)
	FTE (Academic Load)	Continuous	Ratio (<0)

Table 2: Description of the dataset

Data preparation and preprocessing

The methodological process began with a structured data preparation stage to ensure internal consistency, robustness, and suitability for longitudinal efficiency analysis. Given the dataset's educational nature and temporal structure, special attention was paid to preserving the number of observations across academic periods.

Missing values in numerical variables related to students' academic engagement were handled using forward-fill imputation. This decision was motivated by the need to avoid systematic bias that could arise from deleting incomplete observations, particularly in datasets where data are temporarily associated across transitional academic periods.

Variables not directly associated with academic performance, student context, or profiling objectives were excluded from the analysis. This dimensionality reduction step helped to improve model interpretability, reduce noise, and ensure alignment between the theoretical framework and the analytical models. After preprocessing, the resulting dataset was balanced and coherent, suitable for dynamic efficiency assessment and subsequent clustering.

Window DEA

To evaluate student academic performance over time, this study employed Window Data Envelopment Analysis (Window DEA). In this framework, each student was conceptualized as a decision-making unit (DMU), observed across multiple academic terms. DEA is particularly appropriate in educational contexts due to its ability to accommodate multiple inputs and outputs without imposing restrictive assumptions on the underlying production process (Charnes et al., 1978; Mergoni et al., 2025). This interpretation follows the educational production function perspective, in which prior academic preparation represents the initial endowment of academic capital, and university academic outcomes represent the outputs of the learning process.

In the DEA model, two variables capturing students' pre-university academic preparation were used as inputs: the standardized admission test score and the high school grade point average (GPA) from the origin school. These variables represent the academic resources or prior knowledge students bring into the university system.

Three variables were considered as outputs representing academic performance during each academic period: the student's term GPA, the program-specific term GPA, and the FTE indicator reflecting the student's academic load. In this context, efficiency reflects how effectively students transform their prior academic preparation into academic outcomes and sustained academic engagement throughout the program.

For each window, efficiency scores were computed by solving the following linear programming problem:

$$\begin{aligned} \min_{\theta,\lambda} \quad & \theta \\ \text{s.t.} \quad & Y\lambda \geq y_j, \\ & \theta x_j - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{1}$$

where x_j and y_j represent the vectors of academic inputs and outputs for student j, X and Y denote the corresponding matrices for all students within the window. An efficiency score of 1 indicates that the student lies on the efficiency frontier, while values below 1 reflect relative inefficiency.

Unlike static DEA, Window DEA applies this formulation to overlapping time-series subsets. If the dataset spans T academic periods and a window width of w is selected, the number of overlapping windows is:

$$T - w + 1. \tag{2}$$

This approach treats each student–period observation as a distinct unit within each window, thereby increasing discriminatory power and enabling the identification of performance dynamics over time. Window DEA is particularly well-suited for educational settings, where academic performance evolves gradually and cannot be fully captured by single-period efficiency measures. Because academic performance evolves gradually across semesters, a moderate window size (3) is particularly appropriate in educational contexts, where abrupt efficiency shifts are less common than gradual performance improvements.

The application of the Window DEA yields a sequence of efficiency scores for each student across academic periods. These sequences represent efficiency trajectories, reflecting not only the level of academic efficiency but also its evolution over time.

To transform these trajectories into analytically tractable representations, several summary indicators were derived. These indicators were designed to capture complementary dimensions of performance behavior, including overall efficiency, stability, temporal direction, persistence, and recent outcomes.

Let $\theta_{j,t}$ denote the efficiency score of student j in period t. The following indicators were computed:

- **Average efficiency**, capturing the overall level of performance:

$$\bar{\theta}_j = \frac{1}{T_j} \sum_{t=1}^{T_j} \theta_{j,t} \tag{3}$$

- **Efficiency trend**, estimated through a linear regression of efficiency on time:

$$\theta_{j,t} = \alpha_j + \beta_j t + \varepsilon_{j,t} \tag{4}$$

where β_j indicates improvement or deterioration over time.

- **Efficiency variability**, measuring stability across periods:

$$\sqrt{\frac{1}{T_j - 1} \sum_{t=1}^{T_j} (\theta_{j,t} - \bar{\theta}_j)^2} \tag{5}$$

Additional indicators were computed to capture cumulative performance, the frequency of improvements between consecutive periods, and the most recent efficiency outcome. Together, these metrics provide a compact yet informative description of each student's longitudinal efficiency profile.

Gaussian Mixture Modeling

To identify unidentified groups of students exhibiting similar efficiency trajectories and contextual characteristics, a Gaussian Mixture Model (GMM) was employed to operationalize intersectional profiles. This clustering approach is appropriate when group boundaries are not sharply defined and when probabilistic membership is desirable.

The GMM assumes that the observed data arise from a mixture of K multivariate normal distributions, with the probability density function given by:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k), \tag{6}$$

Where π_k denotes the mixing proportion of cluster k, while μ_k and Σk represent its mean vector and covariance matrix. Parameters were estimated using the Expectation–Maximization algorithm, which maximizes the log-likelihood to ensure an optimal probabilistic fit for the intersectional student profiles:

$$\mathcal{L} = \sum_{i=1}^{n} \log\left(\sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k) \right) \tag{7}$$

The clustering model incorporated both efficiency-based indicators derived from Window DEA and a set of contextual and demographic characteristics reflecting students' backgrounds and institutional environments. Continuous variables were standardized before clustering to ensure comparability across scales.

Cluster assignment was based on posterior membership probabilities, allowing students to be assigned to the cluster with the highest likelihood while preserving uncertainty information. This probabilistic approach enables a more nuanced interpretation than hard-clustering methods, particularly in heterogeneous educational populations.

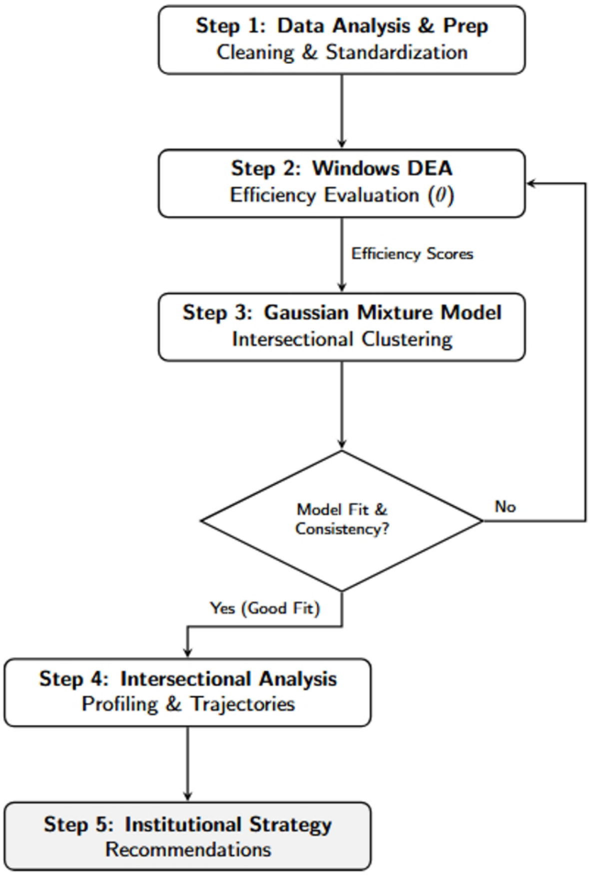

Figure 1: Methodological framework

RESULTS

Window DEA

Window DEA results present a clear temporal structure in students' academic efficiency trajectories, as shown in Figure 1. The evolution of average efficiency across academic semesters indicates that students enter the program operating relatively close to the efficiency frontier, with initial average values around 0.94. This suggests that, even in the early semesters, students can transform their academic inputs into outcomes with greater effectiveness than their peers during the same period. However, the persistence of a measurable efficiency gap during the initial semesters reflects an adjustment phase associated with the transition to higher education.

As semesters progress, average efficiency increases gradually and stabilizes within an approximate range of 0.95 to 0.96 during the middle stage of the academic trajectory. This phase is characterized by steady but modest gains, indicating a process of consolidation rather than rapid improvement. From an educational perspective, this pattern is consistent with the progressive acquisition of academic routines, study strategies, and familiarity with institutional expectations, while students simultaneously face increasing curricular demands (Garnet et al., 2014).

A pronounced shift in efficiency dynamics is observed in the later stages of the trajectory. From the advanced semesters onward, average efficiency rises substantially, approaching values close to 1.00 and ultimately converging to the efficiency frontier. This convergence suggests that most students achieve comparable levels of academic performance as they approach program completion. The stabilization of efficiency at frontier levels in the final semesters indicates that differences in relative performance diminish substantially at this stage of the academic trajectory.

To further examine differences in efficiency trajectories across student profiles, Figure 2 was extended to include both the overall average efficiency trajectory and the cluster-level trajectories identified through the Gaussian Mixture Model. While the global trend shows a gradual increase in academic efficiency across the program, cluster-specific lines reveal important heterogeneity in how students approach the efficiency frontier over time.

Clusters 0 and 3 exhibit the highest efficiency levels throughout most of the trajectory, remaining consistently close to the frontier. Cluster 4 shows a clear upward trajectory, indicating progressive improvement as students advance through the program. Cluster 1 maintains relatively stable efficiency levels with limited variation over time. In contrast, Cluster 2 shows the lowest trajectory and greatest instability, reflecting gradual deterioration in efficiency across periods.

These differentiated trajectories highlight that academic efficiency evolves differently across the intersectional configurations of students' characteristics and institutional context. While the overall trend suggests convergence toward high efficiency levels in later

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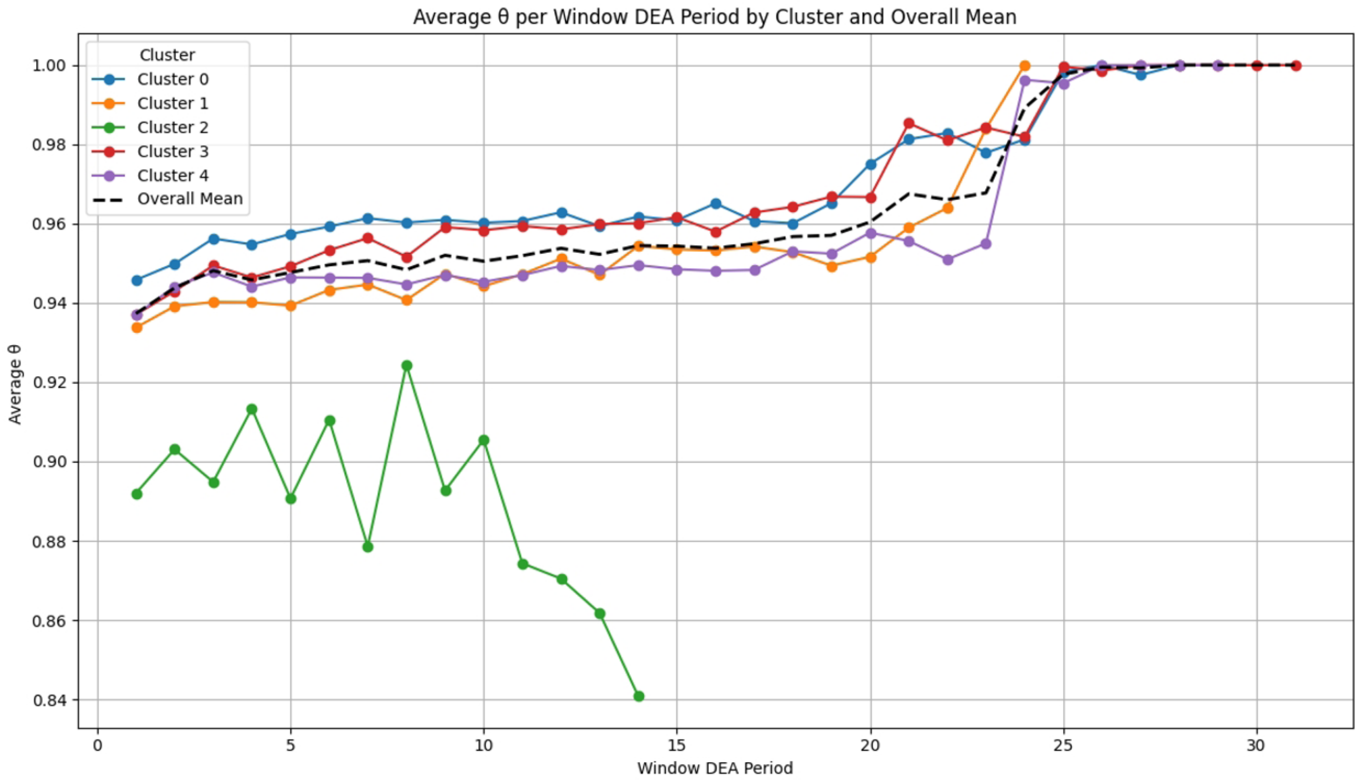

Figure 2: Evolution of average efficiency across Window DEA periods and clusters

stages of the program, the cluster-level analysis reveals persistent structural differences in the pace and stability of this convergence. In general, Window DEA results indicate that academic efficiency among students in the program is a cumulative and dynamic process. While most students exhibit sustained improvement and eventually converge toward high-efficiency levels, meaningful differences in individual trajectories persist throughout the academic lifecycle. These findings underscore the value of a longitudinal efficiency framework for understanding student progression in higher education and motivate further analysis to identify and characterize differentiated academic trajectories.

Cluster description

The information provided by the Window DEA constitutes the empirical foundation for subsequent trajectory-based analysis. By preserving students' relative positions within overlapping time windows, the method captures not only whether academic efficiency improves, but also the consistency and pace of that improvement. The resulting efficiency sequences enable the identification of distinct patterns of academic progression, which are later summarized and differentiated through cluster-level analyses.

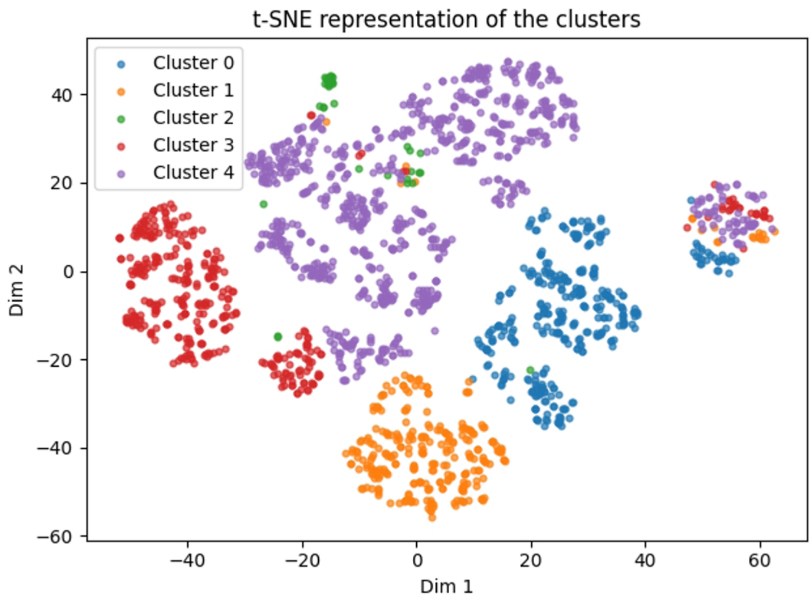

Figure 3: t-SNE visualization of student clusters based on efficiency trajectories and contextual characteristics

Figure 3 presents a two-dimensional visualization of the clustering results using t-distributed Stochastic Neighbor Embedding (t-SNE). Clusters were previously identified using a Gaussian Mixture Model applied to indicators summarizing students' efficiency trajectories derived from the Window DEA analysis, together with contextual variables. The t-SNE projection does not generate the clusters but provides a visual representation of the multidimensional similarity structure of the data. Dim1 and Dim2 correspond to the two coordinates of the t-SNE embedding, which compresses the high-dimensional feature space into two dimensions while preserving local relationships between observations.

The map shows that the identified clusters occupy distinguishable regions of the embedded space, providing qualitative support for the clustering solution. Students assigned to Cluster 3 are primarily located on the left-hand side of the map, indicating strong similarity in their efficiency trajectories and contextual characteristics. Cluster 1 is concentrated in the lower region of the embedding, forming a relatively distinct group. Cluster 0 appears mainly in the center-right portion of the map, while Cluster 4 spans a broader central area, suggesting a more heterogeneous profile that partially overlaps with neighboring groups. Cluster 2 is represented by a smaller and more sparsely distributed set of observations located in the upper-central region of the map.

Some degree of spatial overlap between clusters is expected because the Gaussian Mixture Model assigns probabilistic rather than deterministic cluster membership. Observations near cluster boundaries may exhibit characteristics of multiple profiles, as reflected in the partial mixing visible in the t-SNE representation. Despite this overlap, the overall spatial configuration indicates that the clusters capture meaningful differences in academic efficiency trajectories and contextual student characteristics.

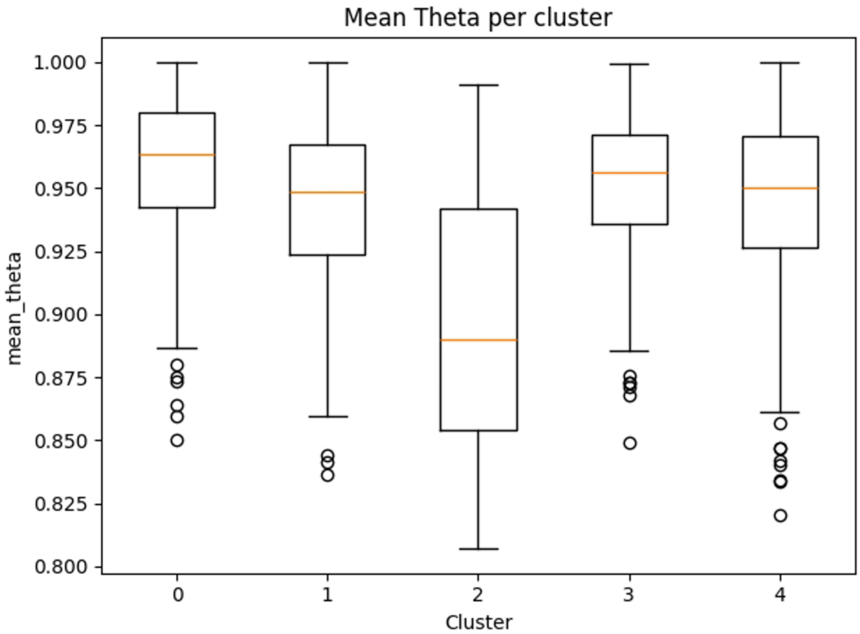

Figure 4: Boxplot of the average variation of the theta parameter

Figure 4 presents the distribution of average efficiency scores across clusters. While clusters 0 and 3 exhibit the highest median efficiency levels, Cluster 2 shows the lowest performance and the greatest variability. Clusters 1 and 4 occupy intermediate positions but differ in dispersion and trajectory direction.

Figure 5 summarizes the standardized characteristics associated with each cluster. The heatmap reveals how demographic, academic background, and institutional variables interact with efficiency trajectories to form distinct intersectional profiles.

Based on Figures 4 and 5, the distinct intersectional profiles were identified and defined. The description of each group is as follows:

Cluster 0: High and stable academic trajectory

Cluster 0 is characterized by consistently high academic performance (Mean: 0.96, Trend: 0.003) and low variability across semesters (Std. Deviation:0.01). Students in this cluster maintain efficiency levels close to the upper bound of the cohort, with a slight but steady improvement over time, indicating early adaptation to academic demands and sustained effective study practices.

From a social and institutional perspective, this cluster shows a distinct composition. Male students are under-represented, while students from rural backgrounds and first-generation students are over-represented. Despite these characteristics, which are often associated with increased educational risk, students in this cluster exhibit stable, high academic trajectories. This pattern is accompanied by a strong concentration in a specific academic school and a moderate association with campus regions, suggesting that institutional and program-level contexts play a compensatory role in supporting sustained academic performance.

Overall, Cluster 0 represents students who require limited academic intervention and benefit from well-aligned institutional environments that enable consistent academic success.

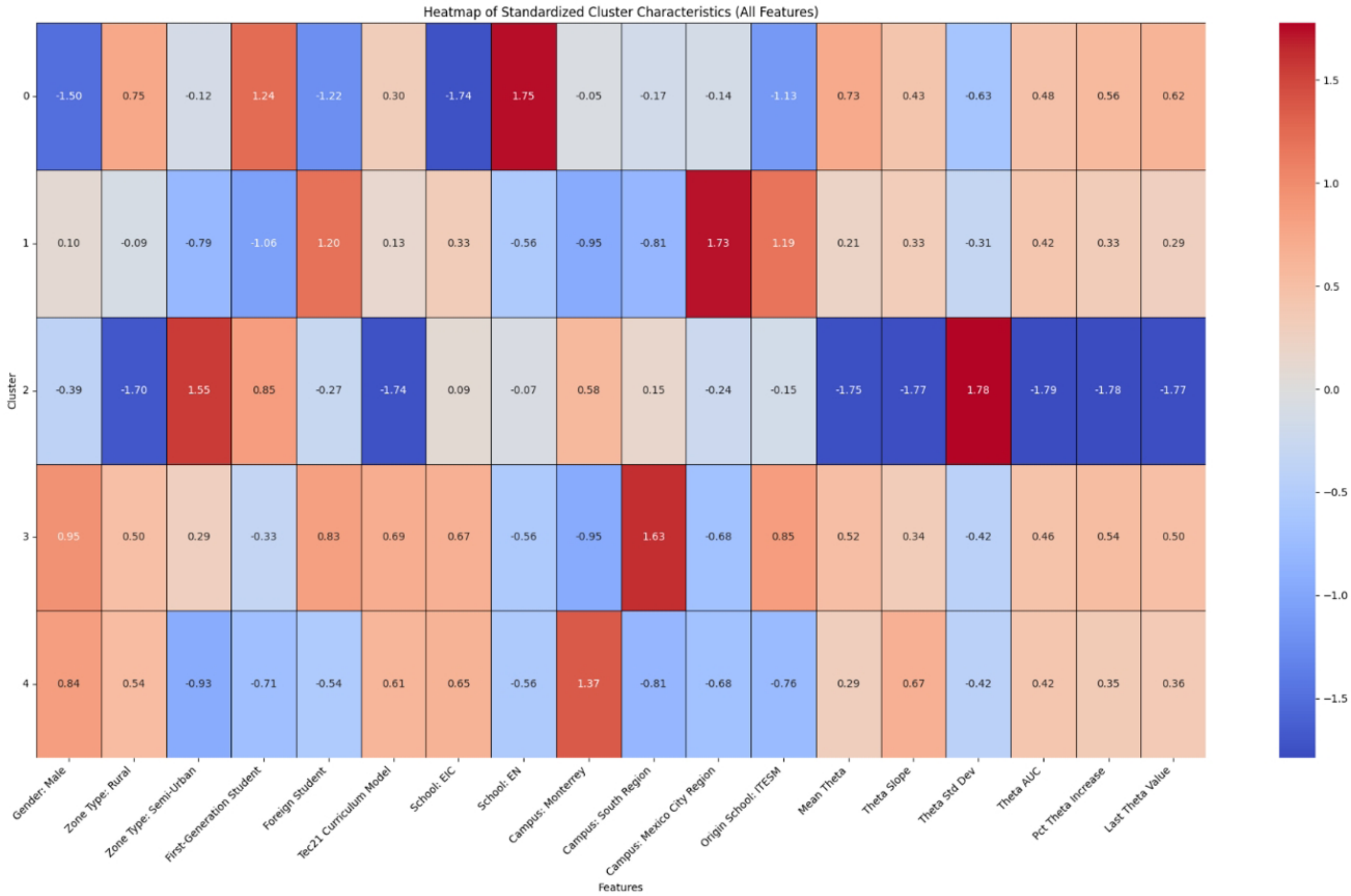

Figure 5: Characteristics heatmap of the features included

Cluster 1: Stable academic outcomes without acceleration

Cluster 1 is characterized by moderately high academic performance (Mean = 0.94, Trend = 0) that remains largely stable over time (Std. Deviation = 0.015). Students in this group maintain efficiency levels above the population average, though consistently below those of the highest performing clusters. Their academic trajectories are essentially flat, showing little systematic improvement or decline across semesters, with moderate variability and some lower-performing cases.

The social and institutional profile of Cluster 1 is marked by an over-representation of out-of-state students and a slight under-representation of students from rural and semi-urban backgrounds. In addition, this cluster shows a strong concentration in specific campus regions and academic schools, indicating a high degree of institutional alignment.

From an educational perspective, this combination of stable academic outcomes and strong institutional concentration suggests that students in Cluster 1 operate within supportive environments that sustain performance but do not appear to promote further academic acceleration. These students consistently meet academic expectations but show limited evidence of progressive improvement, suggesting the potential value of enrichment strategies that foster deeper learning and academic growth rather than remedial support.

Cluster 2: Declining and vulnerable academic trajectory

Cluster 2 represents the most critical profile when academic and social dimensions are considered jointly. From an academic perspective, students in this cluster exhibit the lowest average performance across all groups (Mean = 0.91), the highest variability (Std. Deviation = 0.025), and a clearly negative progression over time (Trend = -0.004). Their academic trajectories deteriorate as semesters advance, and outcomes at the end of the program remain the lowest observed among all clusters. This pattern reflects persistent difficulties in sustaining academic performance under increasing curricular demands.

The social and institutional configuration of this cluster further reinforces its vulnerability. Male students are slightly under-represented, while students from semi-urban backgrounds are strongly over-represented. This prevalence highlights a critical "vulnerability limbo" because, unlike rural students, who are often the primary focus of targeted social interventions, semi-urban populations may receive diluted institutional support. Unlike other groups, Cluster 2 does not display compensatory over-representation of first-generation or out-of-state students that might buffer academic risk. Institutionally, this cluster is markedly under-represented across multiple academic schools and campus regions, indicating limited alignment with supportive academic environments.

From an educational standpoint, the combination of declining academic trajectories, high instability, and unfavorable institutional positioning suggests restricted access to effective academic support structures. The absence of social or institutional buffering effects makes this group particularly vulnerable to academic disengagement and attrition. Consequently, Cluster 2 constitutes the primary target for

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early identification, intensive academic support, and retention-focused interventions.

Cluster 3: High and continuously improving academic trajectory

Cluster 3 is characterized by high academic performance combined with sustained positive progression over time. Students in this group maintain performance levels comparable to those of the highest performing cluster (mean = 0.97), while continuing to improve as they advance through the program (Trend = 0.004). Variability in academic outcomes is low (Std. Deviation = 0.009), indicating consistent learning and stable academic behavior across semesters. Final academic outcomes remain high and are sustained through program completion.

The social composition of Cluster 3 is relatively balanced, with a clear over-representation of male students and a slight over-representation of students from rural backgrounds, alongside a moderate presence of first-generation students. Institutionally, this cluster is over-represented in specific campus regions associated with stronger academic outcomes, suggesting alignment with supportive learning environments.

From an educational perspective, the convergence of stable social conditions and favorable institutional contexts appears to facilitate continuous academic consolidation. Students in Cluster 3 not only perform well but also refine their academic skills and learning strategies over time, demonstrating effective responses to increasing curricular complexity. This profile reflects a resilient and self-reinforcing learning trajectory within the program.

Cluster 4: Improving academic trajectory

Cluster 4 shows significant academic improvement over time. Although students in this group do not begin with the highest performance levels, their trajectories display the most pronounced positive progression among all clusters (Trend = 0.006). Average academic outcomes are moderately high (Mean = 0.95), variability is moderate to low (Std. Deviation = 0.012), and final performance levels exceed the cohort average, indicating convergence toward stronger academic outcomes by program completion.

The social profile of Cluster 4 shows an over-representation of male students, an under-representation of students from semi-urban backgrounds, and a slight under-representation of first-generation students. Institutionally, this cluster exhibits clear concentration within specific academic schools and campus regions, suggesting effective alignment with environments that facilitate academic development.

From an educational perspective, students in Cluster 4 appear to progressively benefit from academic exposure, institutional resources, and learning experiences. Their improvement over time reflects successful adaptation and sustained engagement, highlighting the importance of developmental trajectories in which students close initial performance gaps through continuous participation.

Intersectional Analysis

The five clusters are primarily distinguished by how students' academic performance evolves, rather than by initial performance levels alone. Clusters 0 and 3 both represent high-performing students, but with different patterns. Cluster 0 is defined by early academic adaptation and stable performance across semesters, while Cluster 3 combines high performance with continued improvement. Together, these clusters highlight two forms of academic success: sustained excellence from early stages and progressive consolidation over time.

Clusters 1 and 4 occupy intermediate positions but exhibit distinct trajectories. Cluster 1 is characterized by stable but largely unchanged performance, with students consistently meeting academic expectations without notable improvement. This makes the cluster noteworthy for its potential responsiveness to academic enrichment rather than remediation. In contrast, Cluster 4 is defined by strong academic growth. Although students in this group do not start at the highest performance levels, they show the greatest improvement over time and converge toward above-average outcomes by the end of the program.

Cluster 2 stands out as the most critical group. It is the only cluster showing a clear decline in academic performance over time, combined with high variability and limited institutional alignment. Unlike other clusters, students in this group do not benefit from stabilizing or compensatory conditions, making them particularly vulnerable to academic disengagement and attrition. This cluster, therefore, represents the primary focus for early identification and targeted academic support.

In terms of intersectionality, cluster structure highlights how academic performance emerges from the intersection of personal characteristics and institutional context, rather than from individual attributes in isolation. Clusters 0 and 3 illustrate that high academic performance can be sustained under different intersectional configurations. Cluster 0 combines high and stable performance with a higher presence of first-generation and rural students, suggesting that supportive institutional environments can offset structural disadvantages. Cluster 3, in contrast, pairs high performance with more advantaged contextual positioning, where social stability and favorable institutional placement jointly reinforce continuous academic improvement.

Clusters 1 and 4 show how similar performance levels can arise from different intersectional pathways. Cluster 1 is characterized by stable but non-progressive academic outcomes within strongly structured institutional settings and a higher presence of out-of-state students, indicating adequacy without acceleration. Cluster 4, however, demonstrates that students with fewer structural disadvantages and strong institutional alignment can translate sustained engagement into marked academic improvement over time, even if their initial performance is not among the highest.

Cluster 2 represents the most critical intersectional configuration, where multiple disadvantages converge. Students in this group combine declining academic trajectories with unfavorable institutional positioning and limited compensatory social characteristics. The interaction of these factors amplifies vulnerability, leading to high variability and worsening outcomes over time. This cluster illustrates how academic risk is produced not by single characteristics, but by the cumulative and interacting effects of personal background and institutional context.

DISCUSSION

The integration of quantitative intersectional analysis with dynamic efficiency measurement reveals patterns of educational performance that conventional analytical approaches miss. By combining Window DEA with Gaussian Mixture Modeling, this study demonstrates that academic efficiency in higher education is neither uniformly distributed nor determined by isolated demographic characteristics. Instead, efficiency emerges from the complex interplay between students' intersecting social identities and their institutional environments, producing distinct trajectories that evolve differentially over time.

Theoretical implications

This study makes three important theoretical contributions to the intersection of educational equity and efficiency research. First, it operationalizes intersectionality as a quantitative framework for efficiency analysis, moving beyond single-axis demographic comparisons to reveal how multiple identities interact to shape resource utilization patterns. The identification of five distinct efficiency clusters demonstrates that students with similar demographic profiles may follow markedly different academic trajectories depending on their institutional positioning and the specific configuration of their intersecting identities.

These findings align with and extend prior quantitative intersectional work. Keller et al. (2023) and Prior et al. (2025), both employing MAIHDA, found that between-stratum variation in student achievement is largely driven by additive rather than interactive effects of demographic characteristics. The present study complements this by showing that when efficiency trajectories, rather than static achievement scores, are the outcome of interest, meaningful heterogeneity persists across intersectional profiles even after accounting for additive effects. Similarly, Hanauer et al. (2025) identified four distinct identity orientations among STEM students using hierarchical clustering, concluding that student positionalities are far more complex than single-axis analyses suggest. Our five-cluster solution echoes this finding, though it goes further by linking those positionalities directly to resource utilization patterns over time, a dimension absent from Hanauer et al.'s analysis.

Second, the findings challenge the assumption that educational efficiency is primarily a function of individual characteristics or institutional quality alone. The divergent trajectories of Clusters 0 and 2, both containing students from structurally disadvantaged backgrounds but experiencing opposite academic outcomes, illustrate that efficiency arises from the interaction between student characteristics and institutional context. This suggests that traditional efficiency models that treat student populations as homogeneous or control for demographics through simple dummy variables may systematically misidentify sources of inefficiency.

This finding resonates with Temoso et al. (2023), who, using a network DEA framework, demonstrated that teaching and research efficiency differ substantially within the same institution, underscoring that efficiency is not a uniform property of an institution but varies across processes and contexts. Likewise, Tran et al. (2022) found that institutional type, public versus private, moderates efficiency in Vietnamese universities, suggesting that organizational context shapes how inputs are converted into outcomes. The present study extends this logic to the student level: just as institutional type conditions efficiency at the system level, the intersection of students' social characteristics and their program placement conditions efficiency at the individual level. Critically, however, unlike Tran et al. (2022) and Temoso et al. (2023), who treat student populations as largely homogeneous within institutional categories, our results show that even within a single program, students occupying different intersectional positions experience systematically different efficiency trajectories.

Third, the temporal dimension of efficiency revealed through Window DEA highlights the inadequacy of static, cross-sectional approaches to educational evaluation. The distinction between stable high performance (Cluster 0), continuous improvement (Clusters 3 and 4), stable adequacy (Cluster 1), and progressive decline (Cluster 2) demonstrates that efficiency is a dynamic process that unfolds over time. This has important implications for when and how institutions should intervene to support student success.

The dynamic patterns observed here contrast with the predominantly static designs that dominate efficiency research in education. Kounetas et al. (2023), examining 643 Greek secondary schools over 18 years, found persistent inefficiencies with limited reform impacts, but their analysis aggregated efficiency at the school level across years rather than tracing individual-level trajectories. Zhou et al. (2024) used the Malmquist index to capture efficiency change over time across Chinese provinces, identifying technological progress as the primary driver; however, this approach collapses individual heterogeneity into regional averages. By contrast, Window DEA applied at the student level reveals that efficiency change is not uniform: some students improve continuously (Clusters 3 and 4), others plateau (Cluster 1), and others deteriorate (Cluster 2). This trajectory-level granularity represents a meaningful advancement over aggregate temporal analyses and suggests that the timing and targeting of institutional interventions matter as much as their content.

Practical implications and policy recommendations

The intersectional efficiency profiles identified in this study have direct implications for educational policy and institutional practice, particularly for programs serving underrepresented and economically disadvantaged students. The five clusters require fundamentally different institutional responses.

Cluster 2 emerges as the highest-priority intervention, requiring early identification systems and intensive, sustained academic support. The combination of declining trajectories, high variability, and limited institutional alignment suggests that students in this cluster need comprehensive support that addresses both academic skills and institutional integration. Critically, the over-representation of semi-urban students in this cluster highlights a policy blind spot: unlike rural students, who often receive targeted support, semi-urban populations may fall through the cracks of binary urban-rural intervention frameworks.

The identification of semi-urban students as a particularly vulnerable group within Cluster 2 is a finding with few direct parallels in the efficiency literature, which typically segments populations by institutional type or geographic region rather than by students' origin characteristics. Chiariello et al. (2022), studying Italian primary and secondary schools, found significant North–South efficiency disparities driven by contextual factors including poverty and institutional quality, but did not examine how students' social backgrounds interact with these regional effects. Muniz et al. (2024), focusing on Brazilian schools, identified infrastructure elements such as libraries and computer labs as key determinants of efficiency, yet did not consider how these resources differentially benefit students from distinct social backgrounds. Our results suggest that the policy-relevant unit of analysis should not be the institution or the region alone, but the intersection of student characteristics and institutional environment, since the same institutional resources may produce very different efficiency outcomes depending on who is being served.

Cluster 1 presents a different challenge: these students consistently meet academic expectations but show limited growth over time. Rather than remediation, this group would benefit from academic enrichment initiatives designed to promote deeper engagement and skill development. The strong institutional concentration within this cluster suggests that program-level interventions such as enhanced research opportunities, advanced coursework options, or international experiences may be more effective than individual-level support. Clusters 3 and 4 demonstrate that institutional alignment and supportive environments can facilitate continued academic development, even among students who do not start at the highest levels of performance. This suggests that strategic placement and early connection to effective academic communities may be as important as direct academic support services.

The findings have important implications for how institutions allocate limited support resources. Traditional approaches that distribute resources uniformly across all scholarship recipients or target students solely on the basis of single demographic characteristics, such as first-generation status, may be inefficient (Adamecz-Völgyi et al., 2020; Herbaut and Geven, 2020). The intersectional profiles reveal that vulnerability and need for support are determined by configurations of characteristics rather than isolated attributes. For example, Cluster 0 demonstrates that first-generation and rural students can achieve sustained high performance when positioned within supportive institutional environments. This suggests that investments in institutional capacity, such as strengthening academic programs, developing mentoring networks, and creating inclusive campus communities, may be as important as direct student services. Conversely, Cluster 2's under-representation across multiple academic schools and regions indicates that some students lack access to these supportive contexts, suggesting the need for deliberate efforts to ensure equitable distribution of students across institutional resources.

The finding that first-generation and rural students in Cluster 0 achieve sustained high performance when positioned within supportive institutional environments challenges a common assumption in the efficiency literature that these demographic groups are inherently associated with lower educational efficiency. Ulkhaq et al. (2024), analyzing schools across six South-East Asian countries using PISA data, found that ICT-related resources are positively associated with efficiency, but treated student populations as homogeneous within national and school-level categories. Taleb et al. (2023), in their examination of Taiwanese universities, focused exclusively on institutional-level super-efficiency, without considering student composition. Neither study would be able to detect the compensatory dynamic observed here, where institutional context offsets the risk factors typically associated with first-generation and rural status. This has a direct policy implication: efficiency-improving investments directed at institutional environments, academic programs, mentoring structures, and campus communities may yield higher returns than equivalent investments in student-level remediation alone, particularly for students whose intersectional profiles combine structural disadvantage with high potential.

The temporal patterns revealed by Window DEA suggest that early identification is critical but insufficient on its own. While Cluster 2 students show relatively high initial efficiency (around 0.94), their trajectories begin to diverge by the middle semesters and continue to deteriorate thereafter. This indicates that intervention systems should monitor trajectory patterns rather than just absolute performance levels and should be designed to identify students experiencing declining efficiency even when their current performance remains acceptable. Moreover, the intersection-based clustering approach suggests that risk prediction models should move beyond single demographic indicators to consider configurations of characteristics. A first-generation student from a rural background enrolled in a strongly supportive academic program (likely Cluster 0) faces very different risks than a semi-urban student with weak institutional alignment (likely Cluster 2), even though traditional risk models might flag both.

The over-representation of certain clusters within specific academic schools and campus regions raises questions about whether program structures inadvertently concentrate risk or advantage. If particular academic programs or campus locations consistently produce better outcomes for students with certain intersectional profiles, institutions should examine what features of these environments are protective and whether they can be deliberately cultivated elsewhere. Similarly, the finding that institutional context can buffer structural disadvantages (as in Cluster 0) suggests that program design should prioritize not just admitting diverse students but ensuring they have equitable access to high-quality academic environments. Admissions decisions, program placement, and campus assignment should be informed by understanding which environments best support students with particular intersectional profiles.

Limitations

Several limitations should be acknowledged when interpreting these findings. First, the analysis is based on data from a single scholarship program at one institution in Mexico. While the Líderes del Mañana program serves a diverse, economically disadvantaged population, the specific intersectional configurations and their relationships to efficiency may differ across other institutional contexts or national settings. The transferability of findings to other contexts should be empirically verified rather than assumed. Second, the intersectional profiles identified through GMM reflect the particular set of identity dimensions and institutional characteristics available in the dataset. Other important axes of identity and marginalization, including race, ethnicity, indigenous status, disability, and language background, were not available for analysis but may play critical roles in shaping educational efficiency in other contexts. The clusters identified here represent patterns within the observed data rather than exhaustive categories of intersectional experience.

Third, the efficiency scores derived from Window DEA are inherently relative, comparing students to their peers within specific time windows rather than to absolute performance standards. While this approach is methodologically appropriate for identifying differential resource utilization, it does not directly address questions about whether overall resource levels are adequate or whether all students are achieving desired learning outcomes in absolute terms. Fourth, the causal mechanisms underlying the observed efficiency patterns cannot be definitively established through the clustering and efficiency analysis employed here. While the findings reveal systematic associations between intersectional profiles and efficiency trajectories, the specific processes through which these patterns emerge, whether through differential access to resources, variations in institutional support quality, differences in academic preparation, or other mechanisms, require further investigation through complementary research designs.

Finally, the study focuses on students who remained enrolled in the program across multiple semesters, potentially introducing survivorship bias. Students who left the program early, whether due to academic difficulty, financial constraints, or other reasons, are underrepresented in the later stages of the efficiency analysis. This may lead to underestimation of efficiency gaps and over-optimistic assessments of program effectiveness, particularly for the most vulnerable groups. However, it is important to note that the Líderes del Mañana program has a very low attrition rate, with approximately 1% of students leaving before completion during the study period.

CONCLUSION

This study demonstrates that integrating quantitative intersectional methods with dynamic efficiency analysis reveals patterns of educational performance that remain hidden when student populations are treated as homogeneous. By applying Window DEA and Gaussian Mixture Modeling to longitudinal data from the Líderes del Mañana scholarship program, we identified five distinct intersectional efficiency profiles characterized by different patterns of academic trajectory, institutional positioning, and social background. Critically, structural disadvantages do not deterministically produce poor outcomes; institutional environments can buffer or amplify disadvantage depending on the specific configuration of intersecting identities and institutional factors.

These findings carry direct policy implications. Promoting educational equity requires moving beyond uniform interventions or single-axis targeting toward differentiated support strategies responsive to students' complex, multidimensional positionalities. Efficiency in higher education emerges from the dynamic interaction between students' multiple identities and the institutional contexts they navigate. Several directions remain open for future research, including mixed-methods investigation of the mechanisms behind these patterns, expansion to additional identity axes such as race, ethnicity, and disability status, and cross-institutional comparative studies. Methodological advances, including Bayesian methods, panel DEA, and machine learning approaches, could further refine intersectional efficiency analysis. Ultimately, this study provides both a methodological template and an empirical foundation for demonstrating that efficiency and equity are not competing values but complementary objectives that require an intersectional understanding to be achieved simultaneously.

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