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Technical Section

CSDA-Vis: A (What-If-and-When) visual system for early dropout detection using counterfactual and survival analysis interactions☆

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ABSTRACT

Student dropout is a major concern for universities, leading them to invest heavily in strategies to lower attrition rates. Analytical tools are crucial for predicting dropout risks and informing policies on academic and social support. However, many of these tools depend solely on automate tu d predictions, ignoring valuable insights from professors, mentors, and specialists. These experts can help identify the root causes of dropout and develop effective interventions. This paper introduces *CSDA-Vis*, a visualization system designed to analyze the influence of individual, institutional, and socioeconomic factors on student dropout rates. CSDA-Vis facilitates the identification of actionable strategies to mitigate dropout by integrating counterfactual and survival analysis methods. Unlike traditional approaches, our tool enables decision-makers to incorporate their expertise into the evaluation of different dropout scenarios. Developed in collaboration with domain experts, CSDA-Vis builds upon previous visualization tools and was validated through a case study using real datasets from a Latin American university. Additionally, we conducted an expert evaluation with professionals specializing in dropout analysis, further demonstrating the tool's practical value and effectiveness.

1. Introduction

Student success in higher education depends not only on identifying those at risk of dropping out but also on choosing, timing, and evaluating effective interventions over time. Institutions deploy diverse initiatives—orientation programs, academic advising, accurate course placement, early alerts, tutoring, first-year transition programs, and financial aid [1]—yet resource constraints make it essential to prioritize actions with demonstrable impact. Consequently, analysts need tools that connect risk estimation with prescriptive guidance and longitudinal evaluation to inform decision-making and resource allocation [2].

Data mining and machine learning have been widely used for student dropout analysis, modeling *who* may leave and *when* this may occur from personal, academic, economic, social, and institutional factors (e.g., neural networks, support vector machines, decision trees, logistic regression) [3–8]. While such predictors are valuable for early detection, they seldom answer the actionable question critical to practitioners: *what should change, for whom, and with what expected durability of effect?* In practice, many institutions rely on static business-intelligence dashboards (e.g., Power BI, Qlik) that summarize current and historical status but provide limited support for *interactive* hypothesis formation, prescriptive "what-if" analysis, or longitudinal auditing of intervention quality.

Counterfactual explanations (CFs) offer a prescriptive mechanism to propose concrete, minimally invasive changes to feature values that would alter an outcome in a desired direction [9,10]. In our context, CFs suggest actionable modifications to student-level attributes intended to move a case from the dropout to the non-dropout region. Fig. 1 illustrates original and perturbed instances; multiple, distinct perturbations of a single attribute may yield alternative feasible paths.

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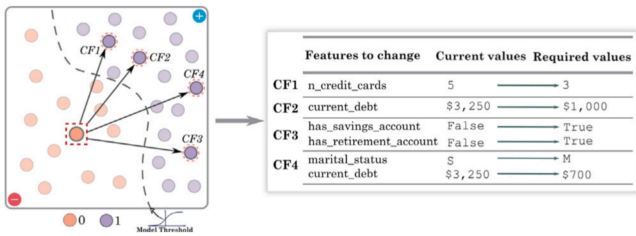

Fig. 1. Counterfactual antecedents (purple) of a given instance (orange into the dotted square).

By leveraging CFs, analysts can reason about *what to do* for specific students or subgroups, subject to institutional constraints and costs.

Dropout is inherently temporal; the effectiveness of an intervention may onset, persist, or decay across semesters. Survival analysis offers a principled approach to estimating time-to-event outcomes and comparing intervention scenarios longitudinally. In our setting, survival curves quantify the evolution of the likelihood of remaining enrolled over time, enabling the quality auditing of corrective actions and the comparison of alternative strategies.

Visualization research gap. Our work addresses four limitations in existing visualization approaches for dropout analysis: **(G1)** the absence of an *end-to-end* workflow that links risk prediction, counterfactual generation, and survival-based evaluation; **(G2)** limited support for subgroup/cohort reasoning when designing and assessing interventions; **(G3)** weak treatment of temporal dynamics, uncertainty, and robustness when estimating intervention effects; and **(G4)** insufficient coordination among views to guide actionable decision-making from selection through explanation to longitudinal evaluation.

To address G1–G4, we introduce *CSDA-Vis* (Counterfactual and Survival Analytics Visualization tool), a *what-if-and-when* system that integrates counterfactual reasoning with survival analysis in a coordinated visual analytics workflow. Building on prior work that implemented "what-if" analysis without temporal evaluation [11], CSDA-Vis adds (i) interactive, constraint-aware CF generation, (ii) subgroup selection and cohort-level aggregation, and (iii) longitudinal impact assessment via survival curves and risk trajectories with uncertainty. To make the workflow concrete, we include a comprehensive toy example that walks through all coordinated components from subgroup definition to longitudinal comparison, complementing our case study on real institutional data. Currently, our system generates individual counterfactuals and assesses their cohort-level impact; synthesizing group/multi-instance counterfactuals is an important avenue for future extension.

Contributions. In summary, this paper offers:

- A methodology that integrates counterfactual and survival analysis to support *prescriptive* and *longitudinal* reasoning about student dropout. Counterfactuals propose actionable changes; survival analysis evaluates their durability over time.
- *CSDA-Vis*, an interactive *what-if-and-when* visualization system that operationalizes this methodology through coordinated views for subgroup selection, counterfactual generation under costs/constraints, and longitudinal impact assessment with uncertainty.
- A comprehensive demonstration comprising (i) a toy example that illustrates the end-to-end workflow across components and (ii) a case study with real institutional data, including feedback from domain experts in student dropout analysis.

2. Related work

The proposed methodology comprises four different areas: (i) Counterfactual explanation, (ii) Survival analysis, (iii) Visual analytics, and (iv) Students' dropout analysis. This section organizes previous studies that consider the areas they encompass.

2.1. Counterfactual explanation

The literature on counterfactual explanations is extensive and could be detailed in different surveys [12–14]. Wachter et al. [9] first proposed the concept of counterfactual explanations through the presentation of a framework to generate counterfactual explanations. Similarly, Spangher et al. [15] proposed a tool that solves an optimization problem to recover counterfactual explanations that are actionable and globally optimal concerning a user-specified cost function. Raimundo et al. [16,17] propose MAPOCAM, which enumerates all Pareto-optimal counterfactual antecedents using multi-objective concepts. In addition to optimization functions, other works employed heuristics [18–20], kNN [21], and A*-like methods [22,23] to extract single and multiple counterfactuals.

Other methods are also based on feature intervention, such as LIME and SHAP [24,25]. Furthermore, many techniques apply feature perturbation to achieve the desired outcome [26–29]. As a way to gain user understanding, some counterfactual works have used visual analytics techniques to understand the decisions of learning systems [30–32].

In addition to generating and exploring counterfactuals, our approach builds upon simple but powerful visualization resources to enable counterfactual and survival analysis. This approach engines a recommendation system to reduce student dropout rates based on restrictions introduced by the user. Furthermore, our approach measures the impact of a particular counterfactual over groups, also considering temporal behavior.

Recently, researchers have begun exploring group or multi-instance counterfactuals [33–35], which generalize instance-based counterfactual reasoning to a group level. Unlike simple aggregations of individual counterfactuals, these methods aim to find counterfactuals that simultaneously cover multiple instances, often leading to higher accuracy and greater robustness to outliers. In the context of student dropout analysis, group counterfactuals could provide actionable insights at the cohort or program level, where interventions are frequently deployed. While our system focuses on individual counterfactuals, we recognize group counterfactuals as a promising extension and highlight them as an important direction for future work.

2.2. Survival analysis

Survival analysis is a collection of statistical procedures for data analysis, for which the outcome variable of interest is the time until an event occurs. Given the versatility of this technique, we find various applications, including [36], Healthcare [37], Reliability [38], Crowdfunding [39], Bio-informatics [40], and Education [41]. Wang et al. [42] presented a comprehensive review of the various machine-learning techniques for survival analysis. First, traditional statistics employed non-parametric methods for survival analysis, such as life tables and the *Kaplan–Meier* (KM) and *Nelson-Aalen* (NA) estimators. These methods do not use attributes to estimate a survival curve; instead, they are used to have an initial approach to evaluate it totally and/or partially [43]. Later, more advanced techniques focusing on probability distributions are presented, such as *Weibull*, *Exponential*, and *Gompertz* distributions, among others. Recently, Taketomi et al. [44] presented a detailed review of parametric methods in this context. Cox [45] introduced a semi-parametric model named *Cox Proportional Hazard regression* (CPH), which is one of the most used methods in the literature, and on which other models such as *Regularized Cox*, *CoxBoost*, and *Time-Dependent Cox* regressions (TD-Cox) are based. For instance, Ameri et al. [41] employed TD-Cox to detect students at risk of dropping out early, and Kleinbaum and Klein [46] presented a profound review on the mathematical and statistical foundations that give theoretical support to non-parametric, semi-parametric, and parametric methods.

On the other hand, Machine Learning (ML) algorithms have become decisive when processing large volumes of data. Zupan et al. [47]

presented one of the first approaches that combine machine learning algorithms with survival analysis methods and conducted a study to detect prostate cancer. There are various survival analysis techniques based on ML, among which we highlight. *Multi-Task Logistic Regression* (MTLR) [48], *Random Survival Forest* (RSF) [49], and *Conditional Survival Forest* (CSF) [50]. A survey that showed the evolution of these techniques in the context of ML algorithms can be found in [42]. In addition, Deep Learning variations have been introduced and tested in biomedical areas such as Nonlinear Cox Regression (DeepSurv) [51] and Neural Multi-Task Logistic Regression (N-MTLR) [52]. Lee et al. [53] propose DeepHit, which uses a deep neural network to learn the distribution of survival times directly. In contrast, S. Hu [54] proposed a transformed-based survival analysis method that estimates the patient-specific survival distribution. In addition, S. Hu [54] uses an ordinal regression to optimize the survival probabilities over time and penalize randomized discordant pairs.

2.3. Visual analytic

Visual analysis techniques have gained much prominence in understanding machine learning models. Different formats to apply visualization over learning models have been reported throughout some surveys [55–57]. Most of the research aims to enable users' understanding [58,59], diagnosis [60–63], and refinement [64,65] or all of them [66]. In this work, we are interested in visualization techniques for diagnosis and refinement.

In the context of visual learning models, various works assist machine learning models, e.g., *VIS4ML* [67], *DiscriLens* [62], The *What-If Tool* [63], *explAIner* [66], *ExplainExplore* [68], *Manifold* [61], and *RuleMatrix* [59]. In a counterfactual context, Gomez et al. [69] proposed *ViCE*, a visual tool to generate counterfactual explanations to contextualize and evaluate model decisions. Cheng et al. [32] proposed *DECE*, which supports the exploratory analysis of model decisions by combining the strengths of counterfactual explanations at the instance and subgroup levels. Kaul et al. [70] propose *CoFact*, an interactive visualization prototype that determines and visualizes counterfactual subsets to support user exploration of feature relationships better. Wexler et al. [63] propose *What-If Tool*, which allows practitioners to probe, visualize, and analyze machine learning systems.

Visual analytics tools could transform complex data into intuitive representations, significantly assisting education data analysis. Some systematic literature reviews explore the application of visual analytics in education from different perspectives, examining learning behavior, content, student interaction, and performance prediction and recommendation [71,72]. The most closely related works are *PerformanceVis* [73], *DropoutVis* [74], and *SDR-Explorer* [75]. *PerformanceVis* aims to analyze student performance in a course using visualization. In contrast, *DropoutVis* aims to explore learning behaviors by extracting dropout patterns and providing a foundation for developing strategies based on counterfactual analyses. Recently, *SDR-Explorer* introduced an interactive system that incorporates simple and familiar visual components, such as Sankey diagrams and multidimensional projection methods, along with a large language model to interact with these visualizations. While *DropoutVis* and *SDR-Explorer* share similarities, they both fall short in considering the survival analysis of students and their counterfactuals over time. Additionally, they do not evaluate the quality of counterfactuals across different groups, nor do they factor in the temporal behavior of counterfactuals. This temporal aspect is crucial for ensuring the effectiveness of any corrective measures implemented.

2.4. Student dropout analysis

Student dropout has been a concern for decades, and its consequences are significant for any educational institution worldwide. Avoiding desertion is a long-term goal and requires decisions over time. The dropout analysis literature has been extensively reviewed and organized in various surveys [76–80]. The contributions have been organized from different perspectives considering the factors: student (age, ethnicity, disability, and gender) [81–83], academic (GPA, cohort, absenteeism, and curricula design) [11,84,85], economic (scholarship, poverty, investment, and family income) [86–88], social (employment status, parents' educational level, social status) [89,90], and institutional dimensions (campus environment, university type, and infrastructure) [77,91,92].

One of the first steps is to detect students at risk. However, this is a complex task, as it requires evaluating numerous diverse variables. In this context, predictive modeling using machine learning has great potential to identify students at risk of dropping out in advance and support them. The risk of dropping out has been identified using different machine learning models such as Neural Network [3,4], Support Vector Machines [3,5,93], Decision Tree [3,5], Self-Regulated Learning [94], and Logistic Regression [3,6–8]. Similarly, Greefrath and Koepf [95] and Xenos et al. [80] implemented traditional statistical tools to understand the problem better and identify the most influential variables.

As discussed above, various methods can identify who and when students are likely to drop out. However, these studies do not help identify and apply corrective actions to prevent student abandonment. For instance, our previous approach, SDA-Vis [11], focused on analyzing academic features and generating counterfactuals. Still, it did not provide mechanisms to evaluate how such corrective measures might impact a student's trajectory throughout the semesters. Our approach goes one step further. We aim to incorporate prescriptive analysis to help decision-makers understand why students drop out and identify corrective measures (utilizing counterfactuals) to reduce dropout rates. The tool incorporates a longitudinal analysis, comparing the effectiveness of corrective actions over time using survival analysis curves. Moreover, we use heuristics based on prediction probability, cumulative risk, and survival scores to accurately select representative students on which to base the corrective measures, counterfactuals to apply, and the group of students on which to measure the effectiveness.

3. Challenges and analytical tasks

In this project, we collaborated closely with domain experts and researchers with previous experience in student dropout analysis. We employed a user-centered, qualitative research approach, grounded in semi-structured interviews and iterative stakeholder feedback [96]. Over the course of six months, we conducted interviews with a purposive sample of twelve key participants involved in dropout management, including three faculty members, three school heads, one welfare director, and five academic tutors.

These semi-structured interviews explored participants' workflows, challenges, and expectations around dropout prevention tools. Participants occasionally provided relevant artifacts such as reports and intervention protocols to enrich the data. Detailed notes were taken during the interviews, which were subsequently organized and thematically coded using an open and inductive process. Core participants remained engaged throughout, allowing us to capture evolving insights.

Following this initial research phase, we collected continuous feedback throughout the tool's implementation via regular meetings and informal communications. This iterative engagement ensured our design stayed aligned with real-world practices and truly reflected the needs of our target users. Through this continuous collaboration, the tool's tasks and features emerged directly from authentic stakeholder input, underscoring both its novelty and practical relevance.

Domain experts highlighted that their traditional analyses tend to focus primarily on economic factors and semester grades, such as flagging students with grades below 5.75 (on a 0–20 scale) as academically at risk. These criteria, however, are based more on experiential judgment than on rigorous analytical methods. This gap revealed a clear need for a more precise understanding of the factors influencing student dropout, as well as for identifying which combinations and value ranges exert the most significant impact.

Identifying dropout patterns is a vital first step, but applying effective corrective actions remains a significant challenge. Although prior research has successfully uncovered dropout indicators, decision-makers often lack clear guidance on which specific steps to take to reduce dropout rates. Effective interventions require insight into which student characteristics must change and to what extent. Without this understanding, interventions risk being misdirected, potentially causing harm rather than providing support.

Another crucial aspect in addressing dropout is evaluating the impact and sustainability of corrective actions. Since these interventions often demand significant resources from universities or government entities, it is essential to assess their effectiveness both at the individual and group levels. Additionally, tracking the temporal quality of interventions—that is, monitoring their effects across semesters—provides key insights for ongoing improvement and resource optimization.

Guided by challenges surfaced by domain experts and the literature, we formalize a task framework that CSDA-Vis should support:

T1 - Distribution Analysis of Student Features. This task allows users to visualize and compare the distribution of feature values across the dataset. Establishing an overview of the current state allows users to define a reference point for comparing individual student instances.

T2 — Select and refine students and counterfactuals based on interest, features, or metrics. According to domain experts, some specific groups of students and counterfactuals require focused analysis. The proposed tool must allow users to utilize their expertise by interactively selecting/grouping students and counterfactuals based on relevant characteristics and metrics. This task enables users to group students based on shared features, select representative counterfactuals based on metrics or interests, and filter the sample to which the corrective actions apply. For instance, students with high or low grades, female or male students, and subjects with a high or low probability/risk of dropping out.

T3 — Summarize the counterfactual samples of a subgroup of instances. To better analyze corrective measures, it is essential to explicitly represent the real and synthetic values to evaluate the feasibility and actionability. Moreover, given the vast alternatives, it is crucial to help users employ automatic operations, such as sorting based on specific metrics. By providing such functionality, users can more efficiently and effectively evaluate possible interventions and identify those with the highest likelihood of success.

T4 — Diagnose the impact of corrective actions. Is it possible to quantify the impact of corrective measures? To approximate reality, it is important to quantify how many students could avoid dropping out due to these measures. Specifically, it is necessary to explore the influence of corrective measures over certain student groups, focusing on how many students will be retained due to these interventions. By quantifying the impact of corrective measures, decision-makers can effectively allocate resources and prioritize interventions with the highest potential to reduce dropout rates.

T5 — Compare the corrective measures along semesters. Can corrective measures be measured over time? Once corrective action is applied to a group of students, it is essential to track its effectiveness over the semesters and across different student groups. By measuring the behavior of corrective actions over time, decision-makers can better understand the long-term impact of an intervention and identify which approaches are most effective at improving retention rates.

4. Dropout analysis based on counterfactual and survival analysis

The framework supports two main activities: Survival analysis and Counterfactual explanations. So, before the CSDA-Vis presentation, we briefly present the mathematical mechanisms used to analyze students' dropout data in this section.

4.1. Survival analysis

Briefly, this section introduces some basic concepts related to survival analysis models. Let n, the number of students; then, for each $i = 1,\dots,n$, we write $\vec{X}_i$ to represent the m- dimensional vector of attributes for the student i. Also, E_i and T_i represent the event and time variables of student i, respectively. One fundamental concept in survival analysis is censoring. Censored information occurs when the student's dropout does not occur during the time interval. Relying on the dropout status, we define the T_i in two ways: (a) If $E_i = 1$, then T_i represents the permanence time. (b) If $E_i = 0$, we only know when it did not occur, and we call it censoring time. As mentioned in Section 2.2, survival analysis models are used to estimate the occurrence of a specific event over time. In the context of student dropout, the aim is to calculate the probability that the student dropout at the time t, given their permanence before t and the attributes $\vec{X}_i$, by $p_i^s = \text{Prob}(T_i = t\,|T_i > t-1\,,\ X = \vec{X}_i)$. Finally, we define the survival probability $S_i(t)$, by:

$$S_i(t) = \prod_{\tau=0}^{t}\left(1 - p_i^s\right), \tag{1}$$

which is a continuous non-decreasing function. The curve $S(t)$ represents the probability of not dropping out until time t, and consequently, $1-S(t)$ represents the cumulative dropout probability up to time t. Also, we write $H_i(t) = -\ln S_i(t)$ to represent the cumulative hazard function. Considering $0 < \tau_1 < \tau_2 < \cdots < \tau_\ell < \max(T_i)$, we compute the dropout risk score of the ith student by

$$r_i = \sum_{j=1}^{\ell} H_i(\tau_j). \tag{2}$$

This metric is essential in our analysis since the higher the value of r_i, the greater the risk that the ith student will drop out. The good adjustment of these techniques is based on specific evaluation metrics, such as the concordance index (*C-index*), Brier Score (*BS*), and Integrated Brier Score (*IBS*). These metrics help generate efficient predictive survival analysis models, while regression metrics, such as MSE and MAE, are used to evaluate the survival analysis models. Although MSE and MAE are used when comparing the survival curve of the proposed model with the actual survival curve obtained from the Kaplan–Meier estimator.

4.2. Counterfactual explanations

A counterfactual explanation identifies some features whose values, when updated, could lead to a desired outcome [97]. Broadly speaking, counterfactuals allow fixing an instance x_i with a bad outcome based on actions to cause a specific result.

Let $C_1,\dots,C_m$ be m features or characteristics, with domains $dom(C_1),\dots,dom(C_m)$. We are given a black box classifier $f(\theta,\vec{X}_i)$ based on parameter vector θ and the vector of attributes for the student i ($\vec{X}_i$). The classifier $f(\cdot)$ returns y_i, a prediction within the range $[0,1]$, and we assume that $y_i \le \tau$ is an "undesired" (bad) outcome, while $y_i > \tau$ is "desired" (good), given a threshold τ (generally, $\tau = 0.5$). In our context, we have worked with a binary classifier, so we replace its outcome with values $0,1$, where 0 is "undesired", and 1 is "desired". Formally, a counterfactual consists of creating a synthetic sample $\vec{X}_i' = \vec{X}_i + \vec{a}$ based on action $\vec{a}$ that achieves the outcome y', thus $f(\vec{X}_i) \le \tau$; values of $\vec{X}_i'$ must be in feature domains.

A counterfactual $\vec{X}_i'$ is required to balance some properties: sparsity (number of features that need to be changed), diversity (wide range of generated counterfactuals), and proximity (similarity between counterfactuals and the original instance). [9] proposed the basic form of counterfactual explanation as a minimization problem.

$$\arg\min_{\vec{X}_i'}\ \text{dist}(\vec{X}_i,\vec{X}_i') \text{ subject to } f(\vec{X}_i') = y_i'. \tag{3}$$

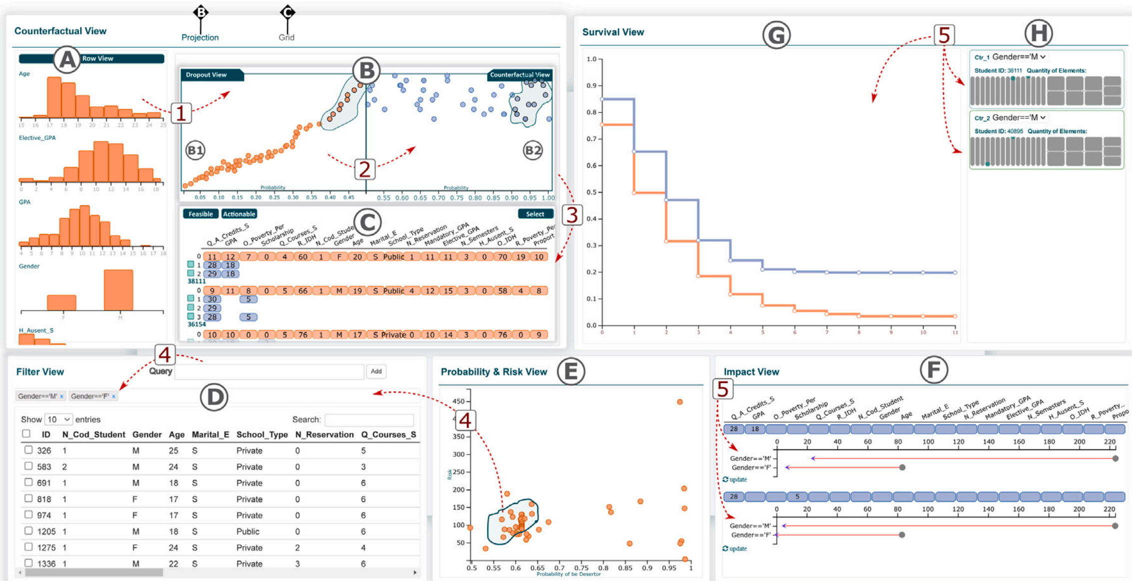

Fig. 2. CSDA-Vis System: A set of linked visual resources for dropout analysis based on counterfactuals and survival methods. (A) Row View, (B) Real-Synthetic dual View, (B1) Students' dropout analysis view, (B2) Counterfactual analysis view, (C) Counterfactual row View, (D) Table View, (E) Probability & Risk View, (F) Impact View, (G) Survival View, and (H) Survival Control View. Section 5.2 uses this figure as the composite reference for the toy example, following the callouts (A–H) and the numbered steps (1–5).

$$\sum_{i=1}^{k} \frac{(f(\vec{X}_i') - y_i)^2}{k} - \lambda_1 \cdot \text{Proximity} - \lambda_2 \cdot \text{DPP-Diversity}, \qquad (4)$$

where λ_1 and λ_2 are parameters associated with Proximity and DPP-Diversity, respectively. Eq. (4) is an improvement to the proposal given in Eq. (3) since proximity and diversity parameters are included. In our context, due to the computational cost and considering experts' recommendations, we calculated five counterfactuals for each student. DiCE guarantees that the synthetic elements of the counterfactuals are balanced between Proximity and DPP-Diversity.

4.3. Running example

To illustrate the combination of survival analysis and counterfactual explanation, we present a hypothetical case based on a real student profile. We considered only a subset of variables for demonstration purposes. Let student x_i have the following characteristics: `Age` 19, `GPA` of 8, 10 passed credits (`Q_A_Credits_S`), 20 absences per semester (`H_Ausent_S`), 3 completed semesters (`N_Semesters`), and an average success rate per semester (`SuccessPer_S`) of 30. Using these variables, the survival model computed by Eq. (1) predicted survival probabilities across four academic periods $[0.86, 0.65, 0.48, 0.32]$, and a cumulative dropout risk score $r_i = 2.47$ (Eq. (2)), which indicates a high risk of dropout. To explore corrective actions, we generate Counterfactuals using Eqs. (3) and (4). For instance, one counterfactual suggests increasing `GPA` from 8 to 13, `Q_A_Credits_S` from 10 to 14, and `SuccessPer_S` from 30 to 65. With these adjustments, the estimated survival probabilities improve to $[0.95, 0.92, 0.89, 0.86]$, leading to a reduction of risk score $r_i' = 0.4$.

This example demonstrates the integration of predictive and prescriptive analytics. By identifying corrective actions or modifications to a student profile and quantifying their impact through survival analysis, our approach enables decision-makers to explore alternative scenarios that can significantly reduce the likelihood of dropout. We revisit this same student and counterfactual in the toy workflow of Section 5.2 (Steps 2–5) to illustrate the end-to-end use of the coordinated views.

Table 1
Analytical tasks and their related visualization tools.

	T1	T2	T3	T4	T5
Row View	✓				
Students Dropout Analysis View		✓			
Counterfactual Analysis View		✓			
Counterfactual Row View			✓		
Table View		✓			
Probability & Risk View		✓			
Impact View				✓	
Survival View					✓
Survival Control View					✓

5. Visual analysis framework

Based on the challenges and analytical tasks described in Section 3, we have designed CSDA-Vis, a visualization tool to facilitate the analysis of dropout patterns based on counterfactual and survival analysis (Fig. 2). To ensure that CSDA-Vis adequately addressed the identified analytical tasks, we systematically mapped the analytical tasks to develop each visual resource. Table 1 shows the relation between visual resources (rows) and analytical tasks (columns). In essence, our framework supports four main activities: student data analysis, counterfactual analysis, survival analysis, and result & quality/impact analysis.

Student data analysis. The framework affords the user multiple overviews using different resources to facilitate the assessment of values and students' distribution that guide the analysis.

- *Row View* provides the distribution of values of students' features,
- *Table view* provides extensive information about the characteristics of each student and
- *Students Dropout Analysis View* provides a scatterplot visualization representing students' similarities based on metrics.

Counterfactual analysis. To depict counterfactual information, we have designed two visual resources to render a projection and visualization on demand.

- *Counterfactual Analysis View* provides a representation of counterfactuals considering percentage metrics,
- *Counterfactual Row View* provides a visualization by demand showing selected students and their synthetic alternatives.

Survival analysis. To explore the survival information, the framework incorporates two visual components to depict the curves and visualization on demand.

- *Probability & Risk View* provides students with a representation using a scatterplot based on survival risk.
- *Survival View* provides an overview of survival curves of dropout and counterfactual students. Moreover, this visual resource also provides a curve representation on demand.

Result and quality/impact analysis. To analyze the results, the framework facilitates the visualization of the effect and quality of corrective measures implemented for a group of students over time.

- *Impact View* represents the impact of corrective actions to reduce the dropout rate.
- *Survival Control View* allows a visualization by demand of survival methods based on different counterfactuals applied over groups of students.

5.1. Visual design

In the following paragraph, we describe each visual component based on the main activities.

Row view (A). To gain insight into the behavior of historical data, our first component (represented in Fig. 2-A) is the distribution of feature values in a row (**T1**). Specifically, the distribution of values for each feature is presented as a histogram, providing the user with a comparison between the values of individual instances and the overall distribution of the entire population of dropout students. By examining these histograms, we aim to gain a deeper understanding of the underlying patterns and trends in the data.

Real-Synthetic dual view (B). To assist domain experts in formulating effective interventions for students at risk of dropping out, our second visual component presents students' distribution based on a metric and their synthetic counterfactuals (**T2**). As illustrated in Fig. 2-B, this component employs a dual visualization. The left side renders the dropout space with dropout students, whereas the right side represents the counterfactual explanations.

+ **Students Dropout Analysis view (B1).** An essential aspect of designing effective corrective interventions is identifying the group of students that will serve as the basis for these interventions. For this, students are ordered by their probability of not dropping out and visualized as a scatter plot. Fig. 3 (left, Dropout space) shows a projection of students based on the output (probability of not dropping out) of the classification model: the horizontal axis (X) represents the predicted probability. In contrast, the vertical axis (Y) reflects the student ID arrangement based on the band scale. Using a *lasso* selection, users can select and refine the group of students on which the corrective actions will be based. For instance, Fig. 3 (left) shows the selection of a single student X_i (only for demonstration purposes), and Fig. 3 (right) shows four corresponding counterfactuals aligned along the same Y axis as X_i, and positioned on the X axis according to their respective probability of non-dropping out. Notice that CF_i3 presents a higher probability than the others, suggesting greater potential of effectiveness, though this does not necessarily imply feasibility or actionability. This targeted selection and refinement process supports the development of interventions based on users' expertise.

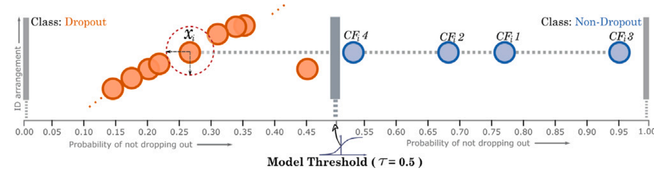

Fig. 3. Real-Synthetic dual View: The left side shows the dropout space (dropout students), while the right side represents the counterfactual of dropout selected students (X_i).

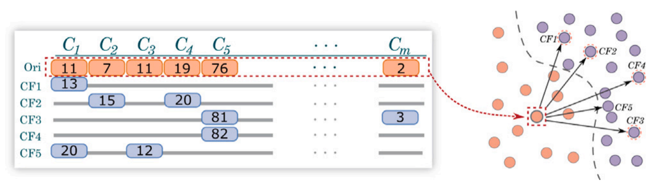

Fig. 4. Counterfactual Row view: $C_i s$ represents the variables, and the orange row (*Ori*) represents the student's real values in dropout space. $CFis$ represents the counterfactuals, and blue cell values are suggested changes to help the student reach the non-dropout space.

+ **Counterfactual Analysis view (B2).** Once students have been selected in *Students Dropout Analysis view* (X_i), the next step involves the analysis of corrective actions. To accomplish this, we compute a set of counterfactuals for each student, comprising information about which characteristics and values of one or more students must be modified to decrease their risk of dropping out. Fig. 3 (Non-Dropout space) displays the counterfactuals ($CF_i1, \ldots, CF_i4$) corresponding to student X_i. The x-axis position of the counterfactuals corresponds to the probability of not dropping out of each counterfactual, while the y-axis is determined by the y-axis position in *Students Dropout Analysis view*. For a more detailed inspection, users can select specific counterfactuals for closer analysis, which can be performed using the *Counterfactual Row View (C)* detailed below.

Our view is designed to help users gain an understanding of the classification model. The model threshold (τ) establishes the linear boundary that divides negative (dropout) and positive (Non-dropout) classes in a classification model. In this project, we have employed the default classification model parameters, wherein the threshold is set to 0.5 ($\tau = 0.5$). Subjects with $p_i^c < 0.5$ are classified as dropout students, while those with $0.5 <= p_i^c$ are considered non-dropout students generated based on dropout students (Counterfactuals), where $p_i^c = \text{Prob}(y_i' = 1 \mid X = \vec{X}_i)$.

Counterfactual Row view (C). Once some counterfactuals are selected in the *Counterfactual Analysis view (B2)*, the next step is a closer inspection to determine the appropriate corrective measure to apply. For this, it is necessary to compare the actual and suggested synthetic values. We embed an illustration of attribute value changes into rows to compare the actual and suggested values. Fig. 4 depicts the representation of actual values and counterfactuals of the students selected in *Real-Synthetic dual view (B)*. The first row displays the values for each feature, and the subsequent rows portray the counterfactuals ($CF1, \ldots, CF6$). Notice that some counterfactuals suggest individual chances such as $CF1$ (from 11 to 13 for C_1) and $CF4$ (from 76 to 82 for C_5); conversely, other counterfactuals suggest combinations of variables such as for $CF2$ (from 7 to 15 for C_2 and from 19 to 20 for C_4) and $CF5$ (from 11 to 20 for C_1 and 11 to 12 for C_3).

However, the principle of "the closest possible world" which advocates for minor changes that lead to the desired outcome — may yield inadequate results [98]. The counterfactuals may not allow for a *feasible path* or *actionable* changes. For instance, impossible changes for some

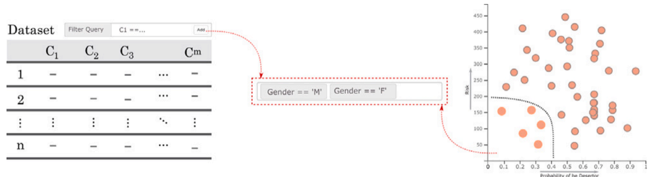

Fig. 5. Group filtering by the query (Table view) and lasso selection based on some metrics (Probability & Risk view).

attributes, such as Age and Gender, or significant steps for others, for instance, from 10 to 20 for GPA. Our approach is concerned with that, and to overcome this, we use metrics to rank the counterfactuals based on their feasibility and actionability. *Feasibility* (Fe) could be defined as the distance between the counterfactual and the original instance it is associated with, while *Actionable* (Ac) refers to the distance between the counterfactual and the closest non-dropout subject in the original space. Re-sorting the students and counterfactuals is possible based on specific metrics (Fe and Ac). This sorting enables analysts to select specific counterfactuals for further investigation and analysis (**T3**).

Table View (D). This visual resource illustrated in Fig. 2-D employs a table-based representation, where each column represents the instance features and each row represents the values of an individual data instance. In addition to helping the user in the extensive inspection of actual values, this representation can also help to group students of interest based on certain filters (**T2**). CSDA-Vis provides an input that uses *Pandas-query* syntax to conduct the filtering. For instance, Fig. 5 - (left) shows an example of the filtering process; once the filter is applied, a group is added into a set (dotted set) for posterior analysis.

Probability & Risk view (E). In the same vein of *Table View*, it is vital to identify the group of students on whom the impact of the counterfactuals will be measured. This can also be accomplished using some metrics, explicitly based on probability of dropout (Pr) and risk (Eq. (2)) (Fig. 2-E). This probability Pr is computed as $1 - f(x_i)$ (One minus the probability of not dropping out given by the classification model). Fig. 5 - (right) shows this resource in detail; this scatterplot is based on the probability of dropout and the survival risk. The students located closest to the origin of the axes have the lowest probability of dropout and the lowest risk. According to expert opinions, these points represent the students with a higher likelihood of success (non-dropout) when corrective actions are applied. It is possible to use *lasso* selection to group some specific students of interest (**T2**).

Impact view (F). To make a decision, the user must audit the quality of corrective measures (**T4**). To assist the user in investigating and measuring the quality, we have designed the Impact View as shown in Fig. 2-F. Fig. 6 shows the entire process. To compute the quality of a counterfactual (Fig. 6-1 counterfactual), we employ an intervention over the groups selected by *Table View* and *Probability & Risk View* (Fig. 6-1 Groups of students). Fig. 6-4 shows each intervention's impact, which can reveal the counterfactual's potential effect on the selected groups. For this purpose, for a group of students, we modify the values based on the counterfactual suggestion (Fig. 6-2), and by using the pre-trained model, we calculate how many of the students are no longer dropouts (Fig. 6-3). For instance, in Fig. 6, two groups are analyzed (female and male), and the same counterfactual impacts each group differently. The gray dot represents the number of dropouts from that group, and the arrowhead represents the number after implementing a corrective measure.

Survival view (G). One of this project's primary objectives is to assess an intervention's effect by measuring the number of subjects who do not drop out after that intervention over some time (**T5**). For temporal quality inspection, we have worked with survival analysis. Fig. 2-G shows this visual component with its respective survival curves. Once groups and counterfactuals are selected, we apply steps 1 and 2 of Fig. 6 (corrective action intervention). Then, we calculate the survival curve for each counterfactual within a group. Fig. 7-Left provides a detailed view of this component, where the orange curve depicts the dropout rates of students, and the blue curve represents the counterfactuals. The x-axis corresponds to the semesters, while the y-axis represents the survival percentage (how many students are non-dropouts). Notice that in the orange curve, S_t exhibits a decreasing trend to zero over time, while the blue curve shows a more favorable trend, with S_t converging toward 0.2, indicating the effectiveness of the counterfactual.

Survival Control view (H). To determine the quality of a counterfactual on different groups over time, CSDA-Vis provides a set of controls that allow users to create survival curves by demand (**T5**). Fig. 2-H, shows small multiples displayed in a row, with each cell corresponding to a counterfactual and the grid containing counterfactual values. Fig. 7-Right shows an example where a corrective measure is applied to a group via the combo-box that includes the groups selected by *Table View* and *Probability & Risk View*. The user can modify the combo-box values to compute the quality of the corrective measure for a specific group over time. In this instance, both counterfactuals were applied to female groups (Gender == 'F'), and the green curves represent the survival curves.

5.2. Toy example: End-to-end workflow

To make the coordinated design concrete, we present a toy example that walks through the full workflow in Fig. 2-(A–H), following Steps 1–5. The goal is to show how the views interoperate to (i) define a subgroup, (ii) generate and inspect counterfactuals (CFs), and (iii) assess both static and longitudinal impacts. For consistency, we reuse the representative student x_i and the selected CF from the running example in Section 4.3.

Step 1 - Distribution inspection (Row View, Fig. 2-A). The analyst begins by examining feature distributions (e.g., GPA, passed credits, success rate) to contextualize individual values against the population. This establishes plausible ranges and highlights the attributes that typically differentiate dropout cases from non-dropout cases (Task T1).

Step 2 - Subgroup definition (Students' Dropout Analysis & Table Views; Fig. 2-B1,D). Next, the analyst defines a subgroup of interest. Two complementary mechanisms are used: a query in the *Table View* (Fig. 2-D) to filter by attributes (e.g., program, semester) and a lasso selection in the *Students' Dropout Analysis* projection (Fig. 2-B1) to refine by model-derived metrics (e.g., probability). From this cohort, the analyst selects the representative student x_i introduced in Section 4.3 to drive the subsequent CF design and evaluation (Task T2).

Step 3 - Counterfactual generation and inspection (Counterfactual Analysis & Counterfactual Row; Fig. 2-B2,C). For x_i, the system proposes multiple CF candidates (Fig. 2-B2) that respect feasibility/actionability constraints (immutability and bounded changes) and are ranked using proximity/feasibility and actionability metrics. The *Counterfactual Row* (Fig. 2-C) reveals concrete value deltas (e.g., modest GPA increase; small reduction in absences) so the analyst can compare alternatives and select one or more CFs for intervention (Tasks T2, T3). In our running-example-consistent selection, the CF changes are: `GPA` $8 \rightarrow 13$, `Q_A_Credits_S` $10 \rightarrow 14$, and `SuccessPer_S` $30 \rightarrow 65$ (with `H_Ausent_S` and `N_Semesters` unchanged).

Step 4 - Apply interventions to groups (Table; Probability & Risk; Impact; Fig. 2-D,E,F). The selected CF(s) are applied to one or more user-defined groups (e.g., two cohorts defined by query and/or lasso). The *Impact View* (Fig. 2-F) then summarizes the *static impact*: the number of students who move from the dropout to the non-dropout class under the CF intervention, enabling quick comparison across CFs and groups (Tasks T3, T4). *Note:* static impact is computed with the classifier used for class prediction, whereas the longitudinal quality in Step 5 is assessed with the survival model (Eq. (1)).

Step 5 - Longitudinal evaluation (Survival & Survival Control; Fig. 2-G,H). Finally, the analyst assesses *temporal quality* with survival

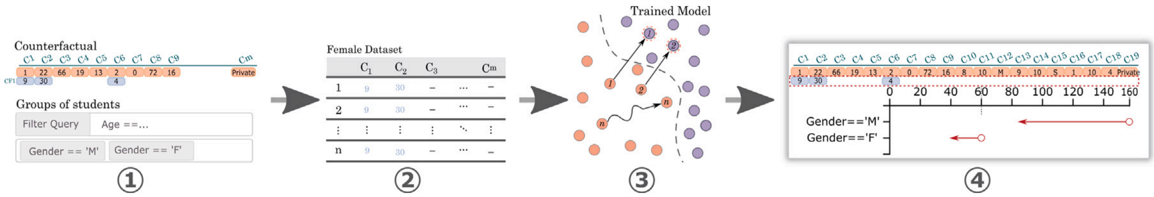

Fig. 6. The process of impact of a counterfactual: (1) select a counterfactual and groups of students, (2) intervention of a counterfactual over each group of students, (3) apply a classification pre-trained model (logistic regression) to (4) count how many students passed to the non-dropout class.

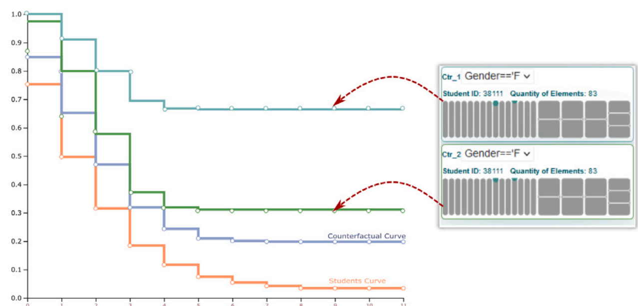

Fig. 7. Survival view and Survival Control view: (left) shows the survival curves of the original values (orange), counterfactuals (blue), and groups (greens). (Right) shows the control view to get survival curves by demand, depending on a group and counterfactual.

analysis. The *Survival View* (Fig. 2-G) compares baseline and intervened survival curves (with uncertainty) to reveal onset, persistence, or decay of effects across semesters; the *Survival Control* (Fig. 2-H) provides small multiples to contrast CF × group scenarios. For the same student x_i, baseline survival is $[0.86, 0.65, 0.48, 0.32]$ and, under the selected CF, improves to $[0.95, 0.92, 0.89, 0.86]$, with a corresponding reduction in cumulative risk from $r_i = 2.47$ to $r_i' = 0.4$ (Eq. (2)). Together, these views reveal whether an intervention's apparent static benefit is durable and for which cohorts it is most effective (Tasks T2, T5).

Iteration. If results are unsatisfactory, the analyst iterates by (a) selecting alternative CFs (Fig. 2-C) or (b) redefining cohorts (Fig. 2-D,E,B1), and then re-assessing both static and longitudinal impacts (Fig. 2-F,G,H). This loop operationalizes a coordinated *what-if-and-when* analysis across all components.

5.3. Implementation details

This section presents the details of the implementation of the CSDA-Vis system. The system comprises two main steps: processing (counterfactual and survival computation) and visual exploration. We use JavaScript to develop the visualization and Python to create the processing parts. To compute counterfactuals, we have used a Python library called *Dice-ml* [9], whereas for the survival analysis, we have used *pySurvival library* [99]. All visualization resources were developed based on the *D3.js* and Flask web framework.

6. Case study

In this section, we present a case study to demonstrate the usability and usefulness of our framework in supporting the analysis of students' counterfactual data from the perspective of data instances, counterfactuals, and the impact of corrective measures.

6.1. Computer science school dataset

We selected an undergraduate Computer Science program to detect and support at-risk students in our context. We have conducted an in-depth examination of various student cases to gain a deeper understanding of how different feature configurations can influence the analysis.

6.1.1. Data set

The data set was obtained in collaboration with the university's welfare and IT departments. The IT department protected the students' identities to ensure their privacy. For instance, we do not have the students' names and identity card numbers; they generated random numbers that were used as their IDs throughout the study.

To sum up, 3,000 students with adequate information from the first semester of 1999 (1999-I) to the second semester of 2020 (2020-II). The dataset was balanced with about 80% enrolled and 20% dropout classes, using 600 randomly sampled students (300 enrolled and 300 dropout students). To enhance our analysis, we included external socioeconomic data. Specifically, we used the addresses of current residences and cities of origin, matching them with the Annual Report on Human Development published by the United Nations Development Programmed.[2] Then, we derived important features as `O_IDH`, `O_PorveryPer`, `R_IDH` and `R_Poverty_Per`, as described in Table 2. We preprocessed the data using SimpleImputer, OneHotEncoder, and StandardScaler from the scikit-learn Python library to handle missing values, encode categorical variables, and scale continuous variables, respectively. We then divide the characteristics into three groups: student, socioeconomic, and academic factors.

Table 2 provides details of these variables. The dataset encompasses academic performance metrics — grades, attendance records, and GPAs — as well as social information, including gender, scholarship, and marital status. Additional demographic variables were sourced from external databases to augment the dataset and provide a broad analysis. For instance, we also gathered information on the residence and origin of the HDI (Human Development Index).

6.1.2. Analysis

As discussed in Section 3, we collaborated with several domain experts and researchers who have extensive experience in analyzing university dropout rates. We consulted with the most experienced expert responsible for dropout analysis across the entire institution, whom we will refer to as "the user".

We conducted a one-and-a-half-hour synchronous session for the case study. During this session, the user operated the system to explore the data and identify students who might be at risk of dropping out. The authors did not carry out the analysis; our role was limited to clarifying the implemented functionalities (e.g., configuring filters, interpreting views, exporting results) and addressing minor usability questions as they arose. We also observed and documented opportunities for improving functionality and user interface issues, such as missing affordances, labeling, and workflow friction. All interactions and analytical results reported in this section reflect actions performed by the user during this session.

Initial Search Space. As detailed in Section 5.2, one of the initial stages in the analysis involves selecting dropout students in *Students*

[2] Available at https://www.undp.org/

Table 2
Feature description of our sample collected. We included mean (M) and standard deviation (SD) statistics for numerical attributes.

Attribute	Variable	Types (range)	M	SD
	Students Factors			
ID	Student ID	String	–	–
N_Cod_Student	Number of enrollments at the university	Numerical	1.02	0.15
Gender	Gender of student	Nominal (Male or Female)	–	–
Age	Age of student (birth date)	Numerical (15–25)	20.41	3.70
Marital_S	Whether the student is married or not	Nominal, (Single or Married)	–	–
	Socio-economic Factors			
O_IDH	Origin HDI (Human Development Index)	Numerical (0 –100)	72.17	7.58
O_Poverty_Per	Origin percentage of poverty	Numerical (0–100)	4.17	7.12
R_IDH	Residence HDI	Numerical (0–100)	69.03	5.46
R_Poverty_Per	Residence percentage of poverty	Numerical (0–100)	5.10	4.68
School_Type	School type	Nominal (Private or Public)	–	–
scholarship	Whether the student has a scholarship	Boolean (Yes or Not)	–	–
	Academic Factors			
N_Reservation	Average number of reservations per semester	Numerical (0–30)	0.55	1.19
Q_Courses_S	Number of enrolled courses per semester	Numerical (0–6)	4.63	1.27
Q_A_Credits_S	Number of passed credits	Numerical (0–40)	11.04	5.24
Mandatory_GPA	Average GPA of the mandatory courses	Numerical (0–20)	11.74	2.62
Grade_EP	Average GPA of elective Professional lectures	Numerical (0–20)	11.6	2.77
Grade_EG	Average GPA of elective General courses	Numerical (0–20)	11.52	2.74
Grade_EH	Average GPA of elective Humanities courses	Numerical (0–20)	12.76	3.31
GPA	Final GPA score	Numerical (0–20)	11.64	2.60
N_Semesters	Number of completed semesters	Numerical (0–12)	5.95	5
H_Ausent_S	Average absence rate per semester	Numerical (0–30)	8.42	8.19
SuccessPer_S	Average success rate per semester	Numerical (0–100)	68.7	24.8
	Target			
Enrolled	The student status	Boolean (Yes or Not)	–	–

dropout analysis view. Afterward, the user must choose the counterfactuals for further examination using *Counterfactual analysis view*. Although user have the flexibility to select their samples for both selections, there are numerous potential areas of selection to consider.

The user investigated various selection regions for this analysis to determine whether specific student/counterfactual selection areas are more appropriate. He considered the *Students dropout analysis view*, the *Counterfactual analysis view*, and the quality metrics (Feasibility (Fe) and Actionable (Ac)). Based on his expertise, he divided *Students dropout analysis view* into three regions (Fig. 8-left). The working hypothesis was that the quality (as measured by better metrics) of counterfactuals would vary depending on the region selected. After defining the student regions, we further divided the *Counterfactual analysis view* into nine grids (Fig. 8-center), considering the probability of not dropping out(X-axis) and the students' distribution (y-axis). To validate this hypothesis, our tool computed Fe and Ac for each of the nine grids. It summarized the results in Fig. 8-right, reporting the Fe, Ac, mean, and standard deviation (std) for each region. For instance, in the first grid (bottom-right), the mean and standard deviation (Std) for Fe are 3.37 and 1.02, respectively, while for Ac, they are 3.05 and 1.04.

By computing the mean and Std of each grid, as shown in Fig. 8-right, it might be possible to determine the most appropriate regions to select students and counterfactuals. Specifically, the user computed the metric that represents the distance between a student's counterfactual and actual feature vector (Fe), and the metric that quantifies the distance between a student's counterfactual and the closest non-dropout student's features (Ac).

Then, the user calculated a low mean in Fe and Ac may represent better alternatives since they indicate a small distance between the original values and their counterfactuals, which serve as the basis for

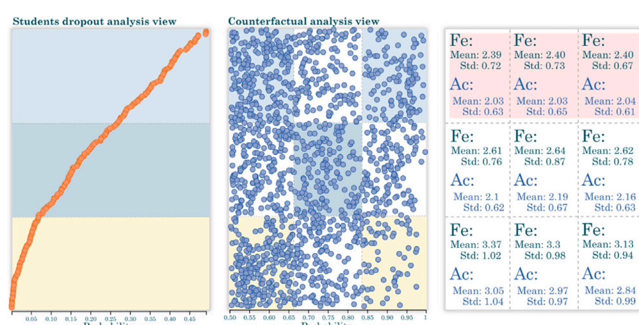

Fig. 8. Area selection quality comparisons: (left) students' selection space, divided into three regions based on their probability of being dropout, (center) Counterfactual selection space divided into nine grids based on their probability, and (right) mean and standard deviation (Std) for Fe and Ac metrics in each grid.

proposed corrective metrics. Similarly, the Std suggests the degree of deviation or spread of the metrics from their respective means. Therefore, lower metric values may correspond to more appropriate counterfactuals. It could be noticed that the lowest values for Fe and Ac are located in the top row (Fig. 8-right), which suggests that counterfactuals within these regions are more likely to actual students' values, making them the optimal regions for selection. Additionally, upon analyzing the columns, we found that the third column exhibited larger mean values than the others, indicating that counterfactuals in this region are most different from the original values. In other words, this region involves significant deviations between the original and suggested values (i.e., changing GPA from 10 to 18, in a 0–20 range).

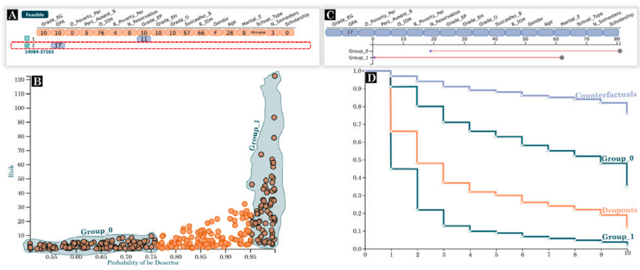

Fig. 9. Counterfactual quality comparison: (A) selection of the most feasible counterfactual, (B) Group filtering (Group_0 and Group_1) based on their probability and risk of being dropout, (C) static impact computing of the corrective action selected in (A) over the student's groups selected in (C), and (D) counterfactual survival curve along time for both counterfactuals and groups.

The findings above suggest that the user can access a wide range of alternatives for analyzing students and their corresponding counterfactuals. Nevertheless, certain regions may lead to more effective analyses. Moreover, it is important to consider the user's expertise. For instance, the top-left region contains the best counterfactuals; these counterfactuals provide small changes but do not guarantee a good outcome probability. Users must search for their balance.

Initial Risk Check. After training the classification model, survival curves and survival risks are automatically calculated using *Pysurvival* library, which is depicted in *Survival view* and *Risk&Probability view* (Fig. 2-B and D). In Fig. 2-B, the x-axis represents the probability of belonging to *Dropout* group, as determined by the classification model, while the y-axis corresponds to the survival risk derived from the survival analysis technique calculated in Eq. (2). Our tool allows the user to segregate the students into two groups based on their metrics (dotted regions in Fig. 9-B) by ranking them according to their probability of dropping out and their survival risk. `Group_0` stands for students with a low probability of being classified as dropouts and a low risk of dropping out. In contrast, `Group_1` contains students with a high probability and risk of leaving college. As shown in Fig. 9-A, he selected a counterfactual and focused on the most *Feasible* counterfactuals related to `GPA`. Therefore, we considered the `GPA` (dotted counterfactual) for this analysis. In the Row view (Fig. 9-C) and Survival view (Fig. 9-D), we computed the impact and survival curves, respectively, for students of `Group_0` and `Group_1` to further inspect the quality of a counterfactual and how it evolves.

The primary purpose of survival analysis is to enable the impact of temporal analysis of a counterfactual on a group. According to user, the `Group_0` of Fig. 9-B contains students *who might need to expend less effort and fewer resources to prevent their dropping out*, while students in `Group_1` may need more resources and effort. Fig. 9-C represents the impact of a counterfactual on both groups. The counterfactual reduces 86% for Group_0, while it achieves a reduction of 100% for `Group_1`. This result suggests that the authorities should focus on the select counterfactual and `Group_1` to prevent dropouts of more students (among all). However, the survival analysis curves present a different perspective. The survival curve for `Group_0` augurs good behavior of this counterfactual (higher probability over time). On the other hand, for `Group_1`, along the semesters, the survival probability declined substantially, suggesting a bad quality over time.

To some extent, calculating only the static impact of a counterfactual may mask poor corrective action performance and fail to alert the authorities about the quality over time. Domain experts highlighted the performance of CSDA-Vis, which combines static and temporal quality analysis to prevent the phenomena mentioned earlier.

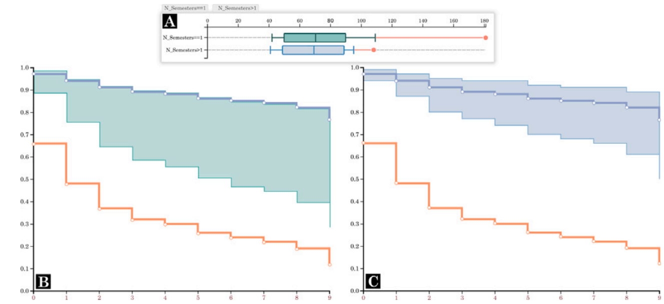

Fig. 10. Corrective action analysis for elective lectures and students from different semesters. (A) impact summary from 15 quality metrics, (B) Survival curves interval for "N_Semesters==1" group, (C) survival curves interval for "N_Semesters> 1" group.

Evaluation and Possible Corrective Action.

While there is no one-size-fits-all approach to analyzing student dropout rates, as they heavily depend on various factors such as socioeconomic context and academic performance metrics, academic variables like low grades and poor attendance can serve as strong predictors of dropout. As mentioned in Section 3, the user is already aware of this, and he employs GPA as a key variable to develop interventions aimed at preventing dropout. Nevertheless, he expressed uncertainty about which lecture type grade to target for such interventions.

His previous observations showed that `GPA` and `SuccessPer_S` are indeed the most relevant variables in many counterfactuals. However, it was noted that certain variables were gaining relevance and even surpassing the importance of previously mentioned variables in some experiments. These variables include `Grade_EP`, `Grade_EG`, and `Grade_EH`, which are associated with grades in Professional, General, and Humanities elective lectures, respectively.

To accomplish his analysis, the user performed 15 interactions. Fig. 10 condensed the results for *Impact view* (A) and *Survival view* (B and C). Consistent with prior research and concerns from domain experts, he proposed conducting a study focused on students' current semesters, particularly expressing concern over the dropout rates of first-semester students. In our sample, 62.4% of dropouts students belong to the first semester, while 37.6% belong to other semesters. Thus, he divided the student population into two groups based on their completed number of semesters: `N_Semesters==1` (for students of the first semester) and `N_Semesters> 1` (for students from the second semester to the final one). The box plots in Fig. 10-A summarize the distribution of the number of students who continue belonging to the dropout class after the application of corrective measures. For the `N_Semesters==1` group, the mean number of students classified as dropouts was 72, ranging from 50 to 90. This indicates that it is possible to reduce the number of dropouts in this group from 50.3% to 72.4% with a mean of 60.8%. For `N_Semesters> 1` group, the mean number of dropouts was 71, ranging from 50 to 87.

Analyzing the *Survival view* representations, the `N_Semesters==1` group has a wider confidence interval than the `N_Semesters> 1` group. However, the confidence interval `N_Semesters==1` in the final semester is [0.3,0.78], and for `N_Semesters> 1` is [0.5, 0.9], representing a better survival probability and stability of the `N_Semesters==1` group.

The user broadened their analysis spectrum based on the new information gathered from our tool. He discovered that providing support in selecting and taking specific elective lectures could help mitigate student dropouts. Specifically, the CSDA-Vis tool showed that Humanities elective lectures are particularly relevant during the first semester. Professional and General elective lectures become more crucial from the second semester onward.

Finally, the user also revealed that he intuited this finding based on his experience. However, he was unable to detect it using their procedures. In addition, he demonstrated that the importance of humanities elective lectures has a significant impact on adaptation to the university environment and interaction with peers and lecturers.

7. Evaluation from domain experts

We conducted a mixed evaluation methodology that combines case studies validation and focus group discussion. The evaluation took place in a meeting room at the university in a two-hour session with a selected group of domain experts. The group consisted of seven participants: the current director of the undergraduate computer science program, two former directors, two faculty members from the same school, and two employees from the university's student welfare department who monitor students' academic performance. Most of the participants collaborated on initial interviews to identify our challenges, with the exception of the former directors. All of them have addressed this problem from their perspectives and have implemented different technological alternatives. As an institutional strategy, a dashboard developed in Qlik Sense has been used as an institutional solution during the last three semesters.

During the first hour, we revisited the case studies together with the expert who collaborated closely with us during the development phase and the design of the case studies. This stage of the evaluation aimed to validate whether the conclusions generated with CSDA-Vis tool were consistent and aligned with institutional expectations. The other participants observed this process and were asked to reflect on how our proposal would impact their decision-making process.

In the second hour, all participants interacted directly with the tool by performing exploratory tasks such as filtering student groups, generating counterfactuals scenarios, and analyzing no-dropout probabilities across semesters. After this exploration, we asked them for a brief description of their experience using the CSDA-Vis in comparison to the dashboard currently used by the university. We have thoughtfully categorized their feedback into three key areas: *Exploration Process*, *Usability*, and *Usefulness*. It is essential to consider the insights within each category, as they offer valuable perspectives that can significantly enhance our approach and outcomes. Below, we elaborate on these critical areas for your consideration.

7.1. Exploration process

All participants agreed that the proposed exploration process is novel and highly productive for identifying students who are at risk of dropping out. Moreover, the combination of counterfactual and survival analysis enables them to extract new levels of insight that a traditional dashboard cannot. Among the main differences pointed out by the participants, we can highlight: (i) the dashboard only allows monitoring and filtering of data, while CSDA-Vis simulates expected scenarios by setting plausible values for a set of students or even just one of them; (ii) initially, counterfactual analysis can be intricate, but after a detailed explanation and a few interactions with the framework, it turns into a powerful mechanism for propounding multiple configurations with a lower dropout probability, at least numerically; (iii) the survival view is the most perceptive component of the proposed framework due to it revealing to the analyst how the selected counterfactual will behave along the subsequent semesters and when it achieves a stable probability of the student/s staying in the program; (iv) the filtering process in CSDA-Vis can be seen as a group generator, where a specific selection is stored according to the analyst' requirements and explored by the linked views. According to the participants, the last feature mentioned is a significant improvement, as it extends the capabilities of selecting and filtering tasks beyond those of traditional business intelligence tools.

7.2. Usability

During the interviews, we allowed the participants to interact freely with CSDA-Vis to confirm their impressions. All of them affirmed that most components are familiar and do not require a profound explanation to be used. It is mainly because our tool is implemented in web browsers, and the visual resources (scatter plots, bar charts, and line charts mostly) are perceptively easy to decode data, according to interviewees. Additionally, they stand out in the presence of a linked student list to each selection/filtering step, as it allows for detailed data inspection. However, the employees from the welfare department defined a couple of views as moderately complex, specifically both the survival control and impact views, as they required a careful explanation and were tested with some selection to obtain a tangible result. Finally, they suggested introducing a temporal view to display academic information from previous semesters, as they typically review it before booking a meeting with any student.

7.3. Usefulness

Although all the interviewees agreed that CSDA-Vis is a tool that would significantly contribute to developing their work at different levels, each had particular reasons for justifying its usefulness and efficiency. The former director affirms that our tool will be widely helpful in making strategic decisions on the school, for instance, to decide which type of courses (e.g., programming, mathematical foundations, human studies, entrepreneurship) need support to be improved or even reformulated. The current director stated: *"CSDA-Vis allows us to make an informed decision based on historical data since the first day our school appeared. Once we detect a particular case – a student or a group with similar behavior – we analyze the main reasons for being categorized as a potential deserter, and we address the case to the competent personnel, e.g., the welfare department, academic tutoring, and legal department, among others. Additionally, we can decide if our department can apply any change to address the issue rapidly and reduce the response time"*. The faculty members concurred that the tool, besides detecting potential dropouts, can confirm their intuitions during the semester, e.g., students who lack attendance or classes (students enrolled in the program in the same semester) who show difficulties in specific courses. Some of these confirmations can trigger necessary corrective actions, such as reevaluating a course's content in relation to prerequisite courses or employing alternative learning approaches. Finally, the welfare department members pointed out important aspects in their evaluation: (i) the tool allows them to identify different variables that their analyses do not have considered previously, such as the importance of residence HDI or performance in humanities courses, (ii) every semester some distinguished undergraduates students are awarded a limited number of scholarships according to its academic performance and an economic evaluation, then the tool will provide a deeper set of variables for this purpose and will support a better decision to determine the specific cases where a scholarship would maximize its utility, (iii) each time that a student arrives to the welfare department (contacted by the own department or referred from any other) they usually take a couple of interviews before obtaining helpful information to support his/her case, however by using this tool they can focus its first interview for confirming the extracted insights and derive the student to psychological assistance, academic tutoring, legal assistance or any other specialized support, and (iv) the methodology employed by CSDA-Vis will show its highest potential when it scales to all academic departments in the university, allowing the heads to make more accurate and rapid decisions.

8. Discussion, limitations and future works

We designed CSDA-Vis to facilitate the analysis, visualization, and prevention of student dropout. Moreover, we guided our design rationale based on domain experts' and research suggestions and analytical tasks described in Section 3. Despite its many strengths, CSDA-Vis has some limitations that should be addressed in future work.

- **Academic monitoring.** University authorities require large-scale instruments to monitor students' progress and identify any difficulties. Based on their experience, they recognize lectures with more significant disapproval. Skewedly, failure in a more challenging lecture has less impact than loss in a more accessible one. Identifying the most challenging lectures will help academic institutions formulate reinforcement workshops that complement specific topics, thereby seeking a practical improvement in students' academic performance. This process is vital for first-semester students, as it allows for a smoother transition from high school to university. In our experiment, we present a case study based on the type of lecture (mandatory or elective). However, we can make a more robust analysis by considering all types of lectures. Even this analysis leads us to propose changes to improve the curricular design of the academic program. In this context, the analyst's background plays a fundamental role. More profound domain knowledge (essentially on student features and program curriculum) should lead to a robust understanding of identified trends/patterns. Thus, the quality of the findings is sensitive to the analyst's expertise in exploratory tasks, especially with this type of data.
- **Learning Model.** We must deal with different concerns by working with counterfactual and survival methods. The first concern inherent to counterfactuals is the use of machine learning models. As detailed in Section 2.4, various learning models could help identify the at-risk students of dropout. We have evaluated three methods with different accuracies: a neural network (84%), a random forest (90%), and a logistic regression (93%). Hence, we used logistic regression as a parameter of DiCE to find all the counterfactuals. As a future direction, we plan to extend our analysis by exploring the interactive use of different learning and survival analysis models. This will enable users to select and apply different models on demand, observe their impact, and compare the results.
- **Feasibility and Actionability.** Different counterfactuals provide variable alterations for the students with very different kinds of information. For instance, a counterfactual could be "Reduce Poverty Index to 20%". This means that if the student reduces their poverty index to 20%, they will not drop out. However, another student with the same poverty index could have other, more feasible alternatives (e.g., grades). This phenomenon could lead to unfair treatment. In this context, authorities' interventions and expertise are crucial to conducting a proper analysis. Moreover, each variable has limited values or ranges to define the alteration. For that, we have to freeze a dimension such as *Gender* and *Age*.
- **Multiple scenarios.** CSDA-vis is a powerful tool designed to analyze student dropout data and implement corrective actions to reduce them. While it can be applied directly to different universities, we believe this tool has broader applicability in various scenarios, such as loan and crime data analysis. For loan phenomena, we can adapt the methodology presented in Fig. 1 to analyze the factors contributing to loan defaults. Similarly, we could consider socio-economic and infrastructure variables to determine their impact on a region's crime rates. By adapting CSDA-Vis, we can identify key variables we should improve to reduce the criminality rates. This has important implications for authorities and researchers seeking to use data-driven approaches to address complex data in multiple domains.
- **Expanding Analysis' Scope beyond Academic Performance.** In this work, we have worked with historical student performance as a dominant variable, such as GPA (from obligatory and elective lectures). However, GPA may not be the best variable for analyzing student dropout rates. GPA is a static variable measured at a specific point in time and may not reflect students' changing circumstances over time. Furthermore, using grading as the primary variable in the analysis may overlook the impact of other variables such as difficulties, personal, university, or lack of social support. To enrich our study, we incorporated external data sources, such as the country's socio-economic environment, into this work. Given the increased number of initiatives by university authorities to provide multiple pieces of information for immediate future work, we will expand the scope of our analysis by considering multiple information sources, including teaching metrics and university, social, and curricular variables.
- **Visual encodings of change detection for decision-making** In this work, we based our visual representation of Counterfactual Row View (Fig. 4) on the DiCE library [100], which allows users to represent multiple counterfactuals simultaneously. The current layout enables users to scan horizontally across each row (counterfactual) and vertically across columns (features) to detect changes. However, this approach presents some limitations in supporting fine-grained change detection and interpretability. The visual scanning strategy may be time-consuming and involve cognitive effort when users need to interpret the direction and magnitude of changes across several features. For instance, in Fig. 4, scanning vertically to detect and interpret changes such as C2 increasing by 8 and C4 increasing by 1 in CF2 requires manual comparison. To address this, as future work, we aim to design a visual representation that encodes the direction and magnitude, as well as indicators of the feasibility and actionability of those changes. Moreover, the improved design should support both numerical and categorical variables, along with their respective transformations.
- **Group Counterfactuals.** Our system currently focuses on individual counterfactual explanations, which are well-suited for personalized interventions at the student level. However, recent works have introduced the concept of group or multi-instance counterfactuals [33–35], which extend instance-based reasoning to cover multiple cases simultaneously. These approaches can offer more robust and generalizable explanations, being less sensitive to outliers and often achieving higher accuracy than simply aggregating individual counterfactuals. In the context of student dropout analysis, group counterfactuals could provide valuable insights for interventions deployed at the cohort or program level. As future work, we aim to incorporate group counterfactual reasoning into CSDA-Vis, enabling both individual- and group-level analyses of dropout interventions.

9. Conclusion

In this work, we presented CSDA-Vis, a powerful tool for exploring, analyzing, and visualizing student dropout data. This interactive and dynamic methodology has enabled domain experts to gain new insights and identify patterns to establish corrective actions. Our system presents a novel approach to preventing student dropout by integrating counterfactual explanations with survival analysis. This method differs from traditional strategies in that it effectively explores and identifies potential solutions to dropout challenges. While survival analysis helps to understand the quality of corrective measures over time, counterfactual explanations identify key factors and frame interventions to prevent student dropout. We consider that a significant opportunity for improvement lies in developing novel visual metaphors that can integrate the various views we currently employ, thereby improving the analyst's data exploration experience.

CRediT authorship contribution statement

Germain Garcia-Zanabria: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Daniel A. Gutierrez-Pachas:** Validation, Investigation, Data curation, Conceptualization. **Jorge Poco:** Writing – review & editing, Validation, Investigation, Conceptualization. **Erick Gomez-Nieto:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2025.104489.

Data availability

The authors do not have permission to share data.

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