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Assessing the Impact of Hybrid Teaching on Students' Academic Performance via Multilevel Propensity Score-based techniques

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ABSTRACT
This study employs multilevel propensity score techniques in an innovative analysis pipeline to assess the impact of hybrid teaching – a blend of face-to-face and online learning – on student performance within engineering programs at Politecnico di Milano. By analyzing students' credits earned and grade point average, the investigation compares outcomes of students engaged in hybrid teaching against those solely in face-to-face instruction that precedes the Covid-19 pandemic. Tailored multilevel models for earned credits and grade point averages are fitted onto meticulously constructed dataframes, effectively minimizing potential biases stemming from variables such as gender, age at career initiation, previous academic track, admission test scores, and student origins across the two groups. The methodology accounts for variations across distinct educational programs and investigates disparities among them. Our findings suggest marginal overall disparities in student performance, indicating, on average, a subtle inclination toward a modest rise in earned credits and a slight decrease in grade point averages among those exposed to hybrid teaching. The use of multilevel models to analyze data within the same institution revealed that the impact of hybrid teaching on students' performances can vary significantly across different engineering programs, providing valuable insights into its effectiveness in diverse educational contexts.

Abbreviations: PS, Propensity Score; EP, Engineering Program; PoliMi, Politecnico di Milano

KEYWORDS
Multilevel models, Propensity Score, Hybrid Teaching, Learning Analytics, Ordinal models

1. Introduction

The implementation of *hybrid teaching* (Linder, 2017; Miller, Sellnow, & Strawser, 2021), allowing students flexibility in attending either face-to-face or online classes, has gained significant prevalence in educational institutions. This trend is especially notable in response to the Covid-19 pandemic that broke out in early 2020 (Deshmukh, 2021; Elkhatat & Al-Muhtaseb, 2021). The literature reports various benefits of hybrid teaching, including increased student engagement and improved learning performance. According to Shehzadi et al. (2021), a notable degree of innovation in e-learning significantly enhances both students' overall satisfaction and the university's brand image. Hybrid teaching offers greater flexibility in attending lessons and accessing courses, allowing more students to benefit from the same resources and

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catering to a wider diversity of students, including working adults, by providing enhanced flexibility in scheduling (Beatty, 2019; K. C. Li, Wong, Kwan, Wu, & Cheung, 2022; Raes, Detienne, Windey, & Depaepe, 2020; Raes, Vanneste, et al., 2020). On the other hand, Sarno (2020) outlines the potential of remote learning to exacerbate educational inequalities, particularly for individuals lacking digital devices or internet access. Additionally, Lechner et al. (2020) emphasizes the adverse impact of campus closures on students' stress levels, leading to an increase in alcohol consumption. Feedback from academics regarding reduced motivation, engagement, and interaction among specific students attending online classes underscores the important role of self-discipline within the hybrid teaching area (Kohnke & Moorhouse, 2021; K. C. Li et al., 2022). Although these innovative teaching methods have ensured uninterrupted education during the pandemic, a debate persists regarding their pros and cons when compared to conventional face-to-face classroom lectures. Understanding the impact of hybrid teaching on student performance holds significant importance for educational institutions, as it guides informed decisions regarding its implementation and effectiveness.

The main objective of this paper is a comprehensive assessment of the impact of hybrid teaching on the academic performance of first-semester bachelor's degree engineering students at Politecnico di Milano (PoliMi). By quantifying students' academic achievements in terms of credits earned within the European Credit Transfer and Accumulation System (ECTS) and Grade Point Average (GPA), we aim to compare the academic performance of students who experience hybrid teaching[1] with those who exclusively receive face-to-face instruction[2]. Additionally, our examination encompasses information related to Engineering Programs (EPs) in which students are enrolled.

This study builds upon two critical findings in the existing literature. First, as highlighted in Masci, Cannistrà, and Mussida (2023), the first semester of a student's academic career can be highly informative and predictive of their ultimate success at university. Focusing on the first semester of the first academic year allows us to gain a deeper understanding of students' performance at the beginning of their careers, offering valuable insights into their future academic performance. Furthermore, research by Cannistrà, Masci, Ieva, Agasisti, and Paganoni (2022) and Masci, Ieva, and Paganoni (2022) demonstrated that the dynamics among EPs can vary significantly, emphasizing the need to incorporate this variability in our analysis. Assessing the effectiveness of hybrid teaching across various EPs provides valuable insights for shaping future educational practices. Moreover, this analysis holds particular significance in light of the impact of the dropout rate on the Italian Higher Education system, as highlighted in previous studies (Bacci, Bartolucci, Grilli, & Rampichini, 2017; OECD, 2016). Our evaluation of academic performance during this critical period, comparing face-to-face and hybrid teaching, will help identify the most effective teaching methods and inform strategies to reduce dropout rates.

To mitigate potential confounding bias inherent in nonrandomized observational data (Austin, 2011) as the administrative records of PoliMi, given the impracticality (and ethical considerations) of randomly allocating students to hybrid teaching, we employ Propensity Score (PS) weighting and matching techniques within a multilevel framework (Arpino & Cannas, 2016; Arpino & Mealli, 2011; Chang & Stuart, 2022; F. Li, Zaslavsky, & Landrum, 2013; Rosenbaum & Rubin, 1983). Specifically, we propose a method utilizing multilevel PS weighting to assess the impact of hybrid

[1]Referred to as the *treated* group.

[2]Referred to as the *control* group.

teaching on the performance of students attending different EPs, investigating disparities among them. Consequently, we establish two distinct mixed models for the outcomes ECTS and GPA. These models are fitted to dataframes in which the confounding bias introduced by variables like gender, age at career start, previous study type and results, admission test scores, and student origins has been mitigated. This is achieved by creating more comparable groups between treated and control subjects.

Acknowledging the cluster structure is widely recognized in the literature as essential for mitigating bias, regardless of the method employed for computing propensity scores. Theoretical literature, primarily prevalent in the medical field, consistently advocates for the incorporation of cluster information both in propensity score estimation and outcome analysis, often using multilevel models (Arpino & Cannas, 2016; Arpino & Mealli, 2011; Chang & Stuart, 2022; F. Li et al., 2013).

Several studies have investigated the fluctuations in students' academic performance within higher education during the Covid-19 pandemic emergency. Positive changes were observed in Spain (Gonzalez et al., 2020; Iglesias-Pradas, Hernández-García, Chaparro-Peláez, & Prieto, 2021), Germany (Hansen, Struth, Thon, & Umbach, 2021), Turkey (Yakar, 2021), the US (Supriya et al., 2021), and Australia (Loton, Parker, Stein, & Gauci, 2020). Conversely, no variations were noted in Belgium (Blondeel, Everaert, & Opdecam, 2021), Egypt (El Said, 2021), and another US study (Kronenfeld et al., 2021). Meanwhile, negative changes were documented in Italy (De Paola, Gioia, & Scoppa, 2022), Malaysia (Tan, 2020), and in other German (Witt, Klumpp, & Beyer, 2021) and US (Bird, Castleman, & Lohner, 2022; Orlov et al., 2021) studies. However, none of these studies account for the hierarchical structure stemming from EPs within universities, and none of them consider the aftermath of the pandemic waves, where a new balance between online and face-to-face instruction was established.

In summary, this study adds to the current body of literature by presenting a comprehensive analytical approach that ultimately furnishes empirical findings and quantifies the influence of hybrid teaching on student performance within different EPs of the same institution (PoliMi, Italy). Through the application of statistical methodologies such as propensity score techniques and incorporation of the clustering structure generated by the EPs, our goal is to provide valuable insights that can guide decision-making and enhance tailored educational strategies in a time marked by dynamic shifts in teaching methodologies.

The structure of the paper is as follows: We begin by describing the data and the variables of interest (Section 2). We then outline the methodology, including the estimation of propensity scores, PS weighting, and PS matching techniques within a multilevel setting (Section 3). Next, we present the results obtained from the analysis, focusing on the estimated average controlled differences and the covariate balance achieved through matching and weighting procedures (Section 4). Finally, we discuss the implications of our findings and conclude with recommendations for future research and educational practice (Section 5).

2. Dataset description

The PoliMi dataset contains administrative details regarding the academic careers of students who were enrolled in Bachelor's degree programs in Engineering at PoliMi between the academic years of 2010/2011 and 2021/2022 (12 years span period). The university systematically gathers data on students' personal characteristics, such as gender, age, residency, citizenship, the fee bracket they belong to - which serves as an indicator of socio-economic status - and which Engineering Program (EP) is attended. For each student, the ECTS and GPA obtained in each semester are recorded. Additionally, the PoliMi collects information on students' educational background, including their high school track, final grades, and performance on the admission test, representing their first academic achievement[3]. Due to privacy considerations, we are unable to disclose the specific names of the EPs and can only refer to them by their anonymized codes (EP01-EP19).

Our primary interest lies in capturing the effects of hybrid teaching on the ECTS and GPA (outcome variables) earned by students, across different EPs. Balancing the treated and control groups in terms of students characteristics will help mitigate potential biases, attain more accurate estimates, and delve deeper into the disparities among the various EPs. In this perspective, a preliminary analysis revealed both positive and negative effects of hybrid teaching across different EPs.

Our analysis starts by narrowing down the time frame of the PoliMi dataset. Since students who received hybrid teaching are limited to those enrolled in the first semesters of the academic years 2020/2021 and 2021/2022, we have limited cases. To ensure a balanced representation of students who received hybrid teaching and those who exclusively had in-presence teaching, we opt to restrict the analysis to the academic years ranging from 2017/2018 to 2021/2022, encompassing both endpoints. This decision is aimed at ensuring a fair and balanced comparison. By doing so, we also strive to minimize the potential influence of hidden unmeasured confounding variables, such as teacher replacements or changings in the study programs, thus enhancing the validity of our findings. The selected dataset includes a cohort of 32411 students who were enrolled between the academic years 2017/2018 and 2021/2022. Within this cohort, we create the binary variable `hybrid_teaching`, which indicates the type of teaching delivered in the first semester (i.e., the *treatment*), standing on the year of enrollment of each student.

The comprehensive list and description of the variables used in the analysis can be found in Table 1. We denote with "pre-treatment covariates" the student's level information collected at the beginning of his/her academic career.

Several pre-processing steps are also performed. Firstly, only students who remained enrolled beyond the initial 60 days are included in the analysis (95.47% of the total). This exclusion criterion accounts for cases where students may have temporarily enrolled at PoliMi while awaiting admission to other university programs or promptly decided to withdraw due to mismatched expectations. Additionally, to address variations in grading systems for students who took their high school diploma before 1999, the `highschool_grade` variable is rescaled to a maximum value of 100, ensuring consistency across all observations. Students with a missing value in the `admission_score` are excluded (3.7%).

Furthermore, the three continuous variables `admission_score`, `career_admission_age` and `highschool_grade` are rescaled to mean zero and standard deviation 1.

The pre-processed dataset contains 29745 students, among which 12039 received treatment hybrid teaching (i.e., the 40.47%). Descriptive statistics for outcomes and pre-treatment covariates after data pre-processing are reported in Table 2. The table provides separate statistics for the two categories of the `hybrid_teaching` variable. For a more detailed inspection, Figures 1-8 in Supplementary Materials allow for an examination of the distributions of PoliMi's variables across the different EPs.

[3]Personal identifiers were removed by the data collectors to ensure anonymity in the dataset.

3. Methods

This section briefly reviews the fundamentals of propensity score within a multilevel framework (Subsection 3.1). The sequential steps and statistical models employed in this study are described in the so-called pipeline of the analysis (Subsection 3.2).

3.1. Basics of Propensity Score within a Multilevel Setting

Within a two-level framework, let $k = 1, ..., n_h$ be the units within the h-th cluster, with $h = 1, ..., H$ and $\sum_h n_h = n$. Let $\mathbf{U}_{hk}$ be a vector of unit-level observed covariates, $\mathbf{V}_h$ a vector of cluster-level observed covariates (the index k in the subscript is omitted since $\mathbf{V}$ is constant within clusters) and define $\mathbf{X}_{hk} = (\mathbf{U}_{hk}, \mathbf{V}_h)$. Let Y_{hk} be the observed outcome for each unit k in cluster h and $Z_{hk} \in \{0, 1\}$ the binary variable indicating whether unit k in cluster h is assigned to the *treatment* ($Z_{hk} = 1$) or *control* group ($Z_{hk} = 0$).

Two different approaches can be employed when dealing with nonrandomized observational data: *controlled descriptive comparison* and *causal comparisons* (Leite et al., 2015; F. Li et al., 2013). In the first case, the assignment is to a nonmanipulable state defining membership to treated and control groups, and the objective is an unconfounded comparison of observed outcomes between the two groups[4]. In the second case, the assignment is to a potentially manipulable intervention, and the objective is to estimate a causal effect by comparing potential outcomes under treatment versus control in a common set of units[5].

Within a descriptive comparison, which is the most suitable approach for our study, the *population Average Controlled Difference* (ACD) is defined[6] as

$$\pi_{\text{ACD}} = \mathbb{E}_{\mathbf{X}}[\mathbb{E}(Y_{hk}|\mathbf{X}_{hk}, Z_{hk} = 1) - \mathbb{E}(Y_{hk}|\mathbf{X}_{hk}, Z_{hk} = 0)] \tag{1}$$

where the outer expectation is with respect to the marginal distribution of $\mathbf{X}$ in the combined population[7]. The *Propensity Score* (PS) is defined as

$$e_{hk} = e(\mathbf{X}_{hk}) := \Pr(Z_{hk} = 1|\mathbf{X}_{hk}) \quad \forall\, h, k\,. \tag{2}$$

The *overlap assumption* $0 < e(\mathbf{X}) < 1$ is required and means that the study population is restricted to values of covariates for which there can be both control and treated units. The utility of the PS lies in the fact that it is a balancing score (i.e., the distribution of the considered pre-treatment covariates, conditional on the PS, are

[4]Examples include comparing outcomes among different racial populations or patients treated in different years, as in the case of the PoliMi dataset.

[5]Examples include evaluating the treatment effect of a drug, therapy, or policy on specific outcomes.

[6]We carry the pedices h and k in the notation to underline the hierarchical structure, even though not strictly necessary.

[7]For completeness, we precise that for a causal comparison, the population Average Treatment Effect (ATE) can be defined as $\pi_{\text{ATE}} = \mathbb{E}[Y_{hk}(1) - Y_{hk}(0)]$ where $Y_{hk}(0)$ and $Y_{hk}(1)$ are the unit's two potential outcomes, defined under the *Stable Unit Treatment Value Assumption*. Under *unconfoundedness*, i.e., no unmeasured confounders, $(Y_{hk}(0), Y_{hk}(1)) \perp Z_{hk} \,|\, \mathbf{X}_{hk}$, we can further assume $\pi_{\text{ACD}} = \pi_{\text{ATE}}$.

balanced across treatment groups (Rosenbaum & Rubin, 1983)) and the following holds

$$\mathbb{E}\left[\frac{Z_{hk}\,Y_{hk}}{e_{hk}} - \frac{(1-Z_{hk})\,Y_{hk}}{1-e_{hk}}\right] = \pi_{\text{ACD}}\,. \tag{3}$$

Thus the ACD can be estimated given the PS estimation. This will be addressed in the next sections.

3.2. Pipeline of the Analysis

The pipeline of the analysis, graphically displayed in Figure 1, is the following: after a preliminary analysis (Subsection 3.2.1), we estimate the PS for clustered data (Subsection 3.2.2), we perform the PS weighting and estimate the ACD (3.2.3) and, lastly, we implement the PS matching and outcome analysis (3.2.4).

3.2.1. Preliminary Analysis

As an initial step, we identify both individual- and cluster-level potential confounding variables that might introduce bias to the treatment effect, to ensure a robust and accurate data comparison (Thoemmes & West, 2011). Then, we assess the degree of bias between the two groups (treated vs control). To this aim, we perform (i) an explorative analysis by carefully checking whether the distributions of the identified potential confounding covariates display significant differences across the two groups over the clusters by making use of boxplots and stacked barplots. To quantify the bias, we employ (ii) the Standardized Mean Difference (SMD) (Austin, 2011)[8]. The SMD quantifies the difference between two group means for one or more variables, serving as a balance measure for individual covariates. Its standardized nature allows for comparisons across variables with varying scales.

A specific covariate is considered imbalanced between the treated and control groups if its SMD exceeds 0.1. This threshold serves as a useful indicator for identifying variables that might introduce bias and compromise the comparability between the two groups.

3.2.2. PS Estimation for Clustered Data

PS can be estimated using various statistical methods (Thoemmes & West, 2011). In this study, we focus on the logistic regression model and, more specifically, on its linear mixed model extension. We examine a *Generalised Linear Mixed Model* (GLMM), also referred in the literature as *Random-effects Model*, for estimating the probability of being treated given the identified confounders, which incorporates a prior normal distribution on the cluster-specific effect (i.e., the random intercept). The model formulation for the GLMM is as follows:

$$\text{logit}(e_{hk}) = \eta_h + \mathbf{U}_{hk}\boldsymbol{\beta} + \mathbf{V}_h\boldsymbol{\gamma} \tag{4}$$

where $\eta_h \sim \mathcal{N}(0, \sigma_\eta^2)$ is the random intercept, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of coefficients for the individual- and cluster-level covariates, respectively. The PS definition in Eq. (2) becomes $e_{hk} = e(\mathbf{X}_{hk}) := \Pr(Z_{hk} = 1|\mathbf{X}_{hk}, \eta_h)$.

[8] Computed through the R package *tableone* (Yoshida, Bohn, & Yoshida, 2020).

While some studies propose the use of a *Fixed-effects Model* (Arpino & Cannas, 2016; Arpino & Mealli, 2011; Chang & Stuart, 2022; F. Li et al., 2013), which involves introducing fixed cluster-specific intercepts, we deem it inappropriate for two main reasons. First and foremost, the fixed-effects approach assumes all observations to be independent and, given the enrollments of students within different EPs, this is hardly verified. Second, this approach would imply a large number of parameters to be estimated, encompassing the 19 dummies that would identify the EPs.Estimating such a large number of parameters would pose challenges and statistical instability. Therefore, we choose to address the GLMM described earlier, which is better suited to address the hierarchical structure of the data and capture variations across the clusters.

For a benchmark analysis, we also take into account a more naive *Marginal Logistic Model* (MLM) or *Single-level Model*, where all units are pooled before parameter estimation, ignoring the clustering structure. In fact, it is well acknowledged in the literature that neglecting the hierarchical structure can lead to increasingly biased estimates of the PSs within clusters. This bias arises because all estimated PSs are derived from the same model. As a result, achieving covariate balance within clusters using a MLM becomes challenging, and residual bias in treatment effects is likely to persist (Thoemmes & West, 2011). By comparing the outcomes obtained under both approaches, we can assess the impact of accounting for clustering effects on the estimation of PSs and subsequent analysis in terms of bias reduction. This comparison will provide valuable insights into the presence and extent of bias when the hierarchical structure is not considered, highlighting the necessity of incorporating it to obtain more reliable and accurate treatment effect estimates. The model formulation for the MLM is as follows:

$$\text{logit}(e_{hk}) = \eta + \mathbf{U}_{hk}\boldsymbol{\beta} + \mathbf{V}_h\boldsymbol{\gamma} \tag{5}$$

where η is an intercept and, as before, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of coefficients for the individual- and cluster-level covariates, respectively.

3.2.3. PS Weighting and the ACD Estimation

Weighting is a statistical technique that involves assigning a different weight to each observation in a dataset, typically computed using the PSs. We make use of Horvitz–Thompson (HT) inverse-probability weights to adjust for confounding bias, defined as $w_{hk} = \frac{1}{e_{hk}}$ for units with $T_{hk} = 1$ and $w_{hk} = \frac{1}{1-e_{hk}}$ for units with $T_{hk} = 0$.

Within our multilevel setting, we then compute the population ACD defined in Eq. (1) by means of nonparametric (i) *Marginal* and (ii) *Clustered Estimators* (Hirano, Imbens, & Ridder, 2003). Specifically,

(i) The *Marginal Estimator* is computed as the difference of the weighted overall means of the outcome between the treatment and control groups, ignoring clustering:

$$\hat{\pi}^{\text{ma}} = \frac{\sum_{h,k} Z_{hk}\, Y_{hk}\, w_{hk}}{\sum_{h,k} Z_{hk}\, w_{hk}} - \frac{\sum_{h,k}(1 - Z_{hk})\, Y_{hk}\, w_{hk}}{\sum_{h,k}(1 - Z_{hk})\, w_{hk}}\,; \tag{6}$$

(ii) The *Clustered Estimator* first estimates the cluster-specific treatment effects as

$$\hat{\pi}_h = \frac{\sum_{k=1}^{n_h} Z_{hk}\, Y_{hk}\, w_{hk}}{\sum_{k=1}^{n_h} Z_{hk}\, w_{hk}} - \frac{\sum_{k=1}^{n_h} (1 - Z_{hk})\, Y_{hk}\, w_{hk}}{\sum_{k=1}^{n_h} (1 - Z_{hk})\, w_{hk}}$$

and then computes their weighted average to estimate the overall treatment effect:

$$\hat{\pi}^{\text{cl}} = \frac{\sum_h w_h\, \hat{\pi}_h}{\sum_h w_h} \quad \text{where} \quad w_h = \sum_{k=1}^{n_h} w_{hk}. \tag{7}$$

Standard errors of these nonparametric estimators are computed through bootstrap by resampling the clusters (F. Li et al., 2013). The cluster-specific $\hat{\pi}_h$ are analyzed.

3.2.4. PS Matching and Outcome Analysis

PS matching involves creating sets of matched individuals, consisting of both treated and control subjects, who have similar PS values. The goal is to balance the distribution of confounding variables between the treatment and control groups, making them more comparable.

We perform the PS matching as follows. We focus on the *greedy nearest neighbour matching*, which is one of the most common types of matching used (Thoemmes & Kim, 2011; Zakrison, Austin, & McCredie, 2018). This approach involves examining the list of treated units and selecting the most similar eligible control unit to be paired with each of them in a "greedy" way (i.e., each pairing is determined without considering how other units are or will be paired). We set a *caliper*[9] of 0.2. Moreover, we focus on matching *without replacement*, meaning that each selected control unit is not returned to the population before the next selection is made. In this way, we do not introduce dependence among observations, and weights due to the use of replacement do not need to be included in the models.

In the multilevel setting, the matching process can be carried out using two distinct approaches: *Within-Cluster* (WC) and *Across-Clusters* (AC). In WC matching, the matching focuses on units within the same cluster, whereas AC matching involves matching across the entire sample, regardless of cluster membership[10]. Given that the PSs are estimated through a GLMM that considers the hierarchical structure, we opt for WC matching, which facilitates achieving balance on individual-level covariates within each cluster. In the comparison scenarios where we employ a MLM for computing the PS, we utilize AC matching. AC matching necessitates a joint PS estimation model to ensure the comparability of PSs across clusters. It is essential to note that while AC matching accomplishes balance across observed covariates within the entire matched dataset, it might not achieve balance on individual-level covariates within each cluster (Thoemmes & West, 2011).

After the matching is performed, we proceed with the so-called *Outcome Analysis*, in which the balance in the post-matching datasets is assessed through the computation of the SMDs as explained in Subsection 3.2.1, and two different mixed models

[9]Which means that the closest control unit is selected for each treated unit within a range of 0.2 standard deviations based on the estimated propensity score and the treated unit is excluded from further analysis if no suitable control unit is found within this range.

[10]The R package *Matching* (Sekhon, 2011) offers the functions *Match* and *Matchby* for conducting the matching process.

for the outcomes are fitted. Specifically, given the hierarchical structure of the PoliMi dataset described in Section 2, since we are interested in capturing the heterogeneity of treatment effects across clusters, we allow the slope associated with the treatment variable to vary across clusters (Chang & Stuart, 2022). The literature suggests that incorporating the hierarchical structure in either the PS estimation or the outcome analysis stages can significantly reduce bias and the least bias is reached when incorporated in both stages (Chang & Stuart, 2022; F. Li et al., 2013; Su & Cortina, 2009). Since in our analysis we deal with `ECTS` and `GPA`, as described in Section 2, we fit two different models, one for each outcome. Specifically, the `ECTS` variable in its nature does not follow a normal distribution, but rather lends itself to be transformed into multiple ordered categories. On the other hand, the `GPA` variable follows a normal distribution. Thus, for the ordinal outcome variable `ECTS`, we employ a *Cumulative Link Mixed Model* (CLMM), which extends the traditional logistic mixed regression and captures the cumulative probabilities of each category along the ordered scale (Christensen, 2018). Instead, for the normally distributed outcome `GPA`, the *Linear Mixed Model* (LMM) is employed (Raudenbush & Bryk, 2002). The CLMM and LMM formulations are as follows:

(i) *Cumulative Link Mixed Model* (CLMM). For each level $j, j = 1, \dots, J$ of the ordinal response Y_{hk}, the cumulative probability of being in level j or lower is modeled through

$$P(Y_{hk} \leq j) = \text{logit}(\alpha_j - (\eta_h + Z_{hk}\nu_h + \mathbf{U}_{hk}\boldsymbol{\beta} + \mathbf{V}_h\boldsymbol{\gamma})) \quad \forall h, k \tag{8}$$

being α_j the threshold parameter for category j, η_h and ν_h the random intercept and slope, respectively, with $(\eta_h, \nu_h)' \sim \mathcal{N}(0, \Sigma_{\eta\nu})$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ the vectors of coefficients for the individual- and cluster-level covariates.

(ii) *Linear Mixed Model* (LMM). The normal response Y_{hk} is modeled through

$$Y_{hk} = \eta_h + Z_{hk}\nu_h + \mathbf{U}_{hk}\boldsymbol{\beta} + \mathbf{V}_h\boldsymbol{\gamma} + \epsilon_{hk} \tag{9}$$

being η_h and ν_h the random intercept and slope, respectively, with $(\eta_h, \nu_h)' \sim \mathcal{N}(0, \Sigma_{\eta\nu})$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ the vectors of coefficients for the individual- and cluster-level covariates and $\epsilon_{hk} \sim \mathcal{N}(0, \delta_\epsilon^2)$.

For completeness, we perform the whole *Outcome Analysis* also on the original and weighted datasets, and we compare the results.

4. Results

This section revisits the pipeline presented in Section 3.2 and discusses the results.

4.1. Preliminary Analysis

In the exploratory analysis, we identify the potential confounding variables, referred to as *pre-treatment covariates* in Table 1, by examining their distributions. In Supplementary Materials, specifically in Figures 3-8, we observe variations in the distributions of these covariates across different EPs upon the introduction of hybrid teaching. These variations manifest as both positive and negative effects or differences in proportions.

We need to specify that for `GPA` outcome models we retain only students with `GPA` greater than zero. Students with a zero or missing value for `GPA`, who are the 20.04% of the sample, are excluded and the numerosity of the PoliMi dataset decreases from 29745 to 23785. The excluded students are the ones whose `ECTS` value is also zero, indicating that they have not successfully passed any exams. Thus, from now on, we deal with two different dataframes: PoliMi (N=29745) and PoliMi_GPA (N=23785). The PS Estimation, Weighting and Matching will be performed separately on each of the two dataframes, to ensure a balance in the pre-treatment covariate distribution in both cases. This careful exclusion is crucial for maintaining the accuracy of the `GPA` values and serves to differentiate the two analyses, attributing distinct meanings to each of them.

We thus compute the SMDs for each variable and for both dataframes, represented in red in Figure 2 ("Original" is the acronym to be considered in the legend). In both the cases of PoliMi and PoliMi_GPA, the SMD for `highschool_grade` and `origins` exceeds 0.1. This indicates an imbalance between the treated and control groups concerning these covariates. Such imbalance can potentially introduce bias when comparing the groups and addressing it is essential to ensure the validity and reliability of our analysis.

In light of the results obtained from this preliminary analysis and our overarching goal to bolster the comparability of the two groups across different EPs by comprehensively considering all available student data, we choose to integrate all accessible covariates in the estimation of the PS.

4.2. PS Estimation for Clustered Data

We estimate the PSs through both the GLMM and the MLM (for comparison) introduced in Section 3.2.2 for both the PoliMi and PoliMi_GPA datasets. The estimated coefficients are reported in Table 3. The random intercepts obtained through GLMMs are displayed in Figure 3.

In the last row of Table 3, we report the Variance Partition Coefficient (VPC)[11], an index commonly computed in the multilevel model framework, to quantify the portion of the unexplained variability in the response given to the grouping level (EPs)(Goldstein, Browne, & Rasbash, 2002). Although the calculated proportions are relatively low, they are not negligible, indicating significant variations in the probability of receiving hybrid teaching across EPs. Furthermore, as indicated by the Akaike Information Criterion (AIC) reported in the penultimate row of Table 3, the GLMM outperforms the MLM for both PoliMi and PoliMi_GPA datasets. This suggests that a more accurate estimation of the PSs is achieved when considering the hierarchical structure. All models consistently show that gender, prior educational background, place of origin, and high school grades exhibit significant associations with the probability of receiving hybrid teaching. Additionally, for PoliMi_GPA, both age and admission scores are also found to play a role. According to Figure 3, the random intercepts' ordering and range for the GLMM fitted both on the PoliMi and PoliMi_GPA datasets exhibit similarities. These similarities indicate consistent patterns across both datasets and offer valuable insights into how EPs influence the probability of receiving treatment (`hybrid_teaching`=1), especially considering that the random intercepts associated with the EPs span into the [-0.5, 0.5] interval. It's worth noting that there are minor discrepancies in the positions of specific EPs between the plots in panels (a)

[11]Computed as $\frac{\sigma_\eta^2}{\sigma_\eta^2+\pi^2/3}$, where σ_η^2 is the random intercept variance.

and (b).

The distributions of the PSs obtained from each of the two models and dataframes are reported in Figure 4. As expected, the distribution of the propensity scores computed for students with `hybrid_teaching`=0 (in the legend denoted as "delivered teaching type: face-to-face") is slightly shifted to the left of 0.5. Notably, in all cases, there is a small peak shifted to the right, close to 1. This suggests that these students have a very high propensity for being in the hybrid teaching group, as they actually do. When a MLM is employed, both the treated and control groups exhibit a higher peak around 0.5 compared to a smoother peak observed when a GLMM is used. This discrepancy in peak shape between the two models reflects differences in the estimated PSs.

4.3. PS Weighting and ACD estimation

The estimation of ACD is performed after calculating the HT inverse-probability weights using the PSs. The ACD is computed using the formulas in Eq.s (6) and (7). We recall that for the dataset PoliMi we consider $Y_{hk} = \mathtt{ECTS}_{hk}$ and for the dataset PoliMi_GPA we consider $Y_{hk} = \mathtt{GPA}_{hk}$.

Table 4 reports the estimated ACDs, together with their standard errors, computed through bootstrap resampling of the clusters (Chang & Stuart, 2022; F. Li et al., 2013). Both the marginal and clustered estimators yield similar results, and the choice of the PS model does not appear to have a substantial impact on the estimated ACDs. The absolute values of the estimated ACDs are very low, indicating a small impact of hybrid teaching on the outcomes. Specifically, ACD results indicate a positive effect of hybrid teaching on the gained ECTS and a negative effect on the GPA. The analysis suggests that students who experienced hybrid teaching were able to gain approximately 0.2 ECTS more than their counterparts who studied before the introduction of hybrid teaching, but their GPA was approximately 0.1 points lower. This observation may be attributed to the possibility that hybrid teaching is effective in helping students pass their exams but may not significantly contribute to achieve higher academic results. A more in-depth examination of this result can be conducted across EPs in Figure 6, which illustrates the clustered estimator $\hat{\pi}_h$ for each dataframe and PS model employed. The plot reveals substantial heterogeneity across EPs. For instance, in panel (a), EP11 and EP03 exhibit different trends compared to EP08 and EP05, while in panel (b), EP14 shows contrasting patterns to EP07 and EP12. It is noteworthy that the impact of hybrid teaching appears to vary across different EPs, suggesting that our hypothesis, which posits that hybrid teaching is effective in helping students pass their exams but may not significantly contribute to achieve higher academic results, should be examined on a case-by-case basis. This indicates that the effect of hybrid teaching is not consistent across all EPs. Moreover, the differences between the GLMM and MLM models for PS estimation are minimal when examining $\hat{\pi}_h$, except for slightly higher estimates when MLM is used.

Furthermore, SMDs are computed after weighting the dataset through HT inverse probability weights. Results are displayed in Figure 2 through yellow and green lines for MLM and GLMM, respectively employed for the estimation of the PSs. In this case, not all the variables reach a value of SMD lower than 0.1. The SMDs of the most unbalanced variables in PoliMi dataset in panel (a), such as `highschool_grade`, `origins`, and `admission_score`, decrease after weighting. However, `highschool_grade` remains above the threshold of 0.1, regardless of the PS estimation model used. In the case

of PoliMi_GPA in panel (b), the SMDs of `highschool_grade` and `origins` decrease, while the SMD of `previous_studies` slightly increases, exceeding 0.1. This suggests that the imbalance has not been adequately corrected.
Given the obtained results, we proceed to the next subsection where we conduct a PS Matching analysis.

4.4. PS Matching and Outcome models

In this section, we delve into the process of PS Matching. In Figure 2, we visually assess the changes in the SMDs of the covariates before (red line) and after matching without replacement (light blue lines, according to whether a GLMM or an MLM was used for the PS computation). All the variables reach a value of SMD lower than 0.1, meaning that a good covariate balance in the dataframe is reached and indicating that the matching procedure effectively reduces bias and enhances the comparability between the treated and control groups. It is worth noting that despite the use of different PS estimation models, the outcomes remain consistent and robust, further supporting the reliability of these findings. This figure also represents the scenario in which matching with replacement is considered (purple and fuchsia lines for MLM and GLMM, respectively), which reaches comparable results to the case without replacement.

We proceed by fitting the CLMM and LMM for the outcomes on the matched datasets without replacement, given that the SMDs results outperform the other methods and we do not want to introduce dependence among observations through matching with replacement. We here specify that prior to any analysis involving the outcomes, `GPA` is made normally distributed through a univariate Box-Cox transformation (estimated transformation parameter equal to 0.85, i.e., the observations are spread). Given that the variable `ECTS` is not normally distributed, as shown in panel (a) of Figure 5, the ordinal variable `ECTS_cat` is created by dividing the continuous variable `ECTS` into the following four quantile groups: $[0, 9)$ (N=7738), $[9, 21)$ (N=10094), $[21, 29)$ (N=5751) and $[29, 50)$ (N=6162). `ECTS_cat` is represented through a bar plot in panel (b) of Figure 5. Thus, for the CLMM in Eq. (8), we consider $Y_{hk} = \texttt{ECTS\_cat}_{hk}$ and $\mathbf{X}_{hk} = \mathbf{U}_{hk} = \big[\texttt{admission\_score}_{hk}, \texttt{career\_admission\_age}_{hk}, \texttt{highschool\_grade}_{hk}, \texttt{gender}_{hk}, \texttt{previous\_studies}_{hk}, \texttt{origins}_{hk}\big]$. For the LMM in Eq. (9), we consider $Y_{hk} = \texttt{GPA}_{hk}$ (Box-Cox transformed) and $\mathbf{X}_{hk} = \mathbf{U}_{hk} = \big[1, \texttt{admission\_score}_{hk}, \texttt{career\_admission\_age}_{hk}, \texttt{highschool\_grade}_{hk}, \texttt{gender}_{hk}, \texttt{previous\_studies}_{hk}, \texttt{origins}_{hk}\big]$.

In Table 5, we present the estimated parameters for the CLMM and LMM fitted respectively on PoliMi and PoliMi_GPA. In both cases, we consider the PSs estimated through both MLM and GLMM. Firstly, we observe that the AICs are lower when a GLMM is employed. This consistently suggests that a more accurate fit is achieved when the hierarchical structure is considered in the computation of the PSs. Moreover, we report the average random effects variances $(\mu^2_{\eta\nu})$[12]. For the two LMMs for the `GPA` we also provide the variance δ^2_ϵ of ϵ_{hk} in Eq. (9) and the Proportion of Variability explained by Random Effects (PVRE)[13], which allows to disentangle the variability between students from that between EPs. In this case, we can conclude that almost

[12] $\mu^2_{\eta\nu} = d_{11} + 2\, d_{12}\, \overline{\texttt{hybrid\_teaching}} + d_{22}\, \overline{\texttt{hybrid\_teaching}^2}$, where $\Sigma_{\eta\nu} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$ is the variance covariance matrix of the random effects in Eq.s (8) and (9) and the overline stands for the average.

[13] $\text{PVRE} = \frac{\mu^2_{\eta\nu}}{\mu^2_{\eta\nu} + \delta^2_\epsilon}$.

the 15% of unexplained variability among students is captured by the random effects, i.e., a joint effect of the EP (random intercept) and hybrid teaching (random slope).

Concerning the coefficients, the impacts of `admission_score`, `gender=Male`, `origins=Foreigner`, `highschool_grade` on `ECTS_cat` and `GPA` are positive and significant. Viceversa, `previous_studies=Classical` and `origins=Milanese` have negative and significant impact on both `ECTS_cat` and `GPA`. Moreover, `career_admission_age`, `previous_studies=Others` and `previous_studies=Technical` have negative and significant impact on `ECTS_cat`, while a positive impact on `GPA` (all significant except `previous_studies=Technical`). Neither `origins=Offsite` nor `hybrid_teaching` are significant.

The latter result should be interpreted in conjunction with the findings presented in Figure 7. This figure provides a visual representation of the random intercept and slope estimates for each EP in the outcome models fitted after PS matching without replacement. Interestingly, while `hybrid_teaching` does not emerge as significant when included in the model as a fixed covariate, differences become evident when it is analyzed as a random slope, with variations observed across different EPs. These models not only enables us to predict student performances, whether in terms of ECTS or GPA, but they also offer valuable insights into the contribution of different EPs to these academic outcomes. By including `hybrid_teaching` as a random slope, we can discern how it interacts with specific EPs, shedding light on whether its effect varies across programs. This deeper understanding is crucial for the optimization of teaching methods within specific EPs.

Moreover, if the cluster-specific $\hat{\eta}_h$ and $\hat{\nu}_h$ in Figure 7 are compared to the results obtained for $\hat{\pi}_h$ in Figure 6, similarities can be observed among $\hat{\pi}_h$ and ν_h (the random slope across EPs of `hybrid_teaching`), especially in terms of extreme contributions. Specifically, for PoliMi dataset and models for `ECTS_cat` (in panel (a) of Figure 6 and panels (a) and (b) of Figure 7), extreme positive contributions for both $\hat{\pi}_h$ and ν_h are `EP03`, `EP06` and `EP15`, extreme negative contributions are `EP05`, `EP08`, `EP18`, `EP14` and `EP12`. For PoliMi_GPA dataset and models for `GPA` (in panel (b) of Figure 6 and panels (c) and (d) of Figure 7), extreme positive contributions for both $\hat{\pi}_h$ and ν_h are `EP09`, `EP14` and `EP03`, extreme negative contributions are `EP07` and `EP12`.

In Supplementary Materials, we report the results obtained from the fit of the models for outcomes both on the original (Table 1 and Figure 9) and weighted (Table 2 and Figure 10) datasets.

5. Discussion

The objective of this study is to investigate the impact of hybrid teaching on the academic achievements of engineering students at PoliMi during the first semester of their first academic year. We aim to quantify this impact while considering the potential variations across different programs. To achieve comparability between the students who received hybrid teaching and those who did not, we employ PS weighting and matching techniques, extended to account for the hierarchical structure present in the data given by EPs. Specifically, we compute the PSs for each student, representing their probability of receiving hybrid teaching, with a multilevel model and we compare the result with the "baseline" marginal model. We then apply weighting and matching techniques, the former to weight the dataset accounting for the estimated probabilities and the latter to form balanced groups by selecting students with similar characteristics while discarding those who differ significantly.

Our study offers valuable contributions to the literature. First, it acknowledges the hierarchical structure stemming from the EPs, a factor often overlooked in prior research, providing a deeper understanding of hybrid teaching's impact. Second, it places in the post-pandemic educational landscape, recognizing the evolving balance between online and face-to-face instruction. Third, it follows an approach that combines both weighting and matching techniques within multilevel propensity score analysis, offering a comprehensive examination that maximizes the strengths of each method. By filling these gaps in existing research, our study provides insights into the complexities of hybrid teaching and serves as a reference for future investigations in the field.

In terms of PSs and the ACD values, the hierarchical and classical frameworks yield similar results, indicating that taking into account the hierarchical structure does not significantly alter the estimates. The fact that results remain consistent across frameworks adds robustness to our findings. Nonetheless, the hierarchical framework allows us to attribute a random intercept and the estimated ACD to each EP, providing a more granular understanding of the impact of hybrid teaching within different academic contexts and investigating the heterogeneity within the same university. This information can be valuable for institutions in making informed decisions and tailoring their educational strategies based on each program's specific needs and characteristics. In summary, our findings suggest that, after achieving balance between the two groups, there are minimal differences on average in terms of ECTS and GPA. On average, students exposed to hybrid teaching tend to show a slight increase in gained ECTS but a slight decline in GPA. Nonetheless, evidences reveal that these effects exhibit considerable variation within the university across different programs. Results obtained through matching appear more robust than those obtained through weighting, as the standardized mean differences of the covariates between the treated and control groups are lower after matching. The matching procedure successfully achieves covariate balance, particularly for variables such as `highschool_grade` and `origins`. While `hybrid_teaching` does not exhibit statistical significance when treated as a fixed covariate in the models for outcomes, its influence becomes conspicuous when analyzed as a random slope, unveiling variations across distinct programs. These models not only facilitate the prediction of student performance but they also yield insights into the unique contributions of different EPs to these academic outcomes. By integrating `hybrid_teaching` as a random slope, we gain a deeper understanding of its interaction with specific EPs, shedding light on whether its effects diverge among programs and holding significant implications for the refinement of tailored teaching approaches within individual EPs.

The obtained results could be attributed to various social and structural factors. The introduction of hybrid teaching was a direct response to the unprecedented challenges posed by the Covid-19 pandemic, requiring significant adaptations in teaching methods and examination formats. These adaptations may have influenced the learning experience, including potential factors such as faster-paced lectures, an increased reliance on slide-based presentations, and modifications to examination procedures aimed at mitigating concerns about academic integrity, which might have made the exams more difficult. These changes, while necessary, could have impacted student performance, potentially leading to less difficulties for them in passing the exams (which would explain the positive ACD for the ECTS), while more difficulties in getting higher grades (which would explain the negative ACD for the GPA).

However, it is important to acknowledge several limitations in our analysis. Firstly, our models for propensity score estimation do not incorporate EP-level covariates. The inclusion of such covariates could provide additional insights and potentially strengthen the results obtained within the hierarchical framework. Secondly, we do not account for potential structural differences in the admission tests and high school final exams across the years, which may influence our findings. Lastly, our study combines data from the academic years 2020/2021 and 2021/2022, despite the potential differences between these periods due to the evolving nature of educational practices. Future research could explore these differences more comprehensively to gain a deeper understanding of the evolving effects of hybrid teaching.

In conclusion, our study reveals that hybrid teaching at Politecnico di Milano, across various engineering programs, has a limited impact on academic achievements, though with considerable variability observed among the programs. Utilizing propensity score weighting and matching techniques, we have identified only marginal disparities in ECTS and GPA between hybrid and face-to-face teaching cohorts. On average, these disparities tend to manifest as negative for GPA and positive for the gained ECTS. These findings provide valuable insights for institutions considering the adoption of hybrid teaching. It underscores the importance of factoring in elements such as examination formats and student support mechanisms when transitioning to hybrid teaching models. Future research can extend our findings by exploring additional variables and assessing long-term effects.

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Disclosure statement

The authors report there are no competing interests to declare.

Data availability

The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

The code, together with a sample input data set and complete documentation, is available at `https://github.com/alessandragni/MlevelPS_HybridTeaching`.

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Table 1.: An overview of the PoliMi dataset variables included in our analysis.

Variable	Description	Type
Outcome variables		
- `ECTS`	ECTS gained on 1st semester of 1st year	Natural number [0, 50]
- `GPA`	Grade average in 1st semester of 1st year	Real number [18, 30]
Treatment indicator		
- `hybrid_teaching`	Binary indicator for the treatment	Categorical {0,1}
Pre-treatment covariates		
- `admission_score`	PoliMi entrance test's admission score	Real number [10, 100]
- `career_admission_age`	Student's age at enrollment	Natural number [18, 65]
- `highschool_grade`	Diploma grade	Natural number [60, 100]
- `origins`	Student's geographic origins	Categorical {`Commuter, Milanese, Offsite, Foreigner`}
- `gender`	Student's gender	Categorical {`Female, Male`}
- `previous_studies`	Type of attended highschool	Categorical {`Scientific, Classical, Technical, Others`}
Grouping variable		
- `engineering_program`	Engineering Program (EP)	Categorical {`EP01, EP02,..., EP19`}

Table 2.: Descriptive statistics for outcomes and pre-treatment covariates after data pre-processing, according to the delivered teaching.

Variable			hybrid_teaching=0	hybrid_teaching=1
Type	**Name**		**Mean (sd)**	**Mean (sd)**
Numerical	ECTS		16.5 (11.3)	17.9 (11.0)
	GPA[a]		23.8 (3.04)	23.9 (3.01)
	admission_score		−0.031 (0.99)	0.046 (1.01)
	career_admission_age		0.011 (1.01)	−0.016 (0.98)
	highschool_grade		−0.109 (0.95)	0.161 (1.05)
Categorical		**Category**	**Frequency**	**Frequency**
	origins	Commuter[b]	68.7%	68.5%
		Milanese	23.4%	22.0%
		Offsite	6.3%	4.9%
		Foreigner	1.6%	4.6%
	gender	Female[b]	24.2%	24.9%
		Male	75.8%	75.1%
	previous_studies	Scientific[b]	76.0%	76.9%
		Classical	4.9%	4.5%
		Technical	14.8%	13.9%
		Others	4.3%	4.7%

[a]Students with GPA=0 or missing were excluded from the computation of **Mean (sd)**. [b]Reference category.

Table 3.: Coefficients estimated through the fitting of an MLM and a GLMM on PoliMi and PoliMi_GPA for the *PS Estimation*.

	PoliMi		PoliMi_GPA	
	PS by **MLM**	PS by **GLMM**	PS by **MLM**	PS by **GLMM**
β_0 (Intercept)	-0.519 (0.027) ***	-0.427 (0.058) ***	-0.523 (0.030) ***	-0.453 (0.055) ***
β_1 (`admission_score`)	-0.016 (0.013)	0.019 (0.014)	-0.071 (0.016) ***	-0.047 (0.017) **
β_2 (`career_admission_age`)	0.015 (0.013)	0.012 (0.013)	0.053 (0.020) **	0.047 (0.020) *
β_3 (`gender=Male`)	0.104 (0.029) ***	0.072 (0.031) *	0.119 (0.032) ***	0.010 (0.034) **
β_4 (`previous_studies=Classical`)	-0.190 (0.058) **	-0.203 (0.058) ***	-0.227 (0.066) ***	-0.244 (0.067) ***
β_5 (`previous_studies=Others`)	0.223 (0.073) **	0.184 (0.074) *	0.337 (0.092) ***	0.310 (0.094) ***
β_6 (`previous_studies=Technical`)	-0.130 (0.037) ***	-0.193 (0.038) ***	-0.181 (0.043) ***	-0.237 (0.044) ***
β_7 (`origins=Foreigner`)	2.197 (0.107) ***	2.265 (0.109) ***	2.586 (0.148) ***	2.645 (0.151) ***
β_7 (`origins=Milanese`)	0.048 (0.029) .	0.063 (0.030) *	0.056 (0.033) .	0.062 (0.033) .
β_8 (`origins=Offsite`)	-0.205 (0.055) ***	-0.251 (0.063) ***	-0.270 (0.061) ***	-0.270 (0.070) ***
β_9 (`highschool_grade`)	0.471 (0.016) ***	0.487 (0.016) ***	0.541 (0.020) ***	0.563 (0.020) ***
Observations	29745	29745	23785	23785
AIC	38876.29	38794.60	31232.16	31166.70
VPC	-	0.014	-	0.011

. p-value<0.1; *p-value<0.05; **p-value<0.01; ***p-value<0.001

Table 4.: Marginal and Clustered Estimators for the ACD quantification when *PS Weighting* is performed, together with standard error.

	$Y_{hk} = \texttt{ECTS}_{hk}$ - PoliMi		$Y_{hk} = \texttt{GPA}_{hk}$ - Polimi_GPA	
	PS by **MLM**	PS by **GLMM**	PS by **MLM**	PS by **GLMM**
$\hat{\pi}^{\mathrm{ma}}$ (std error[a])	0.068 (0.143)	0.143 (0.146)	−0.125 (0.043)	−0.133 (0.044)
$\hat{\pi}^{\mathrm{cl}}$ (std error[a])	0.361 (0.133)	0.175 (0.136)	−0.099 (0.043)	−0.130 (0.043)

[a]Standard error is computed across 500 bootstrap samples.

Table 5.: Coefficients estimated through the fitting of a CLMM and a LMM after *PS Matching* without replacement.

	CLMM for `ECTS_cat` [PoliMi]		**LMM** for `GPA` [PoliMi_GPA]	
	PS by **MLM**	PS by **GLMM**	PS by **MLM**	PS by **GLMM**
β_0 (Intercept)	-	-	23.712 (0.237) ***	23.631 (0.235) ***
β_1 (`admission_score`)	0.525 (0.011) ***	0.518 (0.011) ***	0.867 (0.018) ***	0.847 (0.018) ***
β_2 (`career_admission_age`)	−0.241 (0.014) ***	−0.238 (0.014) ***	0.116 (0.021) ***	0.110 (0.022) ***
β_3 (`gender=Male`)	0.121 (0.023) ***	0.149 (0.023) ***	0.178 (0.036) ***	0.202 (0.037) ***
β_4 (`previous_studies=Classical`)	−0.656 (0.043) ***	−0.644 (0.044) ***	−0.220 (0.071) **	−0.208 (0.072) **
β_5 (`previous_studies=Others`)	−0.402 (0.054) ***	−0.477 (0.056) ***	0.626 (0.094) ***	0.451 (0.097) ***
β_6 (`previous_studies=Technical`)	−0.401 (0.027) ***	−0.381 (0.027) ***	0.026 (0.046)	0.051 (0.047)
β_7 (`origins=Foreigner`)	0.790 (0.090) ***	1.009 (0.095) ***	2.060 (0.158) ***	2.486 (0.162) ***
β_7 (`origins=Milanese`)	−0.121 (0.023) ***	−0.132 (0.023) ***	−0.241 (0.037) ***	−0.205 (0.037) ***
β_8 (`origins=Offsite`)	0.016 (0.051)	0.072 (0.052)	0.118 (0.083)	0.180 (0.083) *
β_9 (`highschool_grade`)	0.761 (0.013) ***	0.773 (0.014) ***	1.016 (0.020) ***	1.071 (0.021) ***
β_{10} (`hybrid_teaching`)	−0.063 (0.063)	−0.064 (0.061)	−0.019 (0.140)	0.017 (0.141)
α_j (Threshold coefficient)				
1 — 2	−1.348 (0.189)	−1.329 (0.182)		
2 — 3	0.511 (0.189)	0.534 (0.182)		
3 — 4	1.731 (0.189)	1.763 (0.182)		
AIC	106546.97	104862.83	177420.50	175212.70
δ^2_ϵ	-	-	7.6412	7.6650
Average random effects variance $\mu^2_{\eta\nu}$	0.7358	0.7081	1.4094	1.4012
PVRE	-	-	0.1557	0.1546

p-value<0.1; *p-value<0.05; **p-value<0.01; ***p-value<0.001

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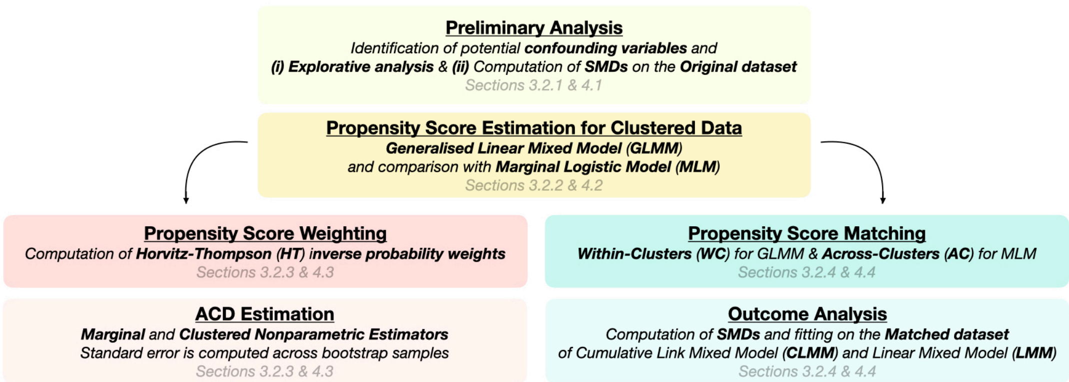
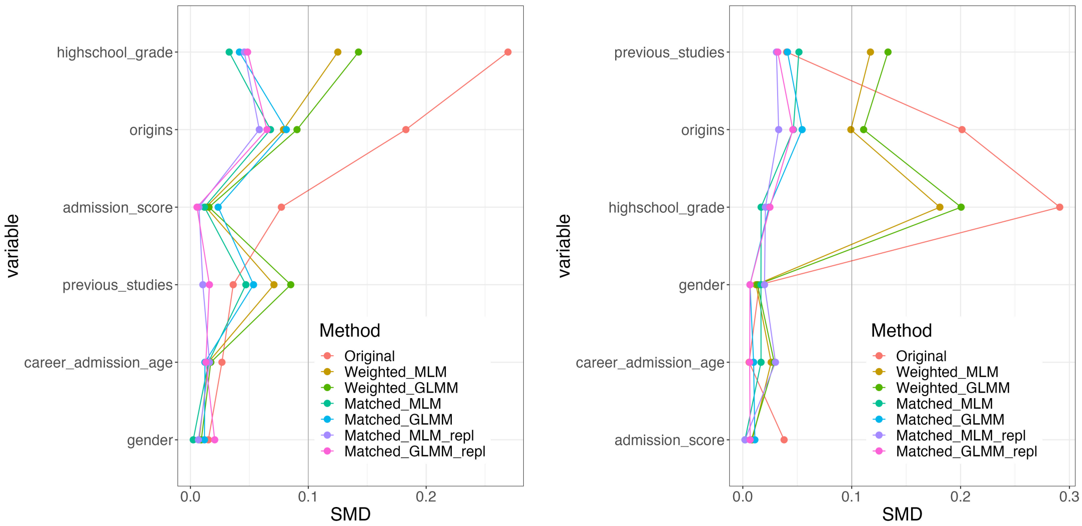
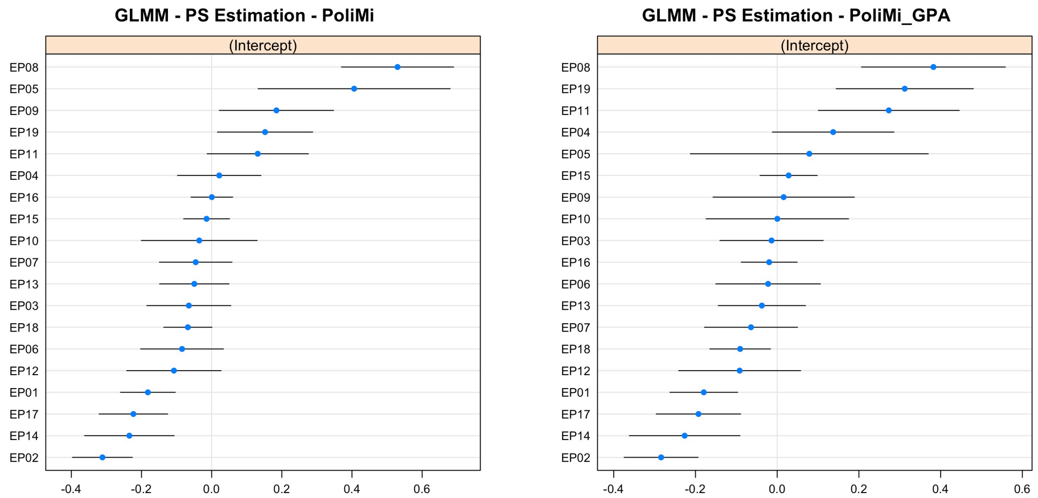


Figure 1.: Summary of the pipeline of the analysis.



(a) PoliMi (b) PoliMi_GPA

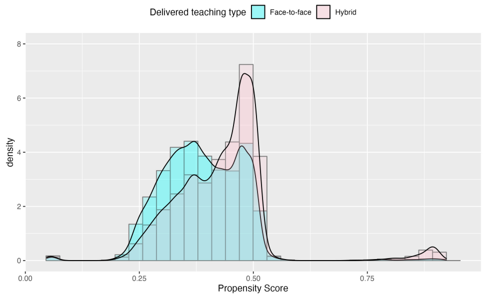
Figure 2.: Piecewise continuous lines represent the SMDs (x-axis) across the pre-treatment variables (y-axis) when different data-preprocessing methods are employed (legend). The computation is performed separately for Polimi (panel (a)) and Polimi_GPA (panel (b)) datasets.



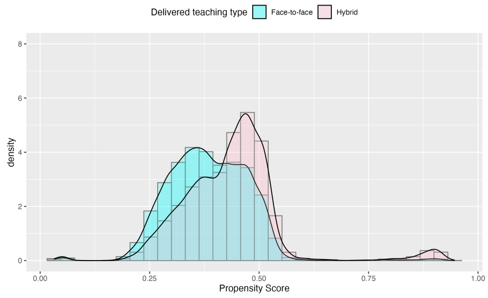
(a) PoliMi

(b) PoliMi_GPA

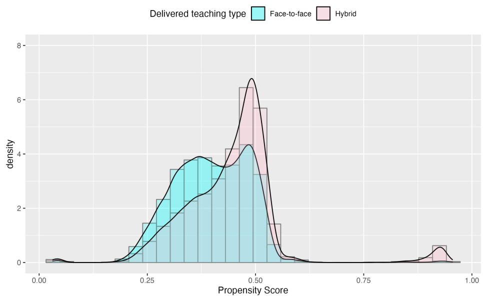
Figure 3.: Random intercept for each EP (y-axes) for the GLMM fitted for the *PS Estimation* on the two dataframes.



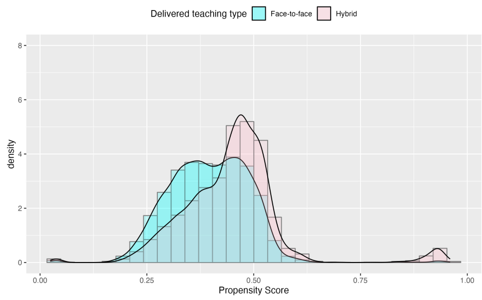
(a) MLM - PoliMi



(b) GLMM - PoliMi

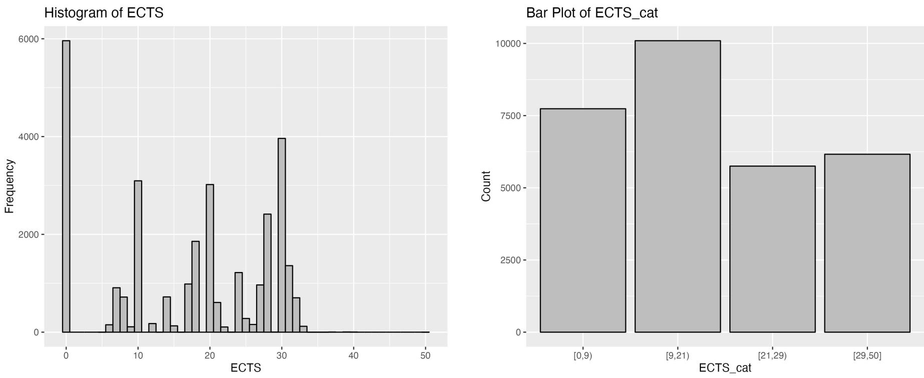


(c) MLM - PoliMi_GPA



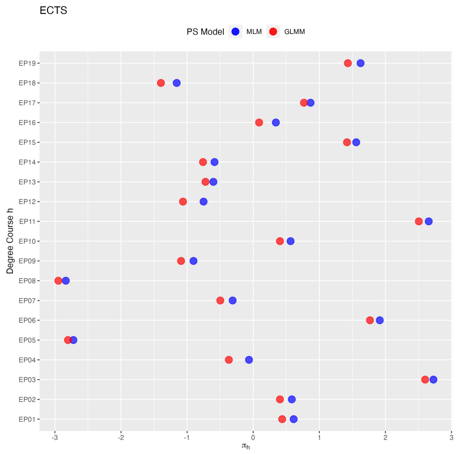
(d) GLMM - PoliMi_GPA

Figure 4.: Histograms of the PSs distributions obtained for different models [MLM in panels (a) and (c) versus GLMM in panels (b) and (d)] and datasets [PoliMi in panels (a) and (b) versus PoliMi_GPA in panels (c) and (d)].

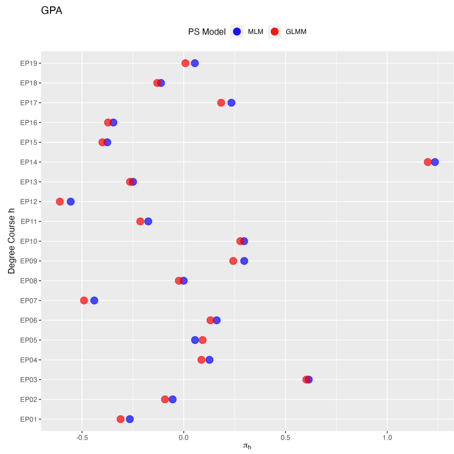


(a) ECTS (b) ECTS_cat

Figure 5.: Representation of the distributions of ECTS in panel (a) and ECTS_cat in panel (b).

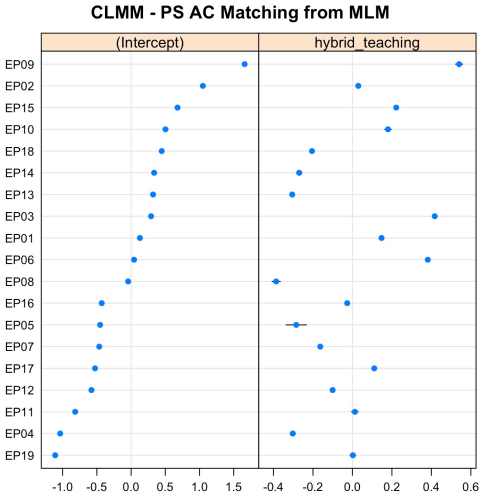


(a) $\hat{\pi}_h$ in PoliMi

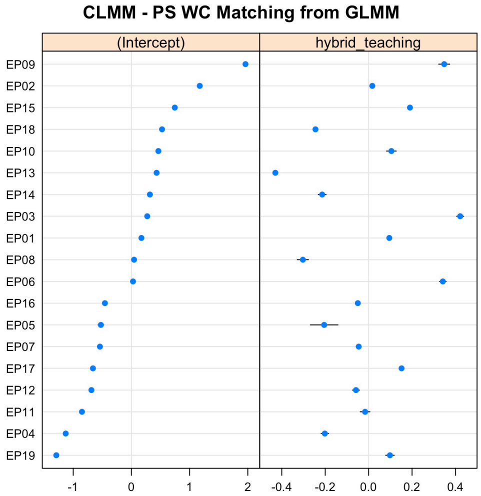


(b) $\hat{\pi}_h$ in PoliMi_GPA

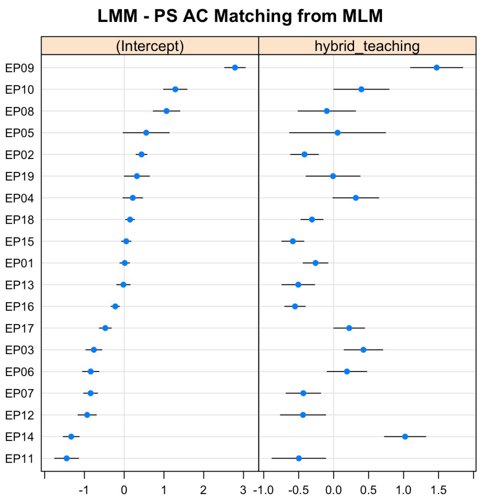
Figure 6.: $\hat{\pi}_h$ across EP (y-axes) depending on whether the PS Model was a MLM (blue) or a GLMM (red), for the two dataframes PoliMi (panel (a)) and PoliMi_GPA (panel (b)).



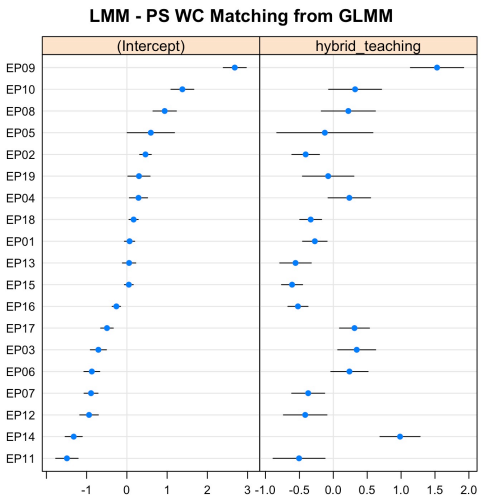
(a) CLMM for `ECTS_cat` in PoliMi - PS estimated through MLM



(b) CLMM for `ECTS_cat` in PoliMi - PS estimated through GLMM



(c) LMM for `GPA` in PoliMi_GPA - PS estimated through MLM



(d) LMM for `GPA` in PoliMi_GPA - PS estimated through GLMM

Figure 7.: Random intercept and slope for each EP (y-axes) for the outcome models fitted after *PS Matching* for different PS estimation models [MLM in panels (a) and (c) versus GLMM in panels (b) and (d)] and datasets/outcome models [PoliMi/CLMM in panels (a) and (b) versus PoliMi_GPA/LMM in panels (c) and (d)].

Supplementary Materials for "Assessing the Impact of Hybrid Teaching on Students' Academic Performance via Multilevel Propensity Score-based techniques"

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1. Figures for the preliminary analysis

Explorative analysis of the covariates can be assessed in Figures 1-8.

2. Comparison with other models for outcomes

The estimated coefficients of the outcome models fitted prior any PS correction are reported in Table 1, while random intercepts and slopes are displayed in Figure 9. The estimated coefficients of the models for outcomes after weighting are reported in Table 2, and the random intercepts for EPs and slopes (e.g., `hybrid_teaching`) are depicted in Figure 10. Results are close to the ones presented in Figure 9. Also, by comparing the random slope results with the ranking induced by $\hat{\pi}_h$ in Figure 6 in Section 4.2, similarities can be observed, especially in terms of extreme contributions. The coefficients obtained from the outcome models before and after weighting (Tables 1 and 2) show some changes. After weighting, all regressors, except `hybrid_teaching`, are significant level 1%.

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Table 1.: Coefficients estimated through the fitting of a CLMM and a LMM prior PS correction.

	CLMM for ECTS_cat [PoliMi]		**LMM** for GPA [PoliMi_GPA]	
	Coeff	(std error) p-value	Coeff	(std error) p-value
β_0 (Intercept)	-	-	16.107	(0.145) ***
β_1 (admission_score)	0.523	(0.014) ***	0.511	(0.014) ***
β_2 (career_admission_age)	-0.248	(0.017) ***	0.080	(0.017) ***
β_3 (gender=Male)	0.105	(0.028) ***	0.106	(0.028) ***
β_4 (previous_studies=Classical)	-0.664	(0.053) ***	-0.136	(0.055) *
β_5 (previous_studies=Others)	-0.283	(0.069) ***	0.575	(0.074) ***
β_6 (previous_studies=Technical)	-0.403	(0.034) ***	0.046	(0.036)
β_7 (origins=Foreigner)	0.483	(0.086) ***	0.500	(0.085) ***
β_7 (origins=Milanese)	-0.149	(0.027) ***	-0.138	(0.028) ***
β_8 (origins=Offsite)	-0.033	(0.058)	0.102	(0.059) .
β_9 (highschool_grade)	0.814	(0.016) ***	0.618	(0.015) ***
β_{10} (hybrid_teaching)	-0.033	(0.058)	0.036	(0.081)
α_j (Threshold coefficient)				
1 — 2	-1.300	(0.180)		
2 — 3	0.554	(0.180)		
3 — 4	1.721	(0.180)		
Observations	29745		23785	
AIC	70561.24		93625.43	
δ^2_ϵ	-		2.9736	
Average random effects variance $\mu^2_{\eta\nu}$	0.6742		0.4823	
PVRE	-		0.1395	

. p-value<0.1; *p-value<0.05; **p-value<0.01; ***p-value<0.001

Table 2.: Coefficients estimated through the fitting of a CLMM and a LMM after *PS Weighting*.

	CLMM for `ECTS_cat` [PoliMi]		**LMM** for `GPA` [PoliMi_GPA]	
	PS by **MLM**	PS by **GLMM**	PS by **MLM**	PS by **GLMM**
β_0 (Intercept)	-	-	16.111 (0.130) ***	16.114 (0.129) ***
β_1 (`admission_score`)	0.546 (0.009) ***	0.547 (0.009) ***	0.516 (0.014) ***	0.516 (0.014) ***
β_2 (`career_admission_age`)	−0.301 (0.012) ***	−0.308 (0.012) ***	0.030 (0.016) .	0.028 (0.016) .
β_3 (`gender=Male`)	0.074 (0.020) ***	0.072 (0.020) ***	0.074 (0.029) ***	0.071 (0.029) *
β_4 (`previous_studies=Classical`)	−0.602 (0.038) ***	−0.591 (0.038) ***	−0.085 (0.057)	−0.075 (0.057)
β_5 (`previous_studies=Others`)	0.272 (0.044) ***	0.334 (0.043) ***	0.983 (0.066) ***	1.016 (0.066) ***
β_6 (`previous_studies=Technical`)	−0.335 (0.024) ***	−0.331 (0.024) ***	0.098 (0.037) **	0.097 (0.037) **
β_7 (`origins=Foreigner`)	−0.309 (0.055) ***	−0.373 (0.055) ***	−0.191 (0.078) *	−0.244 (0.077) **
β_7 (`origins=Milanese`)	−0.189 (0.019) ***	−0.194 (0.019) ***	−0.179 (0.028) ***	−0.181 (0.028) ***
β_8 (`origins=Offsite`)	0.191 (0.039) ***	0.195 (0.038) ***	0.353 (0.055) ***	0.373 (0.055) ***
β_9 (`highschool_grade`)	0.560 (0.009) ***	0.544 (0.009) ***	0.435 (0.013) ***	0.427 (0.013) ***
β_{10} (`hybrid_teaching`)	0.048 (0.065)	0.049 (0.066)	0.079 (0.081) ***	0.077 (0.081)
α_j (Threshold coefficient)				
1 — 2	−1.239 (0.164)	−1.236 (0.163)		
2 — 3	0.542 (0.164)	0.539 (0.163)		
3 — 4	1.684 (0.164)	1.678 (0.163)		
AIC	144635.73	145124.93	95538.27	95686.75
δ^2_ϵ	-	-	6.212	6.235
Average random effects variance $\mu^2_{\eta\nu}$	0.5952	0.4011	0.3951	0.3487
PVRE	-	-	0.0606	0.0596

. p-value<0.1; *p-value<0.05; **p-value<0.01; ***p-value<0.001

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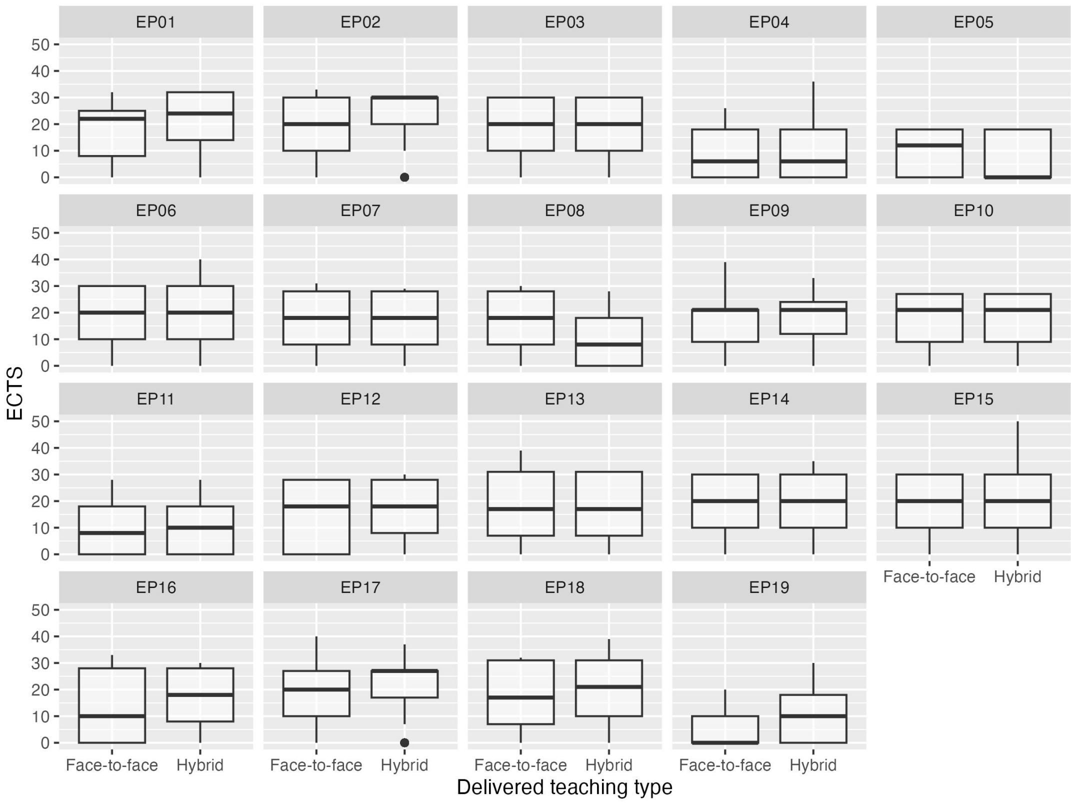


Figure 1.: Distribution of `ECTS` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

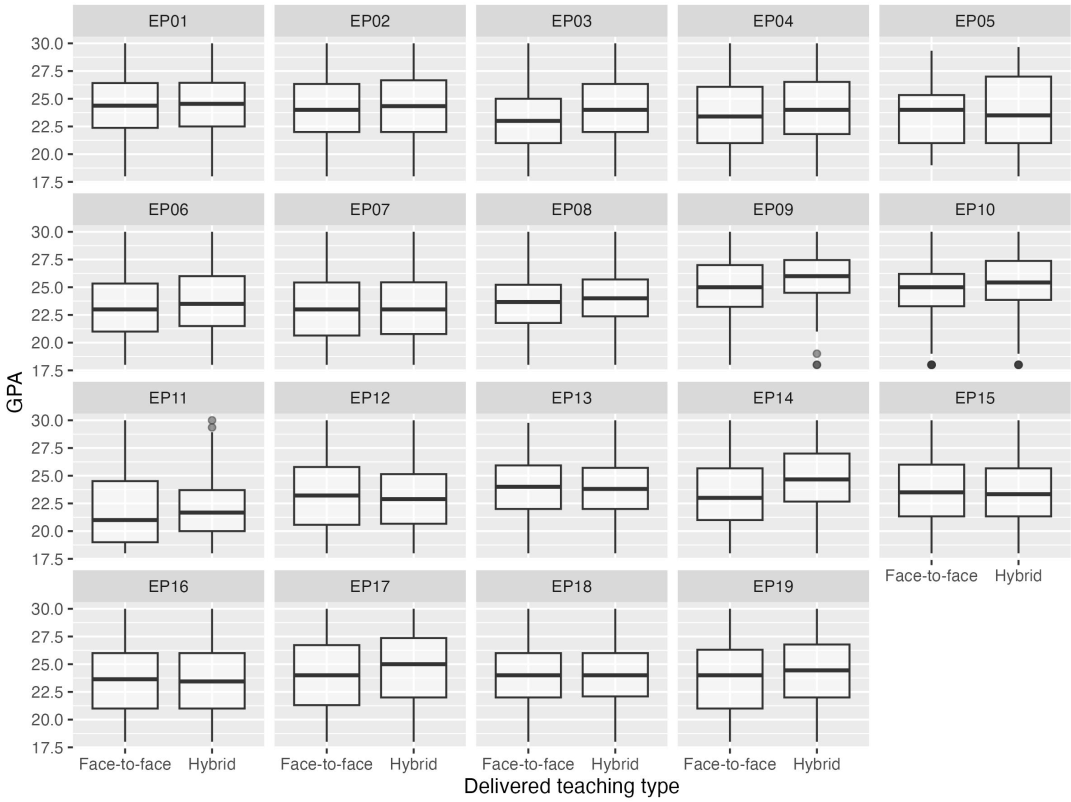


Figure 2.: Distribution of `GPA` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

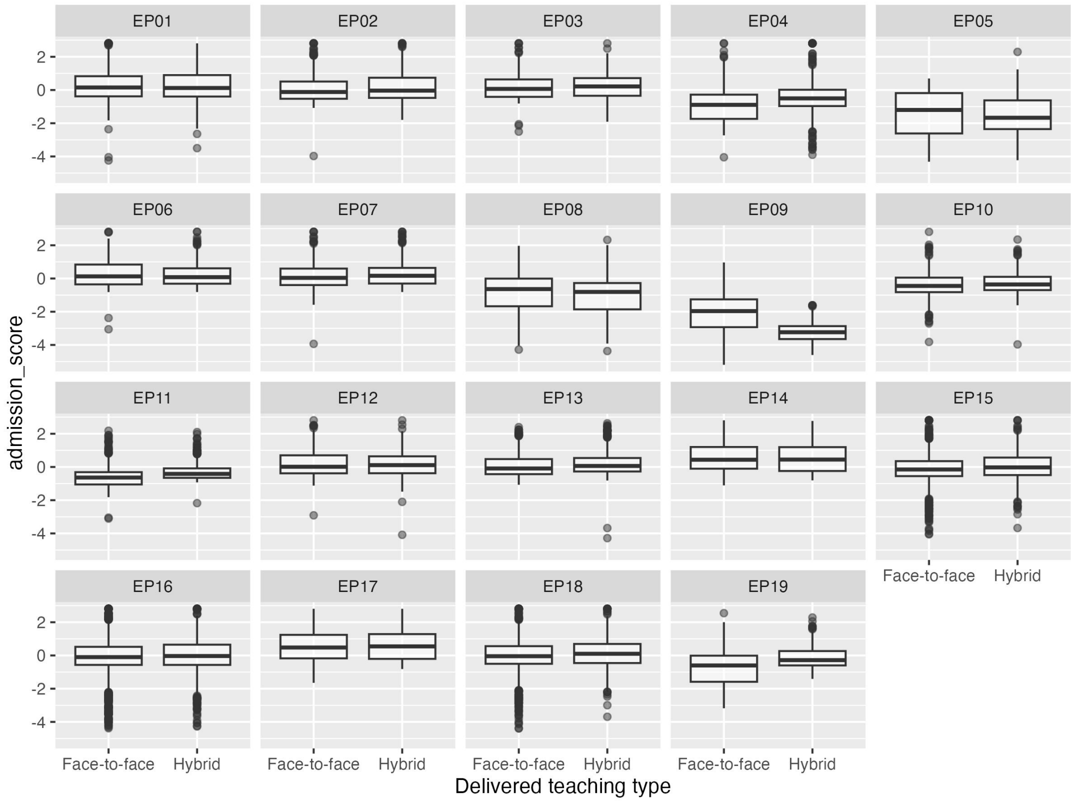


Figure 3.: Distribution of `admission_score` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

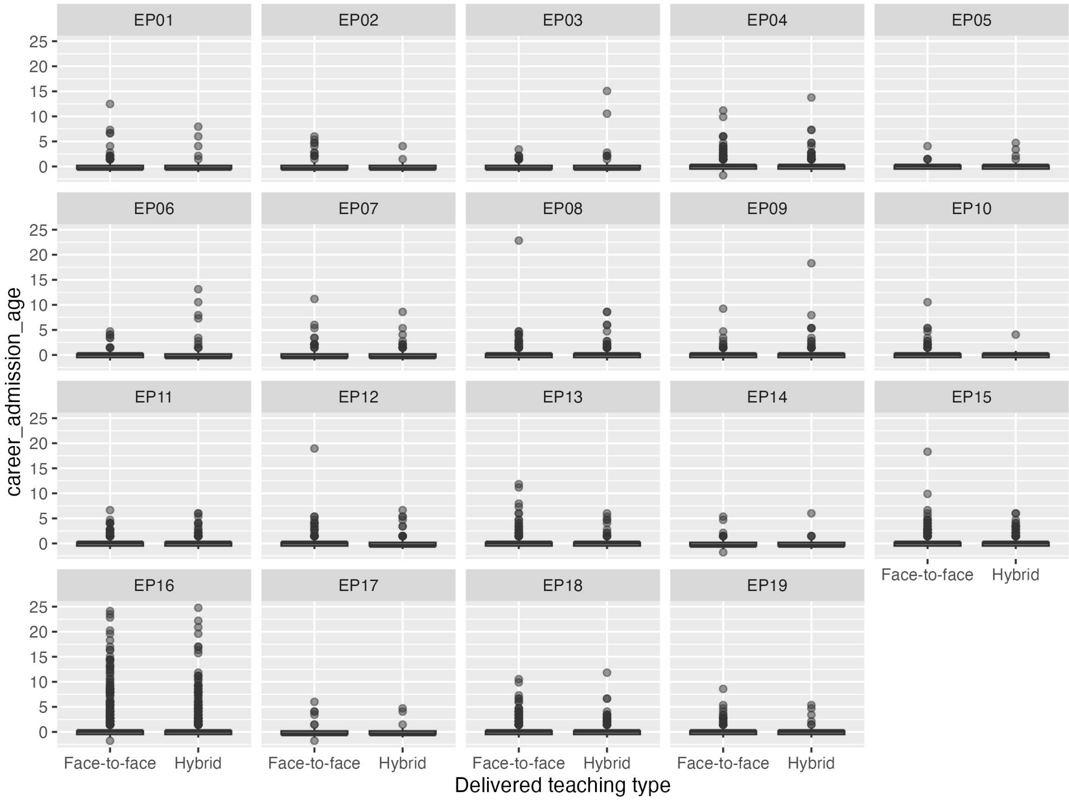


Figure 4.: Distribution of `career_admission_age` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

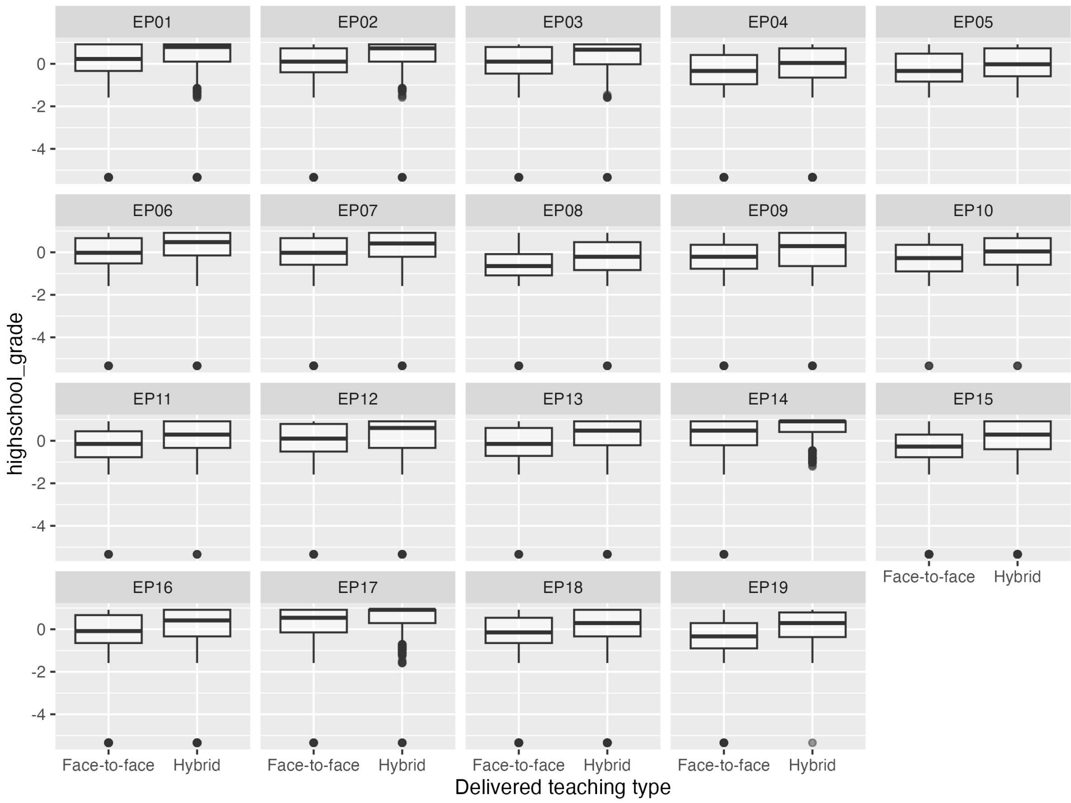


Figure 5.: Distribution of `highschool_grade` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

Figure 6.: Distribution of `origins` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

Figure 7.: Distribution of `gender` covariate across EPs according to delivered teaching type (`hybrid_teaching`).

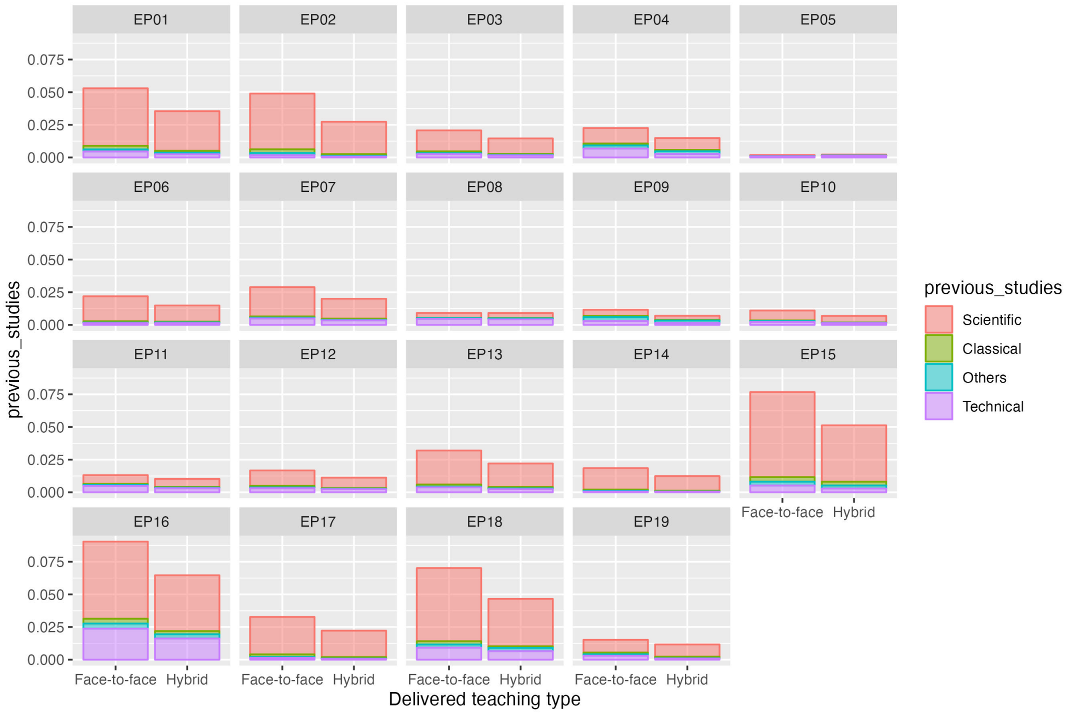
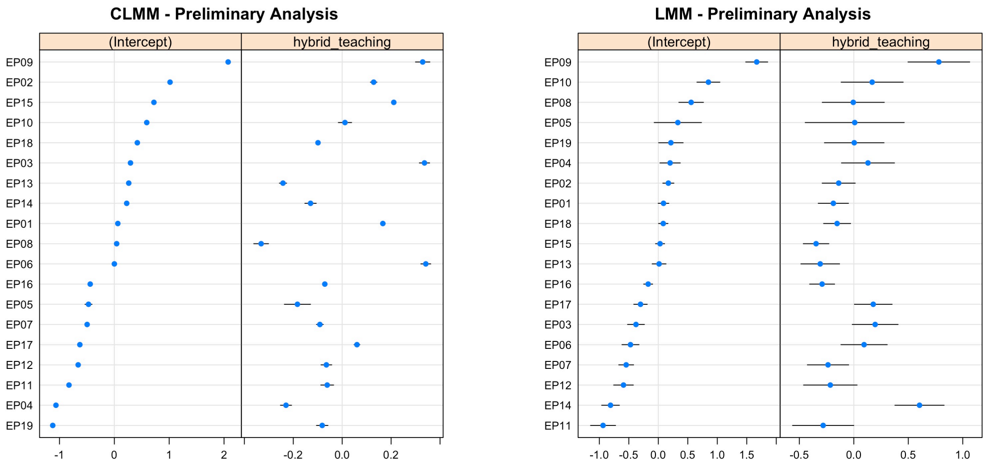


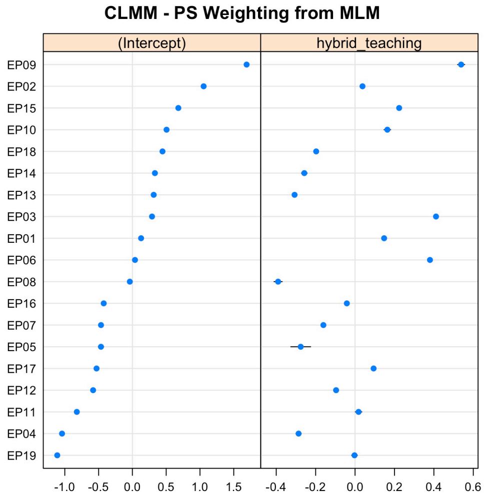
Figure 8.: Distribution of `previous_studies` covariate across EPs according to delivered teaching type (`hybrid_teaching`).



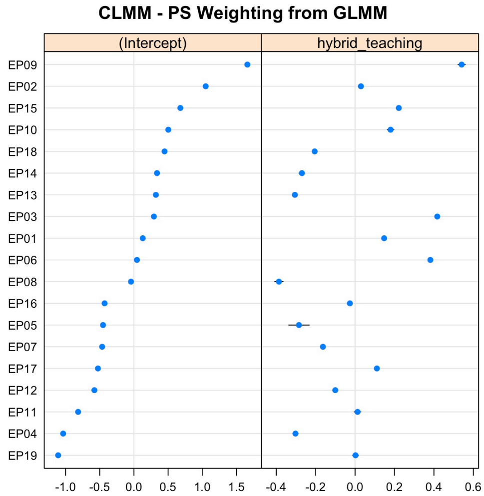
(a) CLMM - Outcome is `ECTS_cat`

(b) LMM - Outcome is `GPA`

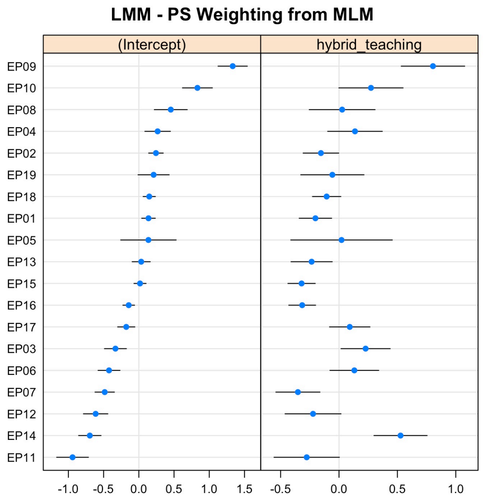
Figure 9.: Random intercept and slope for each EP (y-axes) for the model fitted prior PS correction.



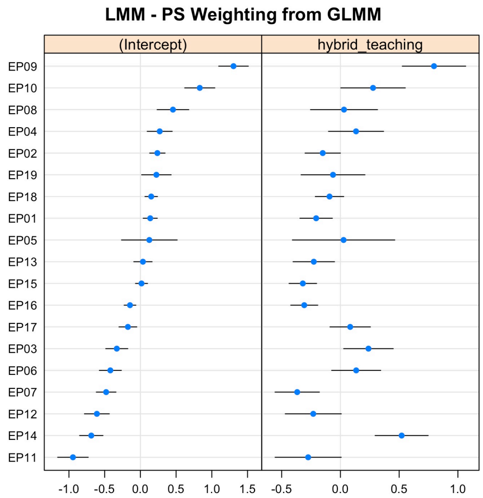
(a) CLMM for `ECTS_cat` in PoliMi - PS estimated through MLM



(b) CLMM for `ECTS_cat` in PoliMi - PS estimated through GLMM



(c) LMM for `GPA` in PoliMi_GPA - PS estimated through MLM



(d) LMM for `GPA` in PoliMi_GPA - PS estimated through GLMM

Figure 10.: Random intercept and slope for each EP (y-axes) for the outcome models fitted after *PS Weighting*.

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