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The Promise and Limits of Digital Nudges: Personalized School Recommendations in Recife's Centralized Admission Platform *

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Abstract

Despite improvements in access to information, digital platforms, and centralized school admission systems, many parents continue to choose seemingly lower-quality schools, often prioritizing proximity over academic performance. We examine the role of information provision in this context through a randomized controlled trial (RCT) within the centralized admission platform of Recife, Brazil – testing whether personalized school recommendations influence parental choice. Specifically, we implemented two treatment arms: one offering recommendations that ranked schools by quality within a defined distance (quality treatment), and another ranking schools solely by proximity (distance treatment). While the overall impact of the treatments was limited, we do find meaningful positive effects among users who actively engaged ("compliers") with the recommendations (14–24% of families). Compliers in the quality treatment were more likely to select higher-performing schools, particularly among first-grade applicants and families without strong prior preferences. These findings underscore both the promise of digital nudges in improving school choices and the challenges of deploying such tools in recently centralized systems, where many families enter with preset preferences and limited familiarity with the process.

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1 Introduction

Centralized school admission systems have emerged as a policy response to unequal access to schools – often stemming from families' limited access to clear and reliable information about available options. These systems are designed to improve transparency and equity by providing families with a structured and comprehensive set of school choices (Elacqua et al., 2021; Hastings and Weinstein, 2008; Valant and Weixler, 2022). Despite improvements, disparities in school choice outcomes persist. Families from disadvantaged backgrounds, in particular, face barriers in navigating these systems, such as difficulties accessing or interpreting detailed information about schools. Even when performance data are available, many of these parents continue to prioritize proximity and other non-academic factors, limiting the ability of centralized systems to reduce inequality in school assignments (Hastings and Weinstein, 2008; Ajayi, 2022; Elacqua and Kutscher, 2023; Elacqua et al., 2024).

One policy tool that has shown promise in addressing these challenges is the use of nudges. Specifically, by improving access to relevant information and restructuring the ways options are presented, nudges can influence family choices in ways that promote equity (Ajzenman et al., 2021; Hastings and Shapiro, 2009; Elacqua et al., 2024; Borger et al., 2024; Andrabi et al., 2017). For instance, Ajayi (2022) shows that well-designed nudges can reduce inequalities in the school choice process by encouraging families to consider higher-quality institutions. Informational interventions, in particular, have proven effective for disadvantaged families—who often prioritize less selective schools—by prompting them to expand the range of options they consider. The growing use of digital platforms for school admissions creates new opportunities to design and deliver such nudges. Simple interface modifications, such as reordering options or adding filters aligned with family preferences, can be implemented at low cost and adapted quickly to user behavior (Caraban et al., 2019; Sunstein, 2016).

This paper examines the impact of digital nudges in a centralized school admission system through a large-scale experiment conducted in the online school admission platform of Recife, Brazil. The intervention was designed to reduce information frictions in the enrollment process. Specifically, we implemented a recommendation engine that generated personalized school suggestions addressing both families' practical needs (e.g., proximity to home) and policy goals (enrollment in higher-performing schools). By presenting this information in an accessible format, the aim was to guide families toward more informed and deliberate choices.[1]

Recife offers a particularly relevant context. Until 2022, admissions operated on a first-come, first-served basis, creating a strong sense of urgency among parents. In 2022—the first year of *Digital Enrollment*—parents spent an average of just three minutes on the platform, underscoring the need for

[1] The literature on recommendation engines examines techniques and algorithms for suggesting relevant items to users based on their preferences or behaviors. Applications such as Netflix, iFood, and Uber Eats use recommendation engines to personalize user experiences and suggest movies, meals, or services.

interventions that guide decision-making more effectively.

Our study builds on a previous experiment conducted in Recife's centralized admission platform, which examined family behavior during the school enrollment process (Elacqua et al., 2024). The findings revealed that ranking schools by quality significantly influenced families' choices, particularly among first-grade applicants living near the top three schools, with effects diminishing as distance from home increased. These results suggest that school quality does matter to families, especially when combined with proximity; aligning interventions with both user priorities and local context is thus important.

With these insights in mind, our experimental design tests two specific recommendation approaches. In the first treatment arm, families were presented with the highest-performing schools in Recife (top 40% based on state assessment results) ranked by proximity to the student's residence. In the second treatment arm, schools were ranked solely by proximity, regardless of performance. The interface visually emphasized these rankings, while the recommendation engine generated a customized set of options for each student based on location and stated preferences (shift, education level, and grade). This approach highlighted potentially overlooked school characteristics—particularly quality metrics that, as prior research shows, often represent new information—prompting parents to update their impressions of institutions (Valant and Weixler, 2022). In the control group, families proceeded without recommendations. Importantly, all school options remained available to families, preserving freedom of choice while strengthening the choice architecture to facilitate more informed decisions.

Given the positive effects observed in our previous experiment with order effects, our outcomes surprisingly indicate that the recommendation "carousel" - a feature that displayed multiple school suggestions simultaneously in a browsable format - did not significantly influence school application patterns. Several factors may explain this outcome: (1) the recommendation carousel may not have been sufficiently prominent within the platform interface; (2) a simple ordering of options (as in our previous experiment) may have a stronger behavioral impact than personalized recommendations; and (3) most critically, our data show that nearly all parents logged into the application platform only once, spent an average of just three minutes on the site, and the great majority (approximately 75%) had already decided on a specific school before accessing the system. These user behaviors suggest limited engagement with the platform's recommendation features.

Nonetheless, a subgroup analysis reveals interesting potential for this recommendation strategy. First, there is substantial room for improvement in school selection: 76% of families in the quality treatment group had higher-quality school options available than put forth in their initial selection, and a similar percentage in the distance group had closer schools available. Second, when examining the subset of parents who actively engaged with recommendations (defined as those who added at least one of the suggested schools to their application list - i.e., "compliers"), we observe significant positive effects. Specifically, parents in the quality-based treatment group who followed the recommendations saw substantial improvements across all quality metrics: in their applications they selected and ranked better-rated schools higher in their preference ordering, included more schools in the top 40% of the IDEPE ratings, and increased the overall average quality of their school selections. Importantly, we also observe positive impacts on distance-related outcomes, suggesting that parents who followed the recommendations were more likely to choose higher-quality schools, even when those schools were farther from their homes. This indicates that the recommendations helped families make more informed quality-proximity tradeoffs and prioritize educational quality when presented with clear information.

This paper contributes to a growing body of work on the impact of informational nudges in education. Existing research shows that families can make more informed school choices when provided with personalized, real-time recommendations during the application process. However, the strength and direction of these effects vary depending on location, institutional features, and socioeconomic context (Weinmann et al., 2016).

In the U.S., Hastings and Weinstein (2008) demonstrate that providing families with information about school performance significantly increases the likelihood of selecting higher-performing schools. Importantly, the effect was strongest when high-quality alternatives were geographically close, underscoring the important role of proximity in families' reactions to new information. Elacqua et al. (2024) observe a similar pattern in Recife: quality-based school ordering most strongly influenced the decisions of first-grade applicants living near top-performing schools.

While our study focuses on individual-level nudges within a centralized platform, broader evidence from market-wide interventions helps illuminate how quality information transforms school choice behaviors across different contexts and scales. In Pakistan, for instance, report cards distributed to all families in treatment villages increased average learning by 0.11–0.13 SD, reduced private fees by 17%, and raised enrollment by 4.5%, with heterogeneous impacts that favored quality improvements among initially lower-performing private schools. These patterns were predicted by canonical asymmetric-information models, where better signals compress price–quality gradients (Andrabi et al., 2017). Such market-level effects demonstrate that when quality information becomes widely available, it can fundamentally reshape both family choices and school behaviors.

In Haiti, a market-level RCT disclosing school test results likewise raised private-school test scores, shifted enrollment toward higher-baseline schools, and—differently than in Pakistan—was accompanied by fee increases at those higher-baseline private schools, yielding a post-disclosure positive price–quality correlation in treated markets (Borger et al., 2024). This outcome suggests strong demand-side sorting when families observe credible quality signals, reinforcing our hypothesis that providing clear performance information through digital platforms could likewise guide families toward higher-quality options, even if the effects may be more modest in a public school system with fixed capacities and no price mechanisms.

Recent evidence also highlights the importance of how information is presented to families. For example, Glazerman et al. (2020) show that small design manipulations on school choice platforms—such as changing the default order of schools, replacing numerical displays with icons or graphs, or concisely summarizing information—can meaningfully shift parents' selections toward higher-performing schools. These findings underscore that not only the content but also the salience and format of recommendations matter for behavioral response.

However, the effectiveness of information provision depends critically on the broader institutional context. In Chile, Gallego (2004) provide mixed evidence on the effects of school choice. While greater competitive pressure from nearby schooling alternatives generally improves exam scores, the benefits are concentrated among students in subsidized private schools. For students in public schools facing fewer competitive pressures, the effects are negligible or even negative, suggesting that institutional incentives and resource constraints shape the effectiveness of choice-based reforms. This contextual sensitivity is directly relevant to our setting in Recife, where we examine digital nudges within a recently centralized public school system with fixed capacity constraints and families still adapting to the new allocation mechanism.

By embedding digital nudges directly into a centralized online platform, our study extends this literature in two ways. First, it tests the potential of recommendation engines—a tool widely used in consumer markets but rarely adopted in education—to support families in their decision-making. Second, it provides large-scale experimental evidence from a middle-income country context, where disparities in access to information and constraints on school supply may alter how families respond to nudges.

The remainder of this paper is organized as follows. Section 2 provides institutional background on Brazil's education system and Recife's transition to centralized digital enrollment. Section 3 describes our experimental framework, including the design of the two recommendation treatments and the randomization procedure. Section 4 presents the data sources, sample construction, and descriptive statistics on applicant characteristics and school choice patterns. Section 5 outlines our empirical strategy, including both intention-to-treat (ITT) and local average treatment effect (LATE) specifications. Section 6 reports our main results, heterogeneous effects by grade level and compliance status, and survey-based evidence on parental preferences. Section 7 concludes with a discussion of policy implications and directions for future research.

2 Institutional Background

Public education in Brazil comprises three levels: preschool (*Educação Infantil*), primary education (*Ensino Fundamental*), and secondary education (*Ensino Médio*). This multi-tiered system operates under a divided governance structure, where municipalities primarily manage early childhood and elementary education up to the fifth grade with limited vacancies for higher grades, while states oversee high school and the final years of elementary education. This administrative division makes it difficult to manage school seat availability, student allocation, and ensure equitable access across the system.

Within this broader context, the enrollment process in Recife has undergone significant changes in recent years. As in most Brazilian cities, school enrollment previously took place in person, with families applying directly at schools. The digitalization of municipal services led to the adoption of an online enrollment system, which initially replicated the in-person model by allocating seats on a first-come, first-served basis. While this digital transition seemed to make the process more efficient and equitable, ultimately it reproduced – and in some cases amplified – existing inequalities. Compared to families in more vulnerable situations, those with reliable internet access and greater digital literacy were better positioned to secure desirable placement.

Technological inequalities compounded existing challenges in the enrollment process, such as the assignment of siblings to different schools and the difficulties faced by children with disabilities needing to secure a seat near their homes. These issues disproportionately affected families in vulnerable situations who often lacked the resources to effectively navigate the system.

From a behavioral perspective, the historical perception of limited available seats in high-demand schools created problematic decision patterns. Families typically accessed the system immediately upon its opening, often rushing through the application process without carefully considering detailed information about the schools. In other words, the in-person application mentality was replicated in the online version, compromising the rationality of the decision-making process and leading families to suboptimal school choices. Such behavior is particularly relevant for our study of recommendation engines, as it limits families' engagement with potentially beneficial information.

The enrollment system also operated within a complex political environment. Community leaders and school administrators claimed to have sway over seat allocation, encouraging families to seek enrollment through informal channels. Additionally, the Child Protection Council (*Conselho Tutelar*) frequently intervened to guarantee school access for children without seats, especially those with disabilities, pressuring public administration for urgent solutions. These external influences further complicated efforts to establish a transparent school admission system.

Historical resource constraints have also shaped family behaviors and expectations, particularly a shortage of seats in early childhood education (i.e., daycare). Although elementary education did not face the same scarcity, families had internalized a competitive logic, and continued to act with a sense of urgency when seeking to secure a seat in schools perceived as of higher quality. Administrative data confirms that the public education system provided an adequate number of vacancies for primary education. Though, these seats were not equitably distributed across the territory.

Geographic and transportation factors also pose additional challenges in Recife, a densely populated city with limited public transport infrastructure. The city's hilly terrain and varied topography further complicate access, as geographic conditions are not always favorable for efficient public transportation routes. Although students benefited from transportation discounts or free passes, parents did not receive the same provision, making distance an important criterion in school selection.

2.1 Matrícula Digital Policy

To address these inefficiencies and inequalities, Recife's city government restructured the enrollment system in 2022, implementing the *Matrícula Digital* platform. This change replaced the first-come, first-served model with a centralized allocation mechanism based on objective prioritization criteria.

The redesigned platform fundamentally changed how families interacted with the enrollment process. The new system allowed parents to select multiple schools within a designated period, after which a deferred acceptance algorithm allocated students based on their preferences, priority criteria, and seat availability.

Several technical improvements enhanced system integrity and fairness, while the mandatory use of the student's CPF (Brazilian unique identification number) eliminated the possibility of multiple registrations for the same child. Prioritization criteria were established, including residence in Recife, siblings already enrolled in the chosen school, disability or special needs status, children under state care, vulnerability (i.e., registration in CadÚnico, the federal government's database for social programs), and school proximity. Although families self-declared this information during registration, enrollment was only confirmed upon presenting supporting documentation.

Beyond technical improvements, the system incorporated behavioral design principles to facilitate the selection of higher-quality schools located closer to families' residences, addressing informational asymmetries and reducing the tendency of families to make rushed decisions, effectively implementing a nudge strategy. Implementation was furthermore accompanied by an experiment to assess the effectiveness of these digital nudges. The results reported in Elacqua et al. (2024) indicate that ranking schools by quality significantly influenced families' choices, particularly among first-grade applicants living near the top three schools, with effects diminishing as distance from home increased.

This experience demonstrates that transitioning from a first-come, first-served model to a centralized system can help reduce access inequalities and improve seat distribution efficiency. However, it also shows that the effectiveness of digital nudges depends on an adequate supply of quality schools within families' geographic reach, thus underscoring the importance of aligning interventions with both user priorities and local context.

Learning from these initial results, the intervention in the *Matrícula Online* system was refined in 2023 to improve the interaction between proximity and quality in school recommendations. Key changes included adjustments to the system's interface, new recommendation criteria, and the introduction of more detailed information on school infrastructure and performance. These refinements form the foundation of our study of personalized recommendation engines.

3 Experimental Framework

The experiment was implemented during Recife's 2023 *Matrícula Online* process, which encompassed all students applying for municipal school vacancies.

Our intervention aimed to reduce information asymmetries, thus helping families increase their chances of securing their preferred spot - ideally in a higher-performing institution. We tested two main hypotheses: (1) *General recommendation effect*: presenting school recommendations - regardless of content - will influence parental choices by increasing the number of schools selected and improving the probability of enrollment; and (2) *Quality recommendation effect*: specifically recommending high-quality schools near students' residences will prompt families to choose better schools, increasing applications to top-performing institutions and the likelihood of enrollment in these establishments.

Upon entering the application platform, users were randomly assigned to one of three experimental groups using a seeded randomization process. This ensured that guardians registering multiple students or returning to the platform remained in their original group, preventing sample contamination. Users were unaware of their assignment, as randomization occurred in the system's backend.

We designed three experimental groups: (1) Control: families proceeded without recommendations; (2) Treatment 1 (Quality Recommendation): a carousel displayed only high-performing schools (top 40% according to IDEPE scores)[2] ranked by proximity within three kilometers; and (3) Treatment 2 (Distance Recommendation): a carousel presented schools solely by proximity, without considering the quality measures. Recommendations were visually highlighted and organized to facilitate comparison. For the Quality Treatment Group, IDEPE score thresholds were set at 4.98 for primary grades and 4.2 for upper elementary grades.[3] Within this subset, schools were ordered by proximity. The carousel displayed five schools at a time, loading the next sequence once all were selected and automatically excluding previously chosen schools.

Two main limitations could affect interpretation. First, an uneven geographic distribution of high-quality schools creates variation in access: some neighborhoods have multiple high-performing schools within walking distance, while others require travel by car or bus. Second, families often have prior knowledge acquired through social networks, personal experience, or school reputation, which could amplify or counteract the recommendations.

[2] IDEPE (*Índice de Desenvolvimento da Educação de Pernambuco*) measures school quality using standardized test scores and student progression rates.

[3] Based on 2022 data, 81.25% of students had at least one higher-quality school within 3 km of their homes.

To explore possible mechanisms underlying families' choices, we also administered a post-application survey before the allocation results. This survey collected information on prior knowledge, distance-quality preferences, and perceived influence of platform recommendations. Combining survey responses with enrollment data allows us to examine how different families responded to digital nudges and whether the intervention shifted preferences toward higher-performing schools, while also accounting for prior information and platform usability.

3.1 Experiment Details

After logging in, parents, guardians, grandparents, adult siblings, or another responsible adult provided their personal information, followed by student details, desired grade, and preferred school shift (morning, afternoon, evening, full-time, or all).[4] A single guardian could register multiple students.

Once registered, guardians were randomized into the Control (C), Quality Treatment (T1), or Distance Treatment (T2) group. All groups could scroll through the school list or use a search function. By default, schools were ordered by walking distance from the provided address, calculated using Google walking routes. Clicking a school opened a pop-up card with the school's name, address, IDEPE score, and additional details (Figure A1a).

The first school clicked by a user, the *trigger school*, activated the recommendation system for T1 and T2. In T1, a carousel displayed schools ranked by both proximity to the student's address and IDEPE score; in T2, schools were ranked solely by proximity. The Control group saw no carousel. If the top recommendation matched the trigger school or had already been selected, the next-best alternative was shown. Users could explore carousel options, though the platform did not record clicks within the latter. Users freely selected schools, ranked their preferences (Figure A2), and reviewed their submission (Figure A3). The platform remained open for four weeks, during which time guardians could modify their choices.

4 Data

The information extracted from the enrollment platform is organized around its three main user profiles: guardians, students, and schools. Unique identifiers – the CPF for guardians and students, and the INEP code for schools – enable consistent merging across datasets.

Guardian data captures information provided during initial platform access, when the individual

[4] In Brazil's public education system, school shifts accommodate different schedules: morning and afternoon shifts are standard for primary education, with each providing the constitutionally mandated minimum of four hours of daily instruction. Full-time shifts offer extended instruction and are becoming more common. Evening shifts primarily serve adult education programs (Educação de Jovens e Adultos - EJA) for students who could not complete their studies at the appropriate age. Parents could also select "all" to indicate flexibility across available shifts.

responsible for enrollment (typically a parent, guardian, or student over 18) creates a login. It includes personal and contact details, including full name, CPF, and phone number or email.

Student data contains demographic information such as reference address, full name, CPF, date of birth, race, ethnicity, disability status, and guardian linkage. It also includes educational preferences and priority criteria, recording the intended education level, grade, preferred shift (full-time, morning, or afternoon), and eligibility for priority allocation (e.g., CadÚnico registration or government custody).

Recommendation data documents experimental group assignment and user interactions with the recommendation system. For treatment group participants, it records both the trigger school (i.e., the first school selected) and the subsequent recommendations displayed by the carousel.

Application data tracks the full school choice process. It indicates whether each selected school came from the general list or the recommendation carousel and records the final ranked preferences. Here, the student's CPF is used as the unique identifier.

We complement these platform-generated datasets with three additional sources: (1) vacancy data, containing school-level seat availability; (2) a complete registry of schools in the system; and (3) a post-application survey, administered after applications closed but before results were released. The survey includes unique user identifiers, allowing it to be merged with platform data, and provides information on prior knowledge, preferences, and perceived influence of recommendations.

Together, these interconnected datasets provide a comprehensive account of the enrollment process, from initial registration to preference formation and school selection.

4.1 Descriptive Statistics

This section provides an overview of the study sample and descriptive patterns, allowing to contextualize the experimental analysis. We begin by describing the dataset and sample selection criteria, and then characterize the student population. We next examine the spatial distribution of schools and applicants, before turning to descriptive evidence on school supply, application patterns, and engagement with the platform. Finally, we document how families interacted with the recommendation system, distinguishing between ”compliers” and ”non-compliers” and comparing placement outcomes across treatment groups.

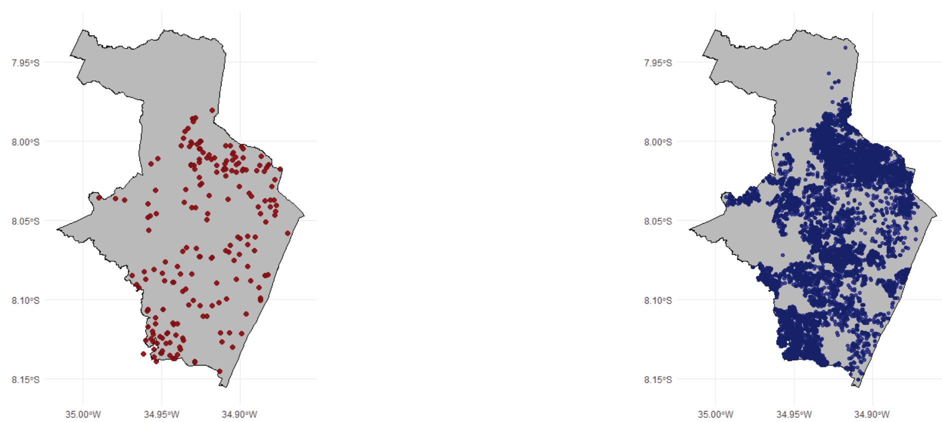
The original dataset includes information on 14,772 students who participated in the admission process. We exclude students under government custody, since their placements are administratively assigned, and restrict the analysis to primary school students, removing those in early childhood or adult education programs.[5] After these restrictions, the analytical sample comprises 8,631 students and 12,034

[5] Early childhood education is excluded because Recife faces acute shortages in this sector and applies prioritization rules that differ from those used in primary education. Adult education programs are excluded as they tend to have excess capacity, are offered in relatively few schools, and include a mix of independent student applicants (aged 18 or older) and parents applying on behalf of their children.

program-school applications. That is, each application corresponds to a specific program or shift at a school (e.g., applying to both the morning and afternoon shifts at the same school counts as two applications).

Figure 1 displays the geographic distribution of students and schools in the *Matrícula Digital* process. Municipal schools are concentrated in the southwest and western zones, while the northern and eastern zones have fewer schools. The north includes wealthier neighborhoods with a higher concentration of private schools, while the east is dominated by commercial districts and environmentally protected mangrove areas, limiting municipal expansion. Low-income neighborhoods are mostly located in hilly areas or along rivers and canals. Although students are spatially dispersed, their distribution broadly mirrors school supply, suggesting that public infrastructure follows population density.

Figure 1: Geographic distribution of students and schools in Recife's *Matrícula Digital*



(a) Schools **(b)** Students

Note: Panel 1a displays the spatial distribution of schools that offered vacancies in the 2022 admission process. Panel 1b illustrates the spatial distribution of applicants in Recife.

Table 1 summarizes baseline characteristics. Among the 8,631 students, 58% are enrolled in CadÚnico and 7% report special needs. The gender distribution is balanced (48% female), and the majority (70%) identify as Black (combining Black and Brown). Over three-quarters of students are in the initial years of elementary education, consistent with the fact that middle school is also served by the state system.[6]

[6]Comparing 2023 to 2022, we observe a modest increase in the share of students classified as poor (58% vs. 55.8%) and with special needs (7.2% vs. 4.7%). The grade distribution remains stable, with a small increase in the share of students in the initial years (75.7% vs. 73.7%). Data on gender and race are not available for 2022.

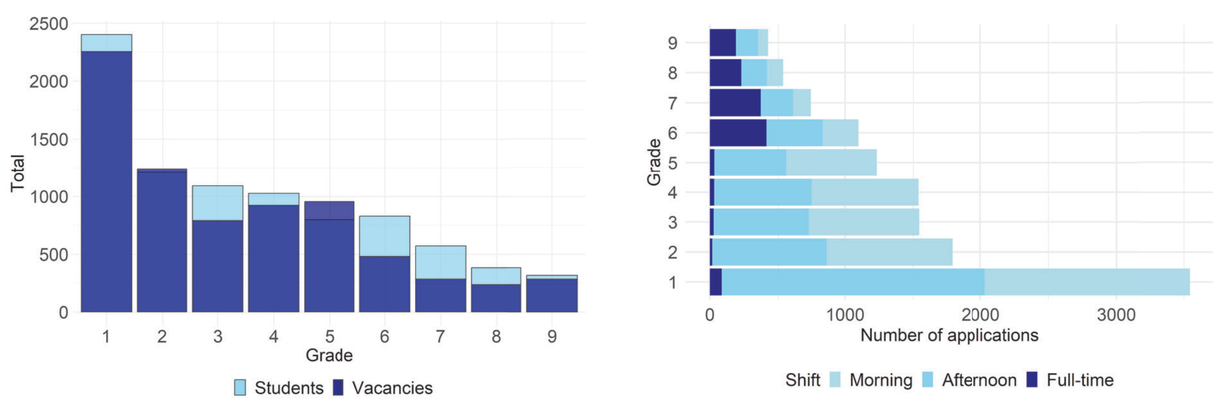
Table 1: Descriptive statistics of applicant baseline characteristics

	Mean	Std. Deviation	Min.	Max.
Student characteristics				
Poverty	0.580	0.493	0.00	1.00
Disability	0.072	0.259	0.00	1.00
Female	0.480	0.500	0.00	1.00
Black	0.700	0.458	0.00	1.00
Grade				
Initial years	0.757	0.429	0.00	1.00
Final years	0.243	0.429	0.00	1.00

Note: This table displays the mean, standard deviation, minimum, and maximum of 8,631 students' baseline characteristics. It also provides statistics for the proportion of students in each grade.

Figure 2a shows the distribution of available seats and applicants by grade. The largest share of seats is offered in grade 1 (29.5%), followed by grade 2 (16.3%). Grade 1 alone accounts for nearly one-third of both applications and seats. In Figure 2b, we observe that shift preferences vary systematically by grade: morning and afternoon shifts dominate in the early years, while full-day schooling becomes more common in later grades.

Figure 2: Descriptive statistics, by grade and shift



(a) Number of applicants and vacancies

(b) Number of applications, by shift

Note: Panel 2a shows the number of applicants and vacancies by grade. Panel 2b illustrates the number of applications by grade, segmented by shift.

4.1.1 Recommendation System

In our experimental design, the recommendation carousel was activated only when a user clicked on a school to view more details. The first school clicked in each session is defined as the "trigger school." This action served as a signal of interest and was required for the system to generate recommendations, since the platform could not otherwise distinguish between passive browsing and active search behavior.

Table 2 shows whether the recommendation was better than the trigger school (i.e., closer to the student's address or higher quality). The results align with expectations: in Group T1, 76.1% of recommended schools had a higher IDEPE score than the trigger school, while in Group T2, 58% of recommended schools were located closer to the student's residence compared to the distance of the trigger school.

These findings demonstrate the system's ability to suggest schools more closely aligned with the intended criteria – especially in Group T1.[7] While families often had an idea of the characteristics of nearby schools, the system generally provided better suggestions. Most notably, in Group T1, it was able to suggest both better quality and proximity options in a large share of the recommendations (76.1% and 75.9% respectively), underscoring its potential to provide support for more informed decision-making.

Table 2: Recommendation accuracy: trigger school vs. first recommended school

(A) Scenario: the recommendation engine suggests a better quality school than the trigger school			(B) Scenario: the recommendation engine suggests a closer school than the trigger school		
	T1: Quality	**T2: Distance**		**T1: Quality**	**T2: Distance**
The recommended school has a higher IDEPE score than the trigger school	76.1%	46.2%	The recommended school is closer than the trigger school	75.9%	58.0%
N*	1,934	1,885	N*	1,934	1,885

Note: To guarantee a fair comparison, we disregard observations from schools with missing or zero IDEPE scores in the analysis (approximately 5% of schools in Recife).

One concern is whether the recommended schools might garner higher demand due to their greater visibility via the carousel. However, we find no evidence of such an effect, as detailed in the analysis presented in Appendix B.

4.1.2 Application Patterns

Despite a one-month application window allowing multiple logins to review and modify school choices, platform usage data indicate that 99% of users accessed the system only once during the selection process. Survey evidence furthermore indicates that 75.6% of families had already decided on a school before logging in (see Figure A6). This helps explain why about 73.5% of students applied to only one school[8].

Taken together, these data suggest that many families had predetermined their school choices before using the platform, reducing the need for repeated access but also limiting the potential impact of

[7] Although Group T1 prioritized quality, it only included schools within a 3 km radius

[8] In total, 6,345 selected only one school on their application list, a number consistent with the survey findings (Figure A7)

the recommendation system. While the survey sample may be biased toward more engaged users, it nonetheless provides valuable insights for interpreting platform behavior.

Application patterns among students are displayed in Table 3. The average IDEPE score of schools listed in applications was 4.99 for early grades and 4.14 for later grades. Meanwhile, families chose schools located an average of 1.9 km from their homes and listed only 1.4 schools.

Table 3: Descriptive statistics, student applications

	Mean	Std. Deviation	Min.	Max.
IDEPE	4.787	0.679	3.24	7.88
IDEPE (initial years)	4.995	0.605	3.51	7.88
IDEPE (final years)	4.146	0.461	3.24	5.87
Proximity (km)	1.880	2.223	0.00	21.28
# Applications	1.415	0.839	1.00	12.00

Note: This table displays the mean, standard deviation, minimum, and maximum of 8,631 students' baseline outcomes.

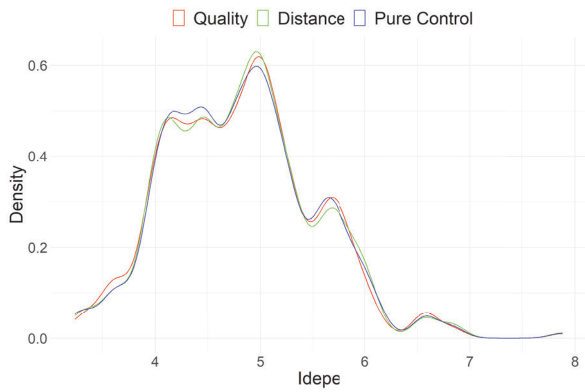
Table 4 presents descriptive statistics of application patterns across treatment groups. The average IDEPE score of chosen schools is very similar, with comparable standard deviations. Similarly, the share of applicants who listed at least one school ranked among the top 40 percent of the IDEPE score distribution is only slightly higher in the Quality group (46.9%) compared to the pure Control group (45.8%). Regarding proximity, the average distance of listed schools is somewhat lower in the treatment groups – particularly in the Distance group. While these differences suggest recommendation effects, they are small in magnitude. The average number of schools listed per applicant are also similar across groups. These findings suggest that, despite differences in the recommendation criteria, average patterns of school choice are largely comparable across groups at the aggregate level. We also display these distributions in Figure 3.

Table 4: Descriptive statistics, by treatment group

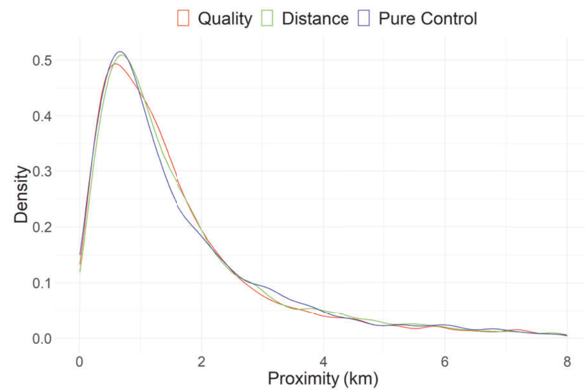
Variable	Pure control	Quality	Distance	Pooled
IDEPE top 1	4.785	4.790	4.799	4.794
	(0.712)	(0.717)	(0.713)	(0.715)
Mean IDEPE	4.785	4.783	4.791	4.787
	(0.681)	(0.680)	(0.677)	(0.678)
IDEPE top 40	0.458	0.469	0.460	0.464
	(0.468)	(0.468)	(0.464)	(0.466)
Mean proximity (km)	1.908	1.872	1.861	1.866
	(2.342)	(2.195)	(2.137)	(2.165)
Proximity top 1 (km)	1.795	1.754	1.751	1.752
	(2.299)	(2.166)	(2.117)	(2.141)
# Applications	1.396	1.411	1.437	1.424
	(0.852)	(0.811)	(0.853)	(0.833)
Number of students	2,791	2,874	2,966	5,840
Number of applications	3,893	3,979	4,216	8,195

Note: This table shows the mean and standard deviation per treatment group for the 8,631 baseline students.

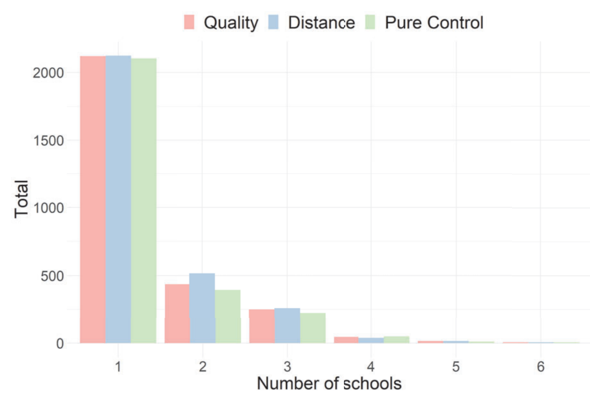
Figure 3: Outcomes distribution, by group



(a) Idepe



(b) Proximity (km)



(c) # applications

Note: Panel 3a shows the distribution of IDEPE scores for all schools applied to, by treatment group. Panel 3b presents the distribution of distances for all schools applied to, also by treatment group. Panel 3c displays the number of schools applied to by treatment group. The outliers are ignored in the bar graph and the IDEPE and proximity curves.

Table 5 presents the profile of submitted applications by treatment group. The majority (around 70%) applied to only one school, which had not been recommended. In contrast, those applicants who did include at least one recommended school in their application list tended to list two or more schools, suggesting higher engagement with the school choice process. Specifically, among applicants who listed two or more schools and included at least one recommended school, almost all had at least one recommended school on their list that was both of higher IDEPE score and closer compared to the non-recommended ones (see Panel 3B of Table 5).[9]

[9] The percentage is not quite 100% because among the applicants with two or more schools and at least one recommended one, two listed only recommended schools, which limited the possibility of comparing recommended versus non-recommended applications.

Table 5: Application profile by group

Variable	Quality	Distance
3A: Preferences distribution		
Application has 1 school, which was not recommended	73.3%	69.8%
Application has 1 school, which was recommended	1.5%	2.6%
Application has 2+ schools and none were recommended	12.7%	6.3%
Application has 2+ schools and at least one was recommended	12.5%	21.4%
3B: School characteristics		
The recommended school is of better quality and is closer	99.4%	99.7%
Observations	2,874	2,966

Note: This table shows application patterns by treatment group. Panel 3A reports the distribution of applications according to the number of schools listed and whether any were recommended, separately for the Quality and Distance treatment groups. Panel 3B presents, among applications with two or more schools where at least one was recommended, the proportion of cases in which the recommended school was both of higher quality and located closer than the non-recommended options. Observations refers to the total number of applications considered in each treatment group.

4.1.3 School Placement

With the application lists finalized, the next question is how many applicants actually secured a vacancy? In this context, "securing a vacancy" refers to being assigned to one of the schools listed in the applicant's online submission. Table 6 presents the distribution of students who were successfully placed in one of their requested schools, showing that approximately 50% of students in each group obtained a desired placement, regardless of whether they were in the treatment or control group. It is worth noting, however, that not all applicants obtained a vacancy through the Matrícula Digital process; those who were not assigned to any of their chosen schools were later allocated through direct contact between the Recife Department of Education and the families.

Among those who secured such a vacancy, a considerable share had followed the recommendation. In the Quality group, 19.1% were compliers, while in the Distance group, 30.6% were compliers.[10]

Although compliers represent only a fraction of the overall sample, they account for a significant portion of those who were successfully placed: over 60% of compliers in both treatment groups secured a vacancy at a recommended school.[11] These findings demonstrate the effectiveness of the recommendation mechanism, which not only guided families toward high-quality or closer schools, but also helped students secure a desired vacancy.

[10] Among recommendation takers who obtained a listed school, 65.4% were in the Quality group and 64.7% in the Distance group.

[11] Specifically, 60.8% of Quality compliers and 66.6% of Distance compliers.

Table 6: Percentage of students who secured a school vacancy, by group

Variable	Pure-Control	Quality	Distance
Students who secured a vacancy, by treatment group	50.4%	47.9%	50.4%
Among students who secured a vacancy:			
A) Recommendation takers with a school placement	–	19.1%	30.6%
B) Recommendation takers placed in a recommended school	–	11.6%	20.4%
Observations			
Recommendation takers	–	402	708
Students	2,891	2,874	2,966
Applications	3,839	3,979	4,216

Note: Group A) corresponds to students who applied to at least one recommended school and secured a school placement (any school), and group B) corresponds to students who applied to at least one recommended school and secured a placement specifically at a recommended school.

4.1.4 Recommendation Takers

Among users who interacted with the recommendation carousel, a notable subgroup emerges: the *compliers*, or recommendation takers, defined as those who applied to at least one recommended school. Since most users ignored the carousel, this group offers valuable insights into the behavior of guardians who engage with recommendation systems.

There were 1,110 recommendation takers: 402 in Group T1 and 708 in Group T2, representing 14% and 24% of each group, respectively. When comparing Table 7, which presents characteristics exclusively for compliers, with the baseline in Table 1, we observe that this subgroup does not differ on average in terms of background characteristics or grade distribution. However, compliers applied to schools with slightly higher average IDEPE scores (4.9 vs. 4.7), chose schools that were farther from their homes on average (2.17 km vs. 1.88 km) and, most notably, listed more schools in their application (2.46 vs. 1.42) (see Table 3). The t-tests in the last column indicate statistically significant differences for disability status, the share of Black students, and grade level (initial vs. final years), suggesting small but non-negligible deviations from the overall population.

Compliers also had a higher placement rate: 65% secured a school placement compared to 49.6% of the overall sample. Most selected more than one recommended school (90%), and nearly all (99.7%) chose recommendations that outperformed non-recommended options in terms of both quality and proximity. These differences emerge more strongly in their application behavior and outcomes (see also Table 3). The t-tests confirm that compliers applied to schools with significantly higher IDEPE scores, chose more distant schools, submitted more choices, and achieved a markedly higher placement rate (all $p < 0.001$).

In addition to comparisons with the overall group averages, we can also examine how participants who followed the recommendation compare to average outcomes when considering only the control group and those in the treatment arm who did not follow the recommendation – that is, the non-compliers. Results show that recommendation takers consistently achieve better outcomes: they choose schools with a higher average IDEPE scores and have a significantly higher placement rate. Unsurprisingly, the results for the treatment group non-compliers closely mirror the overall averages; indeed, non-compliers constitute the vast majority within each treatment group. Consistent with the overall findings, the variables ”Disability” and ”Black” remain positively and significantly associated, though with slightly smaller effects. The ”Grade” and ”Application-characteristics” variables also remain strongly significant ($p < 0.001$).

Table 7: Descriptive statistics of complier characteristics and applications

	Mean			P-val	
	C	N-C	Overall	C vs N-C	C vs O
Student characteristics					
Poverty	0.559	0.583	0.580	0.138	0.192
	(0.497)	(0.493)	(0.493)		
Disability	0.093	0.069	0.072	0.011**	0.026**
	(0.290)	(0.254)	(0.259)		
Female	0.471	0.481	0.480	0.555	0.604
	(0.499)	(0.500)	(0.500)		
Black	0.674	0.704	0.700	0.043**	0.076*
	(0.469)	(0.456)	(0.458)		
Grade					
Initial years	0.785	0.753	0.757	0.016**	0.034**
	(0.411)	(0.432)	(0.458)		
Final years	0.215	0.247	0.243	0.016**	0.034**
	(0.411)	(0.432)	(0.429)		
Application characteristics					
IDEPE	4.903	4.769	4.787	0.000***	0.000***
	(0.576)	(0.692)	(0.679)		
Distance (km)	2.166	1.837	1.880	0.000***	0.000***
	(2.117)	(2.236)	(2.223)		
# Applications	2.463	1.260	1.415	0.000***	0.000***
	(1.043)	(0.679)	(0.839)		
Obtained placement	0.650	0.473	0.504	0.000***	0.000***
	(0.477)	(0.499)	(0.794)		

Note: This table presents the mean and standard deviation (in parentheses) of the characteristics and outcomes for compliant students (C), non-compliant students and control (N-C), and overall sample (Overall). The last two columns report the p-values from two-sample t-tests comparing: (1) compliers vs non-compliers, and (2) compliers vs overall sample.

5 Empirical Strategy

To evaluate the impact of the two distinct recommendation treatments on school selection outcomes, we estimate both Intention-to-Treat (ITT) and Local Average Treatment Effects (LATE).

The ITT captures the effect of being assigned to a treatment group – regardless of whether the recommendations were followed. It provides a policy-relevant estimate of the average effect of offering a recommendation, independent of compliance. The ITT is estimated using the following regression specification:

$$Y_i = \alpha T_i + X_i \beta + \epsilon_i, \tag{1}$$

where Y_i represents the outcome of interest for student i, $T_i = 1$ indicates if candidate i received a recommendation (either treatment group), and the vector X_i includes pre-treatment controls such as disability status, poverty, gender, racial identity, grade level, and school shift preference.

We examine three sets of outcomes. First, we focus on the quality dimension of applicants' choices, measured through (i) the quality of the top-ranked selected school, (ii) the average quality of all selected schools, and (iii) the proportion of selected schools that fall within the top 40 percent of the quality index distribution. Second, we consider proximity-related outcomes, including (iv) distance to the top-ranked selected school and (v) the average distance to all selected schools. Finally, we assess outcomes related to the application scope and placement success, namely (vi) the total number of schools selected and (vii) whether the student ultimately secured a placement in one of their selected schools.

While ITT estimates provide a conservative measure of program impact, they may underestimate the true causal effect among those who complied with the recommendation.

To recover the LATE, we exploit the random assignment as an instrument for actual compliance. Specifically, we estimate the causal effect of following at least one recommendation using a two-stage least squares (2SLS) approach:

$$T_i = \pi Z_i + X_i \gamma + \nu_i \quad \text{(First stage)} \tag{2}$$

$$Y_i = \lambda \widehat{T_i} + X_i \delta + \eta_i \quad \text{(Second stage)} \tag{3}$$

where Y_i is the outcome of interest for student i, T_i is an indicator for actual treatment uptake (e.g., inclusion of a recommended school in the application list), and Z_i denotes the randomly assigned treatment status (recommendation offer). The vector X_i includes pre-treatment characteristics such as disability status, poverty, gender, racial identity, grade level, and school shift preferences. The first stage estimates how random assignment Z_i influences treatment uptake T_i. The second stage recovers the LATE, interpreted as the causal impact of treatment among compliers–i.e., applicants whose behavior changed due to the assignment.

An empirical challenge in evaluating the recommendation mechanism is that not all parents engaged with the system as intended. In practice, many applicants disregarded the suggestions, which dilutes estimated effects. To address this, we complement the main analysis by focusing on recommendation takers, defined as applicants who included at least one recommended school in their submitted preference list. This subgroup captures households that actively engaged with the intervention and therefore provides an opportunity to assess the mechanism's potential impact when used as designed.

Formally, we operationalize this approach by interacting treatment indicators with a binary measure of compliance, distinguishing between compliers and non-compliers within each treatment arm. Unlike ITT and LATE, this is not causal, since compliance is self-selected. Rather, it is a descriptive heterogeneity exercise that illustrates how the intervention operates among those who used it as intended, thus shedding light on the mechanism's potential.

We are especially interested in first-year students, as the greater number of vacancies in this initial year of elementary school enables a more accurate assessment of parental preferences, without capacity constraints. Additionally, parents enrolling their children for the first time may be more receptive to higher-quality school recommendations (Elacqua et al., 2024). Finally, while first to fifth grades are solely managed by the municipality, the state government offers education from sixth to ninth grades. Therefore, families seeking placement in these grades have alternative public school options outside the centralized system, not included in this experiment.

A key limitation of our study is the lack of detailed information on parental behavior during the application process. Specifically, we cannot observe whether parents directly selected a school, explored additional options, or modified their choices throughout the application. This restricts our ability to understand how families interacted with the recommendations. Thus, while our outcomes reflect final school selections, they do not capture the decision-making dynamics or the extent to which the recommendations influenced parents' choices during the process.

Table 8 compares student characteristics across treatment and control groups. Consistent with successful randomization, no significant differences emerge between groups. The balance holds across key characteristics including the percentage of students enrolled in CadÚnico, those with special needs, institutionalized students, and those seeking admission into initial or final years. Table A2 presents a similar result for first-year students: the groups are balanced and the differences are not statistically significant.

Table 8: Balance test

	Control	Quality	P-val C=Q	Control	Distance	P-val C=D	Distance	Quality	P-val D=Q
Disability	0.078	0.071	0.332	0.078	0.069	0.191	0.069	0.071	0.741
Poverty	0.576	0.581	0.706	0.576	0.584	0.547	0.584	0.581	0.823
Female	0.474	0.489	0.264	0.474	0.475	0.980	0.475	0.489	0.268
Black	0.703	0.693	0.419	0.703	0.705	0.867	0.705	0.693	0.322
Initial Years	0.757	0.754	0.765	0.757	0.759	0.846	0.759	0.754	0.617
Morning	0.435	0.457	0.092	0.435	0.449	0.281	0.449	0.457	0.534
Afternoon	0.503	0.496	0.606	0.503	0.502	0.939	0.502	0.496	0.654
Observations	2,791	2,874		2,791	2,966		2,966	2,874	

Note: This table displays the mean and standard deviation of baseline characteristics for both the treated and control groups. The p-value is determined through a t-test of the differences in means.

6 Results

In this section, we present estimates from our main specifications, reporting results for both the ITT and the LATE analyses.

Panel A of Table 9 displays the treatment effects from the ITT estimation. Full regression results including covariates are shared in the Appendix (Table A4). Neither the Quality treatment nor the Distance treatment produced statistically significant effects on the quality of the highest-ranked school, the share of selected schools among the top 40% in the quality index, or the average quality of listed schools. Similarly, we find no effects on measures of school proximity or on the number of schools included in applications.

For enrollment outcomes, we find that the quality-based treatment reduced the probability of securing a seat. This result, however, should be interpreted with caution. For instance, school assignment is a general equilibrium outcome determined by a deferred acceptance algorithm that includes government priorities, meaning that final placements reflect not only individual preferences but also systemic constraints.

Panel B of Table 9 presents the treatment effects from the LATE analysis. Full regression results, including covariates, are provided in Table A7, and the first-stage estimates in Table A6.

When comparing ITT and LATE results, we observe that instrument-based estimates are slightly larger in magnitude, though still statistically insignificant. This similarity between average and local effects can be explained by two interrelated factors. First, low adherence to recommendations: only 14 to 24% of users followed the system's suggestions—meaning that the LATE remain close to the overall average, which primarily reflects the behavior of those who ignored the recommendations. Second, survey data suggests that most guardians had already made their decisions before accessing the platform, strongly reducing the potential influence of the recommendations.

Prior evidence suggests that many families had already formed strong preferences about schools before logging into the platform. As in earlier enrollment process, most, in fact, spent only a few minutes making their selections (Elacqua et al., 2024) – consistent with a perception that acting quickly was a necessity, as in the previous first-come, first-served system. Families may thus have been aware of quality and distance trade-offs but not sufficiently persuaded by the recommendations to reconsider their choices. It is also possible that informational frictions played a role. For example, if the recommendation carousel was not salient enough within the interface, some guardians may not have fully understood its purpose or value (see Appendix A), as opposed to a pop-up or a mandatory section requiring user interaction. The intervention's limited effectiveness might thus in part be explained by entrenched preferences and urgency-driven decision-making.

This convergence between ITT and LATE results reinforces one of the central conclusions of the study: the effectiveness of the recommendation mechanism was severely constrained by both low engagement and pre-existing preferences of families. Although the system theoretically has the potential to improve decision-making by suggesting higher-quality and closer schools, increasing placement chances, and encouraging multiple applications, its practical impact was limited by the context and a reluctance to adjust choices given parents likely strong preferences before logging into the platform.

Table 9: School choice information impact on application outcomes

	School IDEPE			School Proximity (km)			
	1st Ranked	Top 40 Schools	Average	1st Ranked	Average	Obtained Seat	# Applications
Panel A: Intent-to-Treat Effects (ITT)							
ITT – Quality Treatment							
Coefficient	0.008	0.015	0.002	-0.030	-0.031	-0.026**	0.003
	(0.017)	(0.012)	(0.015)	(0.056)	(0.057)	(0.013)	(0.021)
ITT – Distance Treatment							
Coefficient	0.014	0.005	0.006	-0.027	-0.033	0.000	0.032
	(0.016)	(0.012)	(0.015)	(0.056)	(0.056)	(0.013)	(0.021)
Panel B: Local Average Treatment Effects (LATE)							
LATE – Quality Treatment							
Coefficient	0.059	0.106	0.017	-0.222	-0.223	-0.188**	0.026
	(0.118)	(0.085)	(0.107)	(0.412)	(0.410)	(0.093)	(0.150)
LATE – Distance Treatment							
Coefficient	0.061	0.020	0.026	-0.115	-0.140	0.001	0.136
	(0.070)	(0.050)	(0.062)	(0.235)	(0.236)	(0.053)	(0.087)
Control Group Mean	4.785	0.458	4.785	1.795	1.908	0.504	1.396
Observations	8,103	8,103	8,103	8,507	8,623	8,631	8,631

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note 1: Standard errors in parentheses. Panel A shows the intent-to-treat effects of receiving information treatments. Panel B shows the local average treatment effects for compliers who followed the treatment recommendations. Quality treatment provided information about school academic performance. Distance treatment provided information about school proximity.

Note 2: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools in the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Given the null or modest ITT effects observed, we report ex post minimum detectable effects (MDEs) to assess whether the study had sufficient power to detect meaningful differences. Assuming 80% power and a 5% significance level, we estimate that the smallest treatment effects detectable for our key outcomes range from 0.035 (for Top 40 schools) to 0.174 (for Mean Distance) – see Table A3. These values suggest that the design was powered to detect moderate differences in school quality and proximity, as well as smaller differences in application behavior (e.g., number of schools listed or vacancy receipt). The similarity of MDEs across treatment arms reflects comparable sample sizes and outcome variances.

Following Elacqua et al. (2024), we are especially interested in first-grade applicants, who are entering elementary school and are guaranteed enrollment in the assigned school through ninth grade. This is a critical stage in the educational cycle and, for many families, their first interaction with the formal school system. They are thus arguably less likely to have formed strong preferences, and more receptive to quality-based recommendations. Importantly, more vacancies are also available at this entry level.

Table 10 reports results for first-grade applicants under both the ITT and LATE analyses.[12] Overall, the intervention did not generate statistically significant effects for this group, with the exception of a reduction in the average distance to selected schools among applicants in the Quality treatment group. Notably, for these families all recommended schools were located within a 3-kilometer radius of the applicant's residence. This result, consistent with findings from a previous experiment, suggests that quality-based recommendations restricted to a nearby geographic area may be more effective in shaping family choices at entry into elementary school.

[12] Full regression results, including covariates, are provided in the Appendix (Table A8).

Table 10: School choice information impact on application outcomes, first year students

	School IDEPE			School Proximity (km)			
	1st Ranked	Top 40 Schools	Average	1st Ranked	Average	Obtained Seat	# Applications
Panel A: Intent-to-Treat Effects (ITT)							
ITT - Quality Treatment							
Coefficient	-0.009	0.037	-0.017	-0.145*	-0.178**	-0.028	-0.038
	(0.077)	(0.023)	(0.070)	(0.081)	(0.082)	(0.024)	(0.039)
ITT - Distance Treatment							
Coefficient	-0.022	-0.015	-0.075	-0.071	-0.103	-0.012	-0.006
	(0.074)	(0.023)	(0.068)	(0.086)	(0.087)	(0.024)	(0.039)
Panel B: Local Average Treatment Effects (LATE)							
LATE - Quality Treatment							
Coefficient	-0.076	0.291	-0.136	-1.185*	-1.406**	-0.218	-0.303
	(0.628)	(0.183)	(0.556)	(0.676)	(0.670)	(0.195)	(0.320)
LATE - Distance Treatment							
Coefficient	-0.082	-0.055	-0.271	-0.260	-0.372	-0.042	-0.023
	(0.269)	(0.082)	(0.248)	(0.315)	(0.317)	(0.087)	(0.140)
Control Group Mean	4.547	0.422	4.569	1.242	1.345	0.564	1.459
Observations	2,375	2,375	2,375	2,375	2,375	2,375	2,375

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note 1: Standard errors in parentheses. ITT estimates show the intent-to-treat effects of receiving information treatments. LATE estimates show the local average treatment effects for compliers who followed the treatment recommendations. Quality treatment provided information about school academic performance. Distance treatment provided information about school proximity.

Note 2:IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools in the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools in their list. *# Applications* refers to the total number of schools included on the student's application list.

6.1 Impact on Recommendation Takers

Given that low engagement with the recommendation mechanism limited our ability to detect effects in the overall models, we next examine heterogeneous impacts by interacting treatment assignment with compliance behavior. In other words, we focus on applicants who responded to the system by including at least one recommended school on their application list. This analysis is motivated by two factors. First, as previously noted, aggregate estimates may obscure treatment effects among this narrowly defined subgroup of "recommendation takers." Second, descriptive evidence (Table 7) suggests that this subgroup may exhibit distinct and policy-relevant patterns.

Table 11 reports the impacts of the intervention for compliers across both treatment groups. We find consistently positive effects. Among applicants in the Quality treatment, compliance led to statistically significant improvements across all IDEPE-related outcomes: the quality of the top-ranked school, the average quality of selected schools, and the share of schools in the top 40% of the IDEPE distribution. These applicants also selected schools that were, on average, farther from their homes, suggesting a willingness to prioritize quality.

In contrast, parents in the Quality treatment who did not follow the recommendations show negative and significant effects: they applied to lower-quality, closer schools, submitted fewer applications, and were less likely to secure admission to a preferred option.

For the Distance treatment, an initially surprising pattern emerges: compliers also applied to higher-quality schools, despite receiving proximity-focused recommendations. Moreover, these compliers applied to more distant schools than control applicants. While this may seem inconsistent with the treatment's logic, the discrepancy disappears once we account for the fact that compliers submitted significantly more applications overall (2.46 versus 1.42), thereby expanding the geographic range of their selected establishments.

Table 11: School choice information impact on application, recommendation takers

	School IDEPE			School Proximity (km)		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.049^{***}	-0.032^{**}	-0.045^{***}	-0.095	-0.126^{**}	-0.054^{***}	-0.166^{***}
	(0.017)	(0.013)	(0.016)	(0.058)	(0.059)	(0.013)	(0.019)
T. Distance	0.000	-0.007	0.001	-0.061	-0.136^{**}	-0.039^{***}	-0.247^{***}
	(0.018)	(0.014)	(0.017)	(0.061)	(0.061)	(0.014)	(0.018)
T. Quality * Recom	0.406^{***}	0.330^{***}	0.327^{***}	0.468^{***}	0.688^{***}	0.198^{***}	1.224^{***}
	(0.031)	(0.016)	(0.022)	(0.114)	(0.105)	(0.025)	(0.050)
T. Distance * Recom	0.062^{**}	0.048^{***}	0.024	0.144^{*}	0.431^{***}	0.167^{***}	1.177^{***}
	(0.028)	(0.018)	(0.023)	(0.079)	(0.080)	(0.020)	(0.038)
Disability	0.037	0.045^{**}	0.037	0.261^{***}	0.248^{***}	0.342^{***}	0.051
	(0.026)	(0.019)	(0.023)	(0.092)	(0.091)	(0.017)	(0.033)
Poverty	-0.060^{***}	-0.027^{***}	-0.048^{***}	-0.115^{**}	-0.143^{***}	0.205^{***}	-0.017
	(0.014)	(0.010)	(0.013)	(0.047)	(0.047)	(0.010)	(0.015)
Female	0.009	0.003	0.011	0.071	0.044	-0.016	-0.009
	(0.013)	(0.010)	(0.012)	(0.045)	(0.045)	(0.010)	(0.015)
Black	-0.035^{**}	-0.027^{**}	-0.034^{**}	-0.109^{**}	-0.093^{*}	-0.012	-0.015
	(0.015)	(0.011)	(0.014)	(0.050)	(0.050)	(0.011)	(0.017)
Initial years	0.942^{***}	0.201^{***}	0.934^{***}	-1.201^{***}	-1.308^{***}	-0.022^{*}	-0.139^{***}
	(0.015)	(0.012)	(0.013)	(0.073)	(0.073)	(0.013)	(0.020)
Morning	-0.209^{***}	-0.232^{***}	-0.200^{***}	-0.695^{***}	-0.617^{***}	0.089^{***}	0.639^{***}
	(0.021)	(0.014)	(0.019)	(0.095)	(0.095)	(0.015)	(0.033)
Afternoon	-0.222^{***}	-0.224^{***}	-0.216^{***}	-0.986^{***}	-0.910^{***}	0.021	0.606^{***}
	(0.021)	(0.014)	(0.018)	(0.091)	(0.091)	(0.015)	(0.032)
Mean(control)	4.785	0.458	4.785	1.795	1.908	0.504	1.396
R^2	0.292	0.062	0.312	0.115	0.120	0.093	0.323
Adj. R^2	0.291	0.061	0.311	0.114	0.119	0.092	0.322
Num. obs.	8,103	8,322	8,322	8,507	8,623	8,631	8,631

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: *IDEPE Top 1* refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean Idepe* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Overall, both sets of compliers submitted more applications and had greater chances of securing a selected school placement. Within the Quality treatment in particular, compliance clearly translated into higher-quality school choices across all relevant outcomes. These findings reinforce the descriptive evidence that the mechanism effectively recommends schools of higher quality than the applicant's trigger school and highlight the importance of parental engagement in realizing its intended effects.

As mentioned, this is not a causal analysis, since compliance is self-selected. It constitutes a descriptive exercise that examines the intervention effects among those who followed a recommendation. Thus, while we highlight the mechanism's potential, this should not be interpreted as a causal effect for the population.

When analyzing the results for first-year compliers in Table 12, we see that the results for the compliers in the Quality treatment align with the general pattern for compliers presented in Table 11, where academic quality is prioritized. These students listed better schools – both the first-ranked school and the average quality of the list increased – and included a higher proportion of schools among the top 40% of the IDEPE score distribution. To achieve this, they opted for schools that were on average 340 meters farther away, a trade-off that remains within a geographical radius considered acceptable by parents, as designed by the intervention.

Compliers in the Distance treatment, much like compliers in general, reacted primarily by increasing the number of applications and the average quality of schools on their list. They too had a significantly higher success rate in obtaining a vacancy in one of their selected schools.

Table 12: School choice information impact on application, first-year recommendation takers

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.012	0.008	-0.012	-0.163^{*}	-0.222^{***}	-0.046^{*}	-0.180^{***}
	(0.034)	(0.026)	(0.033)	(0.085)	(0.085)	(0.025)	(0.036)
T. Distance	-0.048	-0.020	-0.044	-0.037	-0.124	-0.045^{*}	-0.307^{***}
	(0.034)	(0.027)	(0.033)	(0.095)	(0.095)	(0.026)	(0.032)
T. Quality * Recom	0.327^{***}	0.251^{***}	0.236^{***}	0.135	0.338^{***}	0.149^{***}	1.121^{***}
	(0.058)	(0.033)	(0.048)	(0.110)	(0.121)	(0.050)	(0.103)
T. Distance * Recom	0.036	0.019	0.029	-0.126	0.077	0.121^{***}	1.089^{***}
	(0.051)	(0.033)	(0.041)	(0.108)	(0.114)	(0.036)	(0.064)
Disability	0.046	0.074^{**}	0.024	0.266^{*}	0.283^{**}	0.301^{***}	0.144^{**}
	(0.042)	(0.032)	(0.037)	(0.145)	(0.140)	(0.028)	(0.058)
Poverty	-0.104^{***}	-0.065^{***}	-0.092^{***}	-0.004	0.010	0.158^{***}	0.028
	(0.028)	(0.021)	(0.026)	(0.070)	(0.070)	(0.021)	(0.031)
Female	0.027	0.012	0.024	0.075	0.081	-0.020	-0.010
	(0.026)	(0.020)	(0.024)	(0.065)	(0.066)	(0.020)	(0.028)
Black	-0.061^{**}	-0.036^{*}	-0.072^{***}	-0.001	-0.020	-0.007	-0.013
	(0.029)	(0.021)	(0.027)	(0.070)	(0.070)	(0.021)	(0.031)
Morning	-0.053	-0.058^{*}	-0.055	-0.614^{***}	-0.684^{***}	0.019	0.946^{***}
	(0.061)	(0.033)	(0.053)	(0.192)	(0.198)	(0.035)	(0.084)
Afternoon	-0.081	-0.025	-0.088	-0.756^{***}	-0.816^{***}	-0.122^{***}	0.963^{***}
	(0.062)	(0.033)	(0.055)	(0.196)	(0.202)	(0.035)	(0.084)
Mean(control)	4.960	0.454	4.956	1.242	1.345	0.564	1.459
R^2	0.024	0.024	0.019	0.022	0.024	0.079	0.330
Adj. R^2	0.019	0.020	0.015	0.018	0.020	0.075	0.327
Num. obs.	$2,173$	$2,254$	$2,254$	$2,375$	$2,402$	$2,402$	$2,402$

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

6.2 Survey Respondents

Our analysis of the 2022 enrollment process suggested that many parents accessed the platform with predetermined school preferences, potentially limiting the effectiveness of the recommendations. To further investigate this hypothesis and gain deeper insights into parental decision-making, we complemented our intervention with a post-application survey.

The survey provided an opportunity to explore whether certain subgroups were more responsive to the recommendations and the factors shaping their decisions. Of particular interest for our study are parents who reported being more open to considering alternative school options, and those willing to travel longer distances in exchange for higher-performing schools. Another important aspect is whether parental education influenced receptivity to the recommendations.

Note that the results are not causal due to potential selection bias: the survey was optional and only about 30% of parents in each group responded. Survey respondents may differ from non-respondents in terms of motivation, education levels, and other socioeconomic factors. Nonetheless, our findings offer valuable insights into parental and student behaviors, motivations, and decision-making patterns.

We begin by analyzing responses to a question asking whether parents had a specific school in mind before accessing the *Matrícula Digital* system (Figure A6). We categorized respondents into two groups: those who selected (A) ”Yes, I had already decided on a specific school” and those who selected either (B) ”I had already decided on a list of schools I was interested in” or (C) ”No, I was still considering the options and exploring different schools.” Respondents in the latter group (B/C) had not committed to a single school and were hypothesized to be more receptive to the platform’s recommendations.

In Table 13 we see that parents in the undecided categories (B/C) were indeed more likely to consider higher-quality school options compared to those who had predetermined a single school. However, this effect surprisingly appeared only in the Distance treatment, and not in the Quality treatment group. This finding suggests that these more flexible parents were receptive to incorporating recommendations into their decision-making, but primarily when the recommended schools prioritized proximity rather than academic quality.

Table 13: Recommendation impact, guardian more susceptible to choosing a recommended school

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.006	0.006	-0.034	0.062	0.033	-0.039	-0.008
	(0.070)	(0.027)	(0.066)	(0.124)	(0.129)	(0.029)	(0.046)
T. Distance	-0.016	-0.014	-0.030	-0.003	-0.050	-0.029	-0.016
	(0.069)	(0.028)	(0.064)	(0.118)	(0.122)	(0.029)	(0.045)
Q2	-0.072	-0.022	-0.088	0.492^{***}	0.540^{***}	0.024	0.378^{***}
	(0.095)	(0.038)	(0.085)	(0.182)	(0.188)	(0.040)	(0.085)
T. Quality x Q2	0.074	0.074	0.048	-0.135	-0.317	0.034	-0.149
	(0.137)	(0.054)	(0.128)	(0.257)	(0.250)	(0.057)	(0.111)
T. Distance x Q2	0.236^{*}	0.071	0.251^{**}	0.034	-0.024	-0.017	-0.148
	(0.123)	(0.053)	(0.111)	(0.256)	(0.259)	(0.058)	(0.108)
Disability	-0.060	0.051	-0.011	0.501^{**}	0.518^{**}	0.349^{***}	0.189^{**}
	(0.110)	(0.037)	(0.098)	(0.219)	(0.223)	(0.034)	(0.081)
Poverty	-0.018	-0.008	0.001	-0.118	-0.137	0.209^{***}	-0.031
	(0.049)	(0.019)	(0.046)	(0.088)	(0.089)	(0.020)	(0.033)
Female	0.043	0.024	0.060	-0.057	-0.077	-0.031	0.037
	(0.048)	(0.019)	(0.045)	(0.086)	(0.087)	(0.020)	(0.032)
Black	-0.110^{**}	-0.055^{***}	-0.068	-0.149	-0.164	-0.058^{***}	-0.058
	(0.051)	(0.021)	(0.049)	(0.100)	(0.102)	(0.022)	(0.039)
Initial years	0.896^{***}	0.206^{***}	0.898^{***}	-1.184^{***}	-1.314^{***}	-0.029	-0.181^{***}
	(0.058)	(0.023)	(0.053)	(0.148)	(0.150)	(0.026)	(0.045)
Morning	-0.294^{***}	-0.237^{***}	-0.313^{***}	-0.661^{***}	-0.471^{**}	0.110^{***}	0.733^{***}
	(0.071)	(0.029)	(0.059)	(0.185)	(0.185)	(0.031)	(0.073)
Afternoon	-0.395^{***}	-0.231^{***}	-0.388^{***}	-0.985^{***}	-0.787^{***}	-0.008	0.711^{***}
	(0.072)	(0.028)	(0.060)	(0.181)	(0.182)	(0.029)	(0.070)
Mean(control)	4.565	0.439	4.571	1.795	1.795	0.504	1.396
R^2	0.090	0.047	0.100	0.130	0.123	0.094	0.131
Adj. R^2	0.085	0.042	0.095	0.125	0.119	0.089	0.126
Num. obs.	2,235	2,263	2,263	2,232	2,260	2,263	2,263

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools in the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Second, to assess parents' willingness to enroll their children in higher-performing schools at greater distances, we analyze responses to a survey question on acceptable travel distance for better educational opportunities (Figure A5). Specifically, we identified parents who reported willingness to travel more than 3 kilometers, hypothesizing that these distance-tolerant parents might be more receptive to quality-focused recommendations. However, our analysis, reported in Table 14, reveals no significant impact on application behavior for these parents across different treatment conditions, suggesting that willingness to travel further for quality does not necessarily translate into action within the enrollment process.

Table 14: Recommendation impact, guardians willing to travel for higher-performing schools

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.016	0.015	-0.051	0.031	-0.032	-0.034	-0.039
	(0.069)	(0.027)	(0.065)	(0.106)	(0.110)	(0.028)	(0.044)
T. Distance	0.027	0.002	0.009	0.028	-0.040	-0.054^{*}	-0.042
	(0.065)	(0.027)	(0.060)	(0.101)	(0.106)	(0.028)	(0.042)
Q12	-0.002	0.036	-0.031	0.859^{***}	0.873^{***}	-0.020	0.225^{**}
	(0.097)	(0.039)	(0.084)	(0.211)	(0.211)	(0.040)	(0.090)
T. Quality x Q12	0.138	0.029	0.132	0.135	0.100	0.000	-0.015
	(0.134)	(0.054)	(0.120)	(0.304)	(0.294)	(0.055)	(0.111)
T. Distance x Q12	0.064	0.012	0.071	0.046	0.058	0.088	-0.033
	(0.142)	(0.054)	(0.127)	(0.299)	(0.299)	(0.057)	(0.115)
Disability	-0.079	0.041	-0.032	0.459^{**}	0.534^{**}	0.366^{***}	0.214^{***}
	(0.109)	(0.037)	(0.098)	(0.213)	(0.215)	(0.034)	(0.080)
Poverty	-0.017	-0.004	0.003	-0.077	-0.104	0.211^{***}	-0.029
	(0.048)	(0.019)	(0.045)	(0.085)	(0.086)	(0.020)	(0.032)
Female	0.046	0.020	0.060	-0.042	-0.052	-0.028	0.040
	(0.048)	(0.019)	(0.044)	(0.083)	(0.084)	(0.020)	(0.031)
Black	-0.114^{**}	-0.056^{***}	-0.069	-0.153	-0.164^{*}	-0.059^{***}	-0.061
	(0.050)	(0.021)	(0.048)	(0.097)	(0.098)	(0.022)	(0.038)
Initial years	0.921^{***}	0.214^{***}	0.923^{***}	-1.085^{***}	-1.177^{***}	-0.027	-0.163^{***}
	(0.060)	(0.023)	(0.055)	(0.141)	(0.142)	(0.026)	(0.043)
Morning	-0.286^{***}	-0.229^{***}	-0.307^{***}	-0.574^{***}	-0.410^{**}	0.106^{***}	0.743^{***}
	(0.071)	(0.029)	(0.059)	(0.179)	(0.177)	(0.030)	(0.072)
Afternoon	-0.388^{***}	-0.219^{***}	-0.382^{***}	-0.890^{***}	-0.721^{***}	-0.010	0.723^{***}
	(0.071)	(0.028)	(0.059)	(0.175)	(0.173)	(0.029)	(0.070)
Mean(control)	4.565	0.438	4.572	1.789	1.789	0.503	1.395
R^2	0.093	0.047	0.104	0.154	0.149	0.097	0.118
Adj. R^2	0.088	0.042	0.099	0.149	0.145	0.093	0.113
Num. obs.	$2,302$	$2,330$	$2,330$	$2,299$	$2,327$	$2,330$	$2,330$

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Finally, we analyze whether family socioeconomic background influenced the effect of the recommendation. To this end, we focus on applicants whose mothers have completed at least a high school education or beyond (Tables 15 and 16). While no significant effects were found on the number of applications or securing a seat, we do observe a notable impact in the Distance treatment. Specifically, parents in this group selected schools closer to their residence, both on average and for their top-ranked choice, suggesting that maternal education level may play a role in proximity-based decision-making.

Table 15: Recommendation impact, mother's education level (high school or beyond)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.014	-0.006	-0.060	0.158	0.136	-0.087	-0.016
	(0.151)	(0.059)	(0.147)	(0.176)	(0.190)	(0.060)	(0.077)
T. Distance	0.174	-0.019	0.120	0.492^{***}	0.448^{**}	-0.087	0.054
	(0.135)	(0.057)	(0.128)	(0.191)	(0.205)	(0.060)	(0.082)
Q22	0.012	-0.007	0.008	0.444^{***}	0.443^{***}	-0.021	0.152^{**}
	(0.125)	(0.046)	(0.113)	(0.134)	(0.152)	(0.047)	(0.068)
T. Quality x Q22	0.044	0.033	0.052	-0.154	-0.223	0.069	-0.042
	(0.165)	(0.064)	(0.159)	(0.216)	(0.227)	(0.066)	(0.092)
T. Distance x Q22	-0.150	0.027	-0.103	-0.583^{***}	-0.605^{**}	0.065	-0.134
	(0.149)	(0.063)	(0.140)	(0.225)	(0.238)	(0.066)	(0.096)
Disability	-0.064	0.051	-0.019	0.506^{**}	0.518^{**}	0.355^{***}	0.202^{**}
	(0.110)	(0.037)	(0.098)	(0.217)	(0.220)	(0.034)	(0.080)
Poverty	-0.023	-0.008	-0.001	-0.125	$-0.152*$	0.208^{***}	-0.030
	(0.048)	(0.019)	(0.045)	(0.088)	(0.089)	(0.020)	(0.032)
Female	0.047	0.020	0.062	-0.052	-0.075	-0.032	0.033
	(0.048)	(0.019)	(0.045)	(0.084)	(0.085)	(0.020)	(0.032)
Black	-0.121^{**}	-0.061^{***}	-0.075	-0.185^{*}	-0.195^{*}	-0.053^{**}	-0.062
	(0.050)	(0.021)	(0.049)	(0.100)	(0.101)	(0.022)	(0.038)
Initial years	0.892^{***}	0.209^{***}	0.899^{***}	-1.187^{***}	-1.318^{***}	-0.030	-0.195^{***}
	(0.057)	(0.023)	(0.052)	(0.146)	(0.147)	(0.026)	(0.045)
Morning	-0.286^{***}	-0.233^{***}	-0.304^{***}	-0.653^{***}	-0.450^{**}	0.110^{***}	0.741^{***}
	(0.071)	(0.029)	(0.059)	(0.186)	(0.185)	(0.030)	(0.073)
Afternoon	-0.395^{***}	-0.229^{***}	-0.386^{***}	-0.989^{***}	-0.771^{***}	-0.005	0.717^{***}
	(0.071)	(0.028)	(0.059)	(0.182)	(0.181)	(0.029)	(0.071)
Mean(control)	4.564	0.439	4.571	1.790	1.790	0.503	1.395
R^2	0.090	0.046	0.100	0.126	0.119	0.094	0.110
Adj. R^2	0.086	0.041	0.096	0.121	0.115	0.089	0.105
Num. obs.	2,284	2,312	2,312	2,281	2,309	2,312	2,312

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. # *Applications* refers to the total number of schools included on the student's application list.

Table 16: Recommendation impact, mother's education level (beyond high school)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	0.009	0.018	-0.030	0.056	-0.038	-0.032	-0.012
	(0.060)	(0.024)	(0.056)	(0.109)	(0.110)	(0.025)	(0.039)
T. Distance	0.031	0.015	0.014	0.031	-0.035	-0.029	-0.013
	(0.059)	(0.024)	(0.054)	(0.104)	(0.108)	(0.025)	(0.038)
Q22	0.094	0.055	-0.030	0.630^{**}	0.554^{**}	0.100^{*}	0.467^{***}
	(0.125)	(0.050)	(0.118)	(0.285)	(0.270)	(0.055)	(0.161)
T. Quality x Q22	0.083	0.104	0.074	-0.399	-0.193	-0.032	-0.157
	(0.193)	(0.075)	(0.190)	(0.426)	(0.428)	(0.084)	(0.202)
T. Distance x Q22	0.188	-0.018	0.237	-0.246	-0.296	-0.068	-0.335^{*}
	(0.160)	(0.073)	(0.149)	(0.388)	(0.364)	(0.078)	(0.178)
Disability	-0.094	0.039	-0.029	0.437^{**}	0.500^{**}	0.341^{***}	0.229^{***}
	(0.105)	(0.036)	(0.093)	(0.210)	(0.210)	(0.034)	(0.081)
Poverty	-0.009	-0.001	0.002	-0.117	-0.148^{*}	0.209^{***}	-0.015
	(0.047)	(0.019)	(0.044)	(0.085)	(0.087)	(0.020)	(0.032)
Female	0.052	0.016	0.069	-0.069	-0.082	-0.044^{**}	0.027
	(0.046)	(0.019)	(0.043)	(0.082)	(0.083)	(0.019)	(0.031)
Black	-0.119^{**}	-0.059^{***}	-0.073	-0.172^{*}	-0.194^{**}	-0.056^{***}	-0.054
	(0.048)	(0.020)	(0.047)	(0.098)	(0.099)	(0.021)	(0.036)
Initial years	0.932^{***}	0.210^{***}	0.930^{***}	-1.168^{***}	-1.280^{***}	-0.021	-0.196^{***}
	(0.057)	(0.022)	(0.053)	(0.140)	(0.141)	(0.025)	(0.042)
Morning	-0.279^{***}	-0.216^{***}	-0.288^{***}	-0.624^{***}	-0.455^{***}	0.098^{***}	0.739^{***}
	(0.068)	(0.028)	(0.057)	(0.177)	(0.175)	(0.029)	(0.068)
Afternoon	-0.387^{***}	-0.211^{***}	-0.373^{***}	-0.954^{***}	-0.779^{***}	-0.011	0.715^{***}
	(0.068)	(0.027)	(0.058)	(0.174)	(0.172)	(0.028)	(0.067)
Mean(control)	4.567	0.438	4.573	1.791	1.791	0.502	1.394
R^2	0.099	0.045	0.109	0.124	0.120	0.094	0.123
Adj. R^2	0.095	0.041	0.104	0.120	0.116	0.090	0.119
Num. obs.	2,417	2,447	2,447	2,414	2,444	2,447	2,447

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

7 Conclusion

The transition to centralized school admission systems represents a significant development in making school choice more transparent and equitable. However, our research demonstrates that simply providing a platform is insufficient - families need support to effectively navigate their options.

Our RCT shows that digital nudges, implemented through a recommendation engine, can influence school choice decisions when families engage with the suggestions. The Quality treatment group, in particular, demonstrated that receptive families can be guided toward higher-performing schools while maintaining reasonable proximity to their homes. This suggests that well-designed digital interventions can help balance the trade-off between school quality and convenience for responsive users.

The heterogeneous effects we observed are particularly instructive. First-grade applicants and families without predetermined school preferences showed greater responsiveness to recommendations, indicating that timing and openness to alternatives are crucial factors in the effectiveness of choice architecture. This finding aligns with previous research suggesting that families are more receptive to information during initial school selection.

However, the modest overall effects highlight important contextual constraints. In Recife, the transition from the traditional school selection process to a centralized digital platform is relatively recent. A "system adoption lag" means that most families are not yet accustomed to systematically comparing school options on a digital platform. Our data indicate that most users entered the process with predetermined preferences and limited understanding of how the new system works, including the possibility of selecting multiple schools, the importance of truthful preference ranking, and the transparency of the assignment algorithm. This resistance to adopting new digital decision-making practices, combined with structural barriers such as transportation challenges for young children, significantly limit the intervention's effectiveness. These findings underscore the need to consider both preexisting preferences and adaptation to new systems when designing digital nudges.

The experiment underlines the importance of user interface design in choice architecture. Our recommendations were shown to users after their initial school selection, but the brief average platform engagement time (approximately 3 minutes) suggests that more prominent placement might increase interaction rates. The recommendation engine's ability to generate real-time, personalized suggestions based on both quality and proximity criteria represents a promising approach to helping families navigate complex school choice decisions. However, the varying levels of engagement with these recommendations suggest that future interventions should focus on increasing user interaction with such tools.

Our findings have important implications for policy design. While digital nudges can be effective tools for improving school choice, they should be part of a comprehensive strategy that includes expanding access to high-quality schools, reducing information barriers, and engaging families earlier in the decision-making process. Additionally, policy efforts should focus on building system literacy. That is, helping families understand how centralized assignment works and how to effectively use digital platforms to explore their options. Future research could explore how to combine digital interventions with complementary support mechanisms, such as targeted information campaigns conducted before the application period, so as to help families make more informed school choices. Although the intervention was grounded in behavioral insights, its limited effectiveness suggests the need for a deeper understanding of the underlying mechanisms at play.

One important consideration is the role of preexisting beliefs. The survey data indicate that more than 70% of the parents had already decided on a school before interacting with the platform. This indicates that many families entered the process with strong priors about school quality or proximity, potentially limiting the persuasive power of the recommendations.

In fact, most families did not choose the recommended schools, even when these options were objectively better and closer to their residence. This pattern implies that prior beliefs, local reputation, or community-based heuristics may have outweighed the information presented by the system. Future interventions could thus benefit from not only improving the salience and placement of recommendations but also addressing the informational and motivational roots of resistance to change.

Taken together, our results suggest that digital nudges, when carefully designed and implemented, can help families make more informed school choices. However, their effectiveness depends critically on addressing underlying constraints in school access, family preferences, system understanding, and engagement with choice platforms. The substantial positive effects observed among recommendation takers demonstrate the potential of such interventions for engaged users. As education systems continue to adopt centralized admission platforms, understanding how to effectively support families in their decision-making process is increasingly important.

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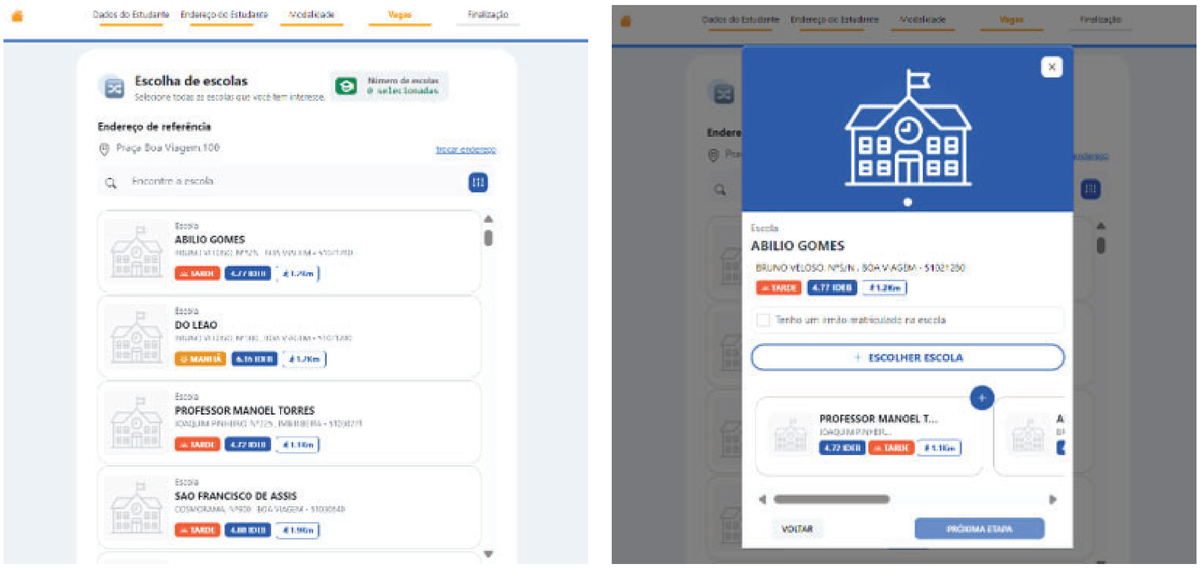
Appendix

A Application Platform

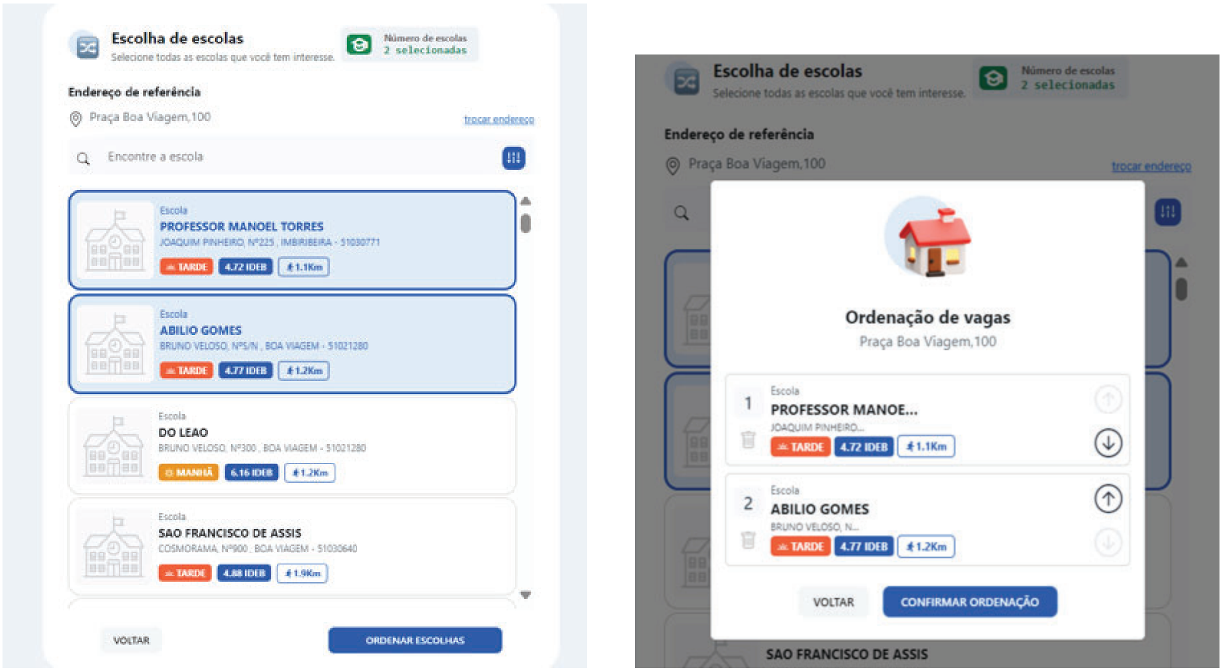
Figure A1: Shopping list and trigger school



(a) (b)

Note: This figure shows a simulation on the platform. After completing the registration data and student information (such as grade, class shift, and modality of education), all users access the school selection screen (the "shopping list," Panel A1a). This default list displays schools based on the student's information, ordered by distance from the reference address provided at registration. Both the control and treatment groups view this screen. To select or view additional details about a school, the user must click on one of the listed options. At this point, the recommendation engine is triggered. The school the user clicks is referred to as the trigger school, illustrated in Panel A1b. For the control group, only the information of the chosen school is displayed. For the Distance treatment, a carousel of suggested schools is also displayed at the end of the card, ordered by distance from the registered address. For the Quality treatment, a list of recommended schools is shown, ordered by distance and limited to schools within the top 40% of IDEPE scores. The user may select the trigger school, any of the schools in the carousel (if in the treatment group), or return to the initial shopping list as many times as desired. Each time a school is clicked on, the card behaves in the same way, according to the treatment or control assignment.

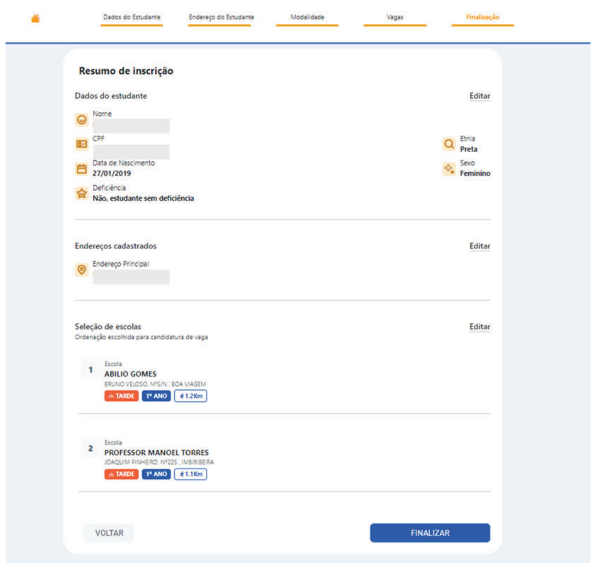
Figure A2: The preferences



(a) (b)

Note: This figure shows a simulation on the platform of selected schools and ordering of preferences. In Panel A2a the user selects the schools to which the student will apply, and the system highlights these schools to indicate selection. The user must then assign an order of preference, with 1 as the most preferred and N (Panel A2b) as the least preferred.

Figure A3: Application



Note: The figure shows a simulation on the platform involving the final screen – data review and application submission. This final screen of the process displays a summary of the registration data and the selected schools according to the stated order of preference. The application process remained open (for four weeks) during which time the guardian could return and revise or modify their application. These revisions did not affect either the randomization process or the behavior of the recommendation engine.

B Assessing Potential Demand Effects of Recommendations

One concern is whether the recommended schools might face increased demand due to their greater visibility in the recommendation carousel. We explore this in Table A1, which presents the distribution of the "IDEPE Top 40%" schools compared to all others, along with the average number of students per school.[13]

We see that, except for first grade, the proportion of Top 40% schools is similar to that of the remaining schools, and the average number of seats available per school is also fairly balanced across grades. Furthermore, the expected overload in recommended schools did not materialize. When examining the 40% highest-quality schools, we observe that many did not receive enough applications to fill all available seats. In contrast, several schools ranked among the bottom 60% in terms of quality received more applications than vacancies. This mismatch can largely be attributed to the limited uptake of the treatment among families, which curtailed the overall impact of the recommendations on school choice patterns.

[13] IDEPE scores as the quality criterion, with minimum thresholds of 4.98 for primary grades and 4.2 for upper elementary grades.

Table A1: Distribution of vacancies by school quality: Top 40% vs remaining schools

Grade	% Vacancies		Average Vacancies per School		Summary Stats	
	Top 40%	Bottom 60%	Top 40%	Bottom 60%	# Institutions	Total Vacancies
1st	36.5%	63.5%	10.99	10.84	133	2,255
2nd	44.2%	55.8%	7.32	6.48	121	1,242
3rd	47.6%	52.4%	6.06	5.24	94	790
4th	42.5%	57.5%	6.02	5.82	107	921
5th	43.5%	56.5%	5.76	5.93	106	955
6th	42.5%	57.5%	25.63	27.70	16	482
7th	52.1%	47.9%	14.90	9.79	22	286
8th	54.2%	45.8%	14.33	8.38	18	238
9th	50.5%	49.5%	14.40	10.07	21	285

Note: The table shows, for each grade, the share of vacancies offered by the top 40% highest-quality schools and the bottom 60%, the average number of vacancies per school, and summary statistics on the total number of institutions and vacancies available.

C Results

C.0.1 Balance

Table A2: Balance test, first year students

	Control	Quality	P-val C=Q	Control	Distance	P-val C=D	Distance	Quality	P-val D=Q
Disability	0.108	0.096	0.439	0.108	0.079	0.050	0.079	0.096	0.242
Poverty	0.640	0.666	0.276	0.640	0.657	0.474	0.657	0.666	0.697
Female	0.464	0.477	0.603	0.464	0.489	0.320	0.489	0.477	0.642
Black	0.684	0.689	0.836	0.684	0.703	0.423	0.703	0.689	0.556
Morning	0.441	0.465	0.332	0.441	0.460	0.452	0.460	0.465	0.816
Afternoon	0.579	0.565	0.575	0.579	0.569	0.684	0.569	0.565	0.872
Observations	789	782		789	831		831	782	

Note: This table displays the mean and standard deviation of baseline characteristics for both the treated and control groups. The p-value is determined through a t-test of the differences in means.

C.0.2 Minimum Detectable Effects (MDEs)

Table A3: MDEs for treatment vs. control comparisons

Variável	**Quality (T1)**	**Distance (T2)**
IDEPE Top 1	0.053	0.053
IDEPE (mean)	0.051	0.050
IDEPE Top 40	0.035	0.035
Distance Top1	0.171	0.170
Distance (mean)	0.174	0.173
Obtained Seat	0.037	0.037
# Applications	0.063	0.063

Note: The table presents the MDEs for outcome variables across the two treatment groups: Quality and Distance.

C.0.3 ITT Results

Table A4: School choice information impact on application outcomes, overall (ITT)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	0.008	0.015	0.002	-0.030	-0.031	-0.026^{**}	0.003
	(0.017)	(0.012)	(0.015)	(0.056)	(0.057)	(0.013)	(0.021)
T. Distance	0.014	0.005	0.006	-0.027	-0.033	0.000	0.032
	(0.016)	(0.012)	(0.015)	(0.056)	(0.056)	(0.013)	(0.021)
Disability	0.043^{*}	0.051^{***}	0.042^{*}	0.270^{***}	0.269^{***}	0.349^{***}	0.097^{***}
	(0.026)	(0.019)	(0.023)	(0.092)	(0.090)	(0.017)	(0.037)
Poverty	-0.064^{***}	-0.031^{***}	-0.052^{***}	-0.121^{**}	-0.151^{***}	0.203^{***}	-0.033^{*}
	(0.014)	(0.010)	(0.013)	(0.047)	(0.047)	(0.010)	(0.017)
Female	0.007	0.002	0.010	0.070	0.043	-0.016	-0.010
	(0.014)	(0.010)	(0.013)	(0.045)	(0.045)	(0.010)	(0.017)
Black	-0.037^{**}	-0.029^{***}	-0.036^{***}	-0.112^{**}	-0.099^{**}	-0.014	-0.029
	(0.015)	(0.011)	(0.014)	(0.050)	(0.050)	(0.011)	(0.019)
Initial years	0.937^{***}	0.198^{***}	0.931^{***}	-1.208^{***}	-1.323^{***}	-0.027^{**}	-0.173^{***}
	(0.015)	(0.012)	(0.014)	(0.074)	(0.073)	(0.013)	(0.022)
Morning	-0.190^{***}	-0.216^{***}	-0.186^{***}	-0.666^{***}	-0.554^{***}	0.111^{***}	0.787^{***}
	(0.021)	(0.015)	(0.019)	(0.094)	(0.093)	(0.015)	(0.036)
Afternoon	-0.204^{***}	-0.209^{***}	-0.203^{***}	-0.959^{***}	-0.853^{***}	0.041^{***}	0.740^{***}
	(0.021)	(0.014)	(0.018)	(0.090)	(0.090)	(0.015)	(0.035)
Mean(control)	4.785	0.458	4.785	1.795	1.908	0.504	1.396
R^2	0.279	0.041	0.302	0.113	0.114	0.080	0.119
Adj. R^2	0.278	0.040	0.302	0.112	0.113	0.080	0.118
Num. obs.	8,103	8,322	8,322	8,507	8,623	8,631	8,631

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools in the student's list that fall within the top 40% of performance (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Table A5: School choice information Impact on application outcomes, first-year students (ITT)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
T. Quality	-0.009	0.036	-0.017	-0.146^{*}	-0.179^{**}	-0.027	-0.039
	(0.077)	(0.023)	(0.070)	(0.082)	(0.083)	(0.024)	(0.039)
T. Distance	-0.022	-0.015	-0.075	-0.071	-0.103	-0.012	-0.006
	(0.074)	(0.023)	(0.068)	(0.086)	(0.087)	(0.024)	(0.039)
Disability	0.289^{***}	0.082^{**}	0.195^{**}	0.264^{*}	0.287^{**}	0.304^{***}	0.174^{***}
	(0.085)	(0.032)	(0.080)	(0.145)	(0.140)	(0.028)	(0.065)
Poverty	0.008	-0.049^{**}	0.026	-0.007	0.006	0.157^{***}	0.023
	(0.067)	(0.020)	(0.062)	(0.070)	(0.070)	(0.021)	(0.034)
Female	0.037	0.010	0.050	0.073	0.080	-0.020	-0.007
	(0.062)	(0.019)	(0.057)	(0.065)	(0.066)	(0.020)	(0.032)
Black	-0.007	-0.028	0.005	-0.001	-0.017	-0.006	-0.001
	(0.069)	(0.020)	(0.064)	(0.070)	(0.070)	(0.021)	(0.034)
Morning	-0.130	-0.038	-0.139^{*}	-0.621^{***}	-0.654^{***}	0.042	1.145^{***}
	(0.106)	(0.032)	(0.082)	(0.188)	(0.193)	(0.034)	(0.088)
Afternoon	-0.284^{***}	-0.016	-0.293^{***}	-0.762^{***}	-0.781^{***}	-0.095^{***}	1.182^{***}
	(0.106)	(0.032)	(0.083)	(0.192)	(0.197)	(0.035)	(0.087)
Mean(control)	4.547	0.422	4.569	1.242	1.345	0.564	1.459
R^2	0.007	0.009	0.007	0.021	0.023	0.072	0.156
Adj. R^2	0.004	0.006	0.004	0.018	0.019	0.069	0.153
Num. obs.	$2,375$	$2,402$	$2,402$	$2,375$	$2,402$	$2,402$	$2,402$

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools in the list. *Idepe Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. # *Applications* refers to the total number of schools included on the student's application list.

C.0.4 LATE Results

Table A6: First-stage regressions, overall

	(1) Complier Quality	(2) Complier Distance
T. Quality	0.139***	-0.001
	(0.006)	(0.001)
T. Distance	0	0.238***
	(0)	(0.008)
Disability	0.014	0.025*
	(0.009)	(0.011)
Poverty	-0.01*	-0.003
	(0.004)	(0.005)
Female	-0.003	0.003
	(0.004)	(0.005)
Black	-0.004	-0.008
	(0.005)	(0.006)
Initial years	-0.008	-0.021**
	(0.005)	(0.007)
Morning	0.036***	0.088***
	(0.008)	(0.009)
Afternoon	0.033***	0.08***
	(0.007)	(0.009)
Observations	8,631	8,631
Residual variance	0.04	0.061
Joint F-stat (T. quality and T. distance)	235.00***	476.14***

Notes: The dependent variable in column (1) is the binary indicator for whether the family followed the top-quality recommendation. In column (2), the outcome is whether they followed the closest school recommendation. Robust standard errors in parentheses. Stars denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A7: School choice information impact on application outcomes, overall (IV estimation – second stage)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
Quality	0.059	0.106	0.017	-0.222	-0.223	-0.188^{**}	0.026
	(0.118)	(0.085)	(0.107)	(0.412)	(0.410)	(0.093)	(0.150)
Distance	0.061	0.020	0.026	-0.115	-0.140	0.001	0.136
	(0.070)	(0.050)	(0.062)	(0.235)	(0.236)	(0.053)	(0.087)
Disability	0.041	0.049^{***}	0.042^{*}	0.275^{***}	0.276^{***}	0.352^{***}	0.094^{**}
	(0.026)	(0.019)	(0.024)	(0.092)	(0.091)	(0.017)	(0.037)
Poverty	-0.063^{***}	-0.030^{***}	-0.051^{***}	-0.123^{***}	-0.154^{***}	0.201^{***}	-0.032^{*}
	(0.014)	(0.010)	(0.013)	(0.047)	(0.048)	(0.011)	(0.017)
Female	0.007	0.003	0.010	0.069	0.042	-0.016	-0.010
	(0.013)	(0.010)	(0.012)	(0.045)	(0.045)	(0.011)	(0.017)
Black	-0.036^{**}	-0.028^{***}	-0.036^{***}	-0.114^{**}	-0.101^{**}	-0.015	-0.028
	(0.015)	(0.011)	(0.014)	(0.050)	(0.050)	(0.011)	(0.019)
Initial years	0.939^{***}	0.199^{***}	0.932^{***}	-1.212^{***}	-1.327^{***}	-0.028^{**}	-0.170^{***}
	(0.015)	(0.012)	(0.014)	(0.074)	(0.074)	(0.014)	(0.022)
Morning	-0.197^{***}	-0.221^{***}	-0.189^{***}	-0.648^{***}	-0.533^{***}	0.118^{***}	0.774^{***}
	(0.023)	(0.016)	(0.020)	(0.100)	(0.099)	(0.017)	(0.038)
Afternoon	-0.211^{***}	-0.214^{***}	-0.206^{***}	$-0.942^{***}1$	-0.834^{***}	0.047^{***}	0.728^{***}
	(0.022)	(0.016)	(0.020)	(0.096)	(0.095)	(0.017)	(0.036)
Mean(control)	4.785	0.458	4.785	1.795	1.908	0.504	1.396
Num. obs.	8,103	8,322	8,322	8,507	8,623	8,631	8,631

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included on the student's application list.

Table A8: School choice information impact on application outcomes, first year students (IV estimation – second stage)

	School IDEPE			School Proximity		Obtained Seat	# Applications
	1st ranked	Top 40	Average	1st ranked	Average		
Quality	-0.076	0.291	-0.136	-1.185^{*}	-1.406^{**}	-0.218	-0.303
	(0.628)	(0.183)	(0.556)	(0.676)	(0.670)	(0.195)	(0.320)
Distance	-0.082	-0.055	-0.271	-0.260	-0.372	-0.042	-0.023
	(0.269)	(0.082)	(0.248)	(0.315)	(0.317)	(0.087)	(0.140)
Disability	0.290^{***}	0.081^{**}	0.202^{**}	0.271^{*}	0.307^{**}	0.307^{***}	0.177^{***}
	(0.085)	(0.032)	(0.081)	(0.145)	(0.142)	(0.028)	(0.067)
Poverty	0.008	-0.044^{**}	0.027	-0.020	-0.008	0.155^{***}	0.019
	(0.067)	(0.020)	(0.062)	(0.073)	(0.074)	(0.021)	(0.035)
Female	0.038	0.012	0.052	0.070	0.077	-0.021	-0.008
	(0.062)	(0.019)	(0.058)	(0.066)	(0.068)	(0.020)	(0.032)
Black	-0.006	-0.031	0.007	0.005	-0.008	-0.003	0.001
	(0.069)	(0.020)	(0.065)	(0.072)	(0.072)	(0.022)	(0.035)
Morning	-0.116	-0.049	-0.099	-0.524^{***}	-0.524^{**}	0.061	1.165^{***}
	(0.117)	(0.037)	(0.097)	(0.198)	(0.204)	(0.041)	(0.093)
Afternoon	-0.269^{**}	-0.031	-0.249^{**}	-0.646^{***}	-0.629^{***}	-0.074^{*}	1.208^{***}
	(0.121)	(0.039)	(0.103)	(0.205)	(0.210)	(0.042)	(0.093)
Mean(control)	4.547	0.422	4.569	1.242	1.345	0.564	1.459
Num. obs.	$2,375$	$2,402$	$2,402$	$2,375$	$2,402$	$2,402$	$2,402$

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: IDEPE Top 1 refers to the IDEPE score of the highest-performing school included on the student's application list. *Mean IDEPE* is the average IDEPE score across all schools on the list. *IDEPE Top 40* is the share of schools on the student's list that fall within the top 40% of the IDEPE score distribution (defined as IDEPE $\geq$ 4.98 for early years or IDEPE $\geq$ 4.2 for later years). *Distance Top 1* is the distance (in kilometers) between the student's residence and the best IDEPE school on the list. *Mean Distance* is the average distance to all schools on the list. *Obtained Seat* is a binary variable indicating whether the student was placed in any of the schools on their list. *# Applications* refers to the total number of schools included in the student's application list.

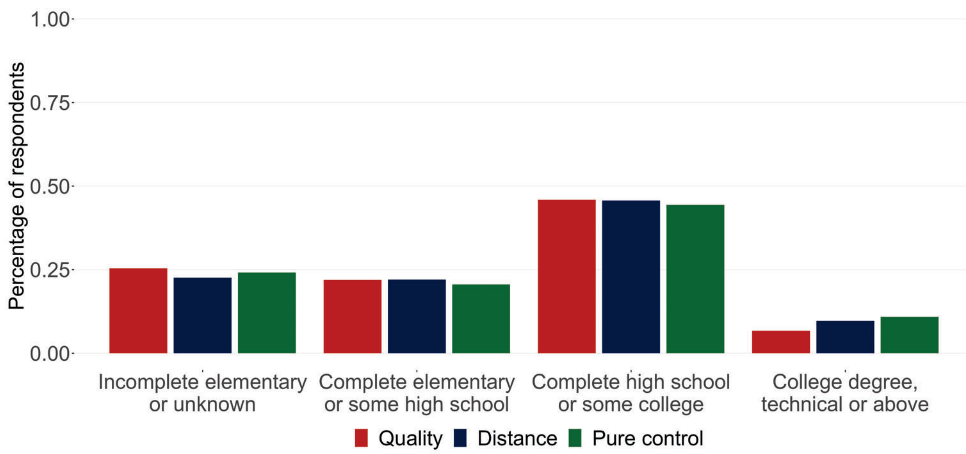
D Survey

To better understand parents' beliefs before using the *Matrícula Digital* app, their decisions, and their future expectations, we conducted a survey with guardians. The survey gathered information from 2,551 respondents, comprising 30.1% (864) from the quality treatment group, 29.1% (863) from the distance treatment group, and 29.5% (824) from the pure control group. The education literature observes that parent surveys can be subject to various biases, especially when participation is voluntary. In our study, respondents tend to be more engaged, have specific motivations, and often higher levels of education – as seen in Figure A4, where over 50% have completed at least high school.

With nearly one-third of responses from each group, we consider this sample size sufficient to shed light on parental behavior, even accounting for potential biases. These parents may furthermore have stronger expectations regarding the impact of the *Matrícula Digital* tool, making them an interesting group for assessing program impact and heterogeneity.

The survey included 23 questions gathering personal information about the student. Responses were gathered via open-text and multiple-choice answers, as well as single-answer objective questions. Our quantitative analysis focuses on single-answer questions.

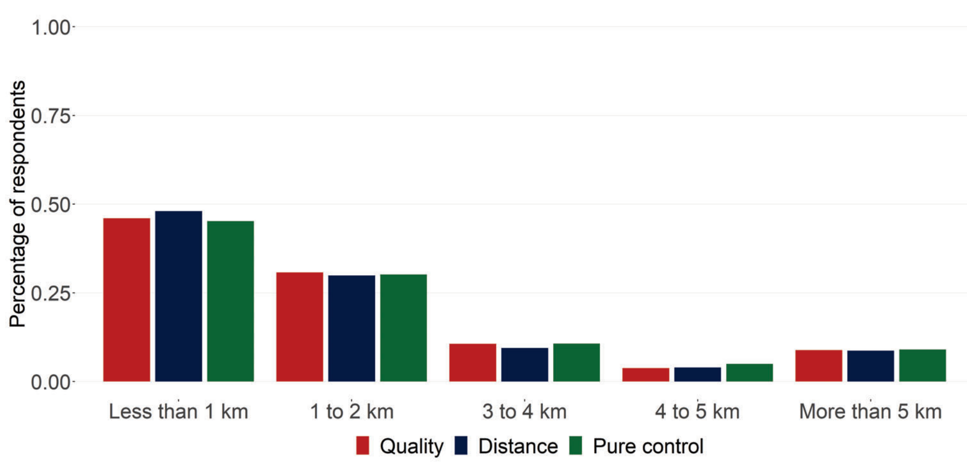
Figure A4: What is the education level of the student's mother (stepmother or female guardian)?



Note: This figure presents the distribution of the educational level of the students' mothers, based on survey responses.

We examine parents' preferences in Figure A5 and Figure A6. In Figure A5, we observe the importance of school proximity in parents' enrollment decisions. This finding aligns with both the 2022 results and education literature, which both demonstrate parents' preference for schools near their homes.

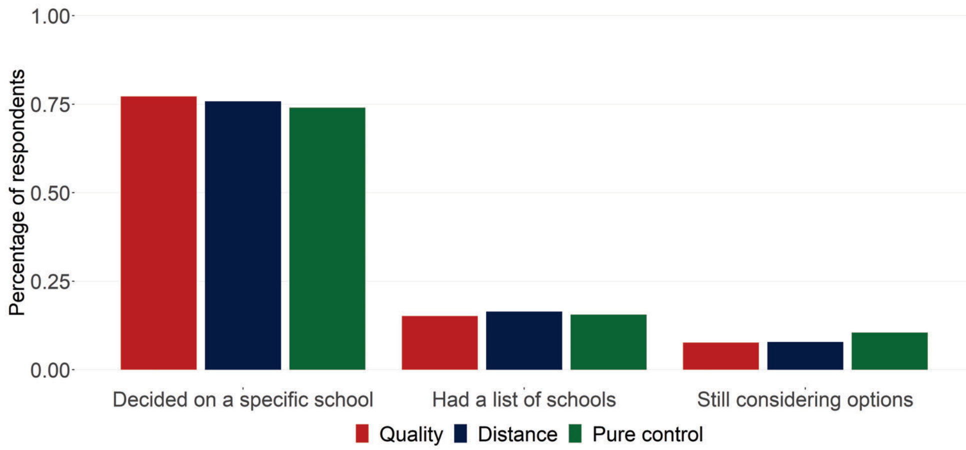
Figure A5: How far away would you be willing to enroll a student if it were a high-performance school (students with higher learning outcomes)?



Note: This figure presents the maximum distance between home and school that parents would be willing to enroll their children, based on survey responses.

Figure A6 displays parents' predetermined enrollment choices. In line with our descriptive analysis, most guardians had already chosen a specific school. Only 25% of guardians indicate a list of schools they would consider, while fewer have no predefined school choice. This suggests that, despite the alternatives offered by the platform, most parents entered the platform with a preferred school. Moreover, we observe similar trends in responses across all groups, indicating that guardians' preferences and beliefs remain consistent, regardless of treatment.

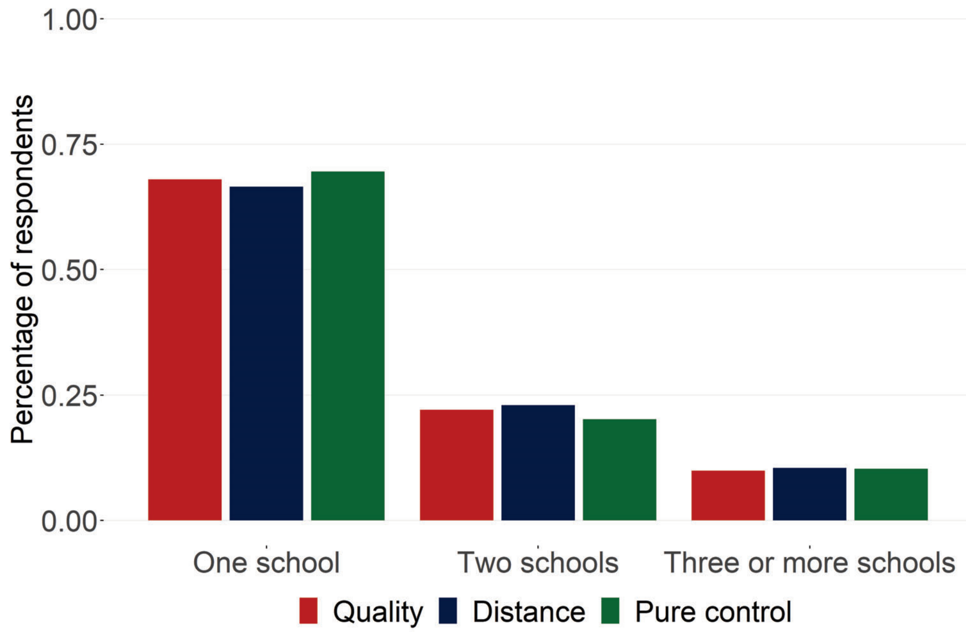
Figure A6: Before entering the *Matrícula Online* system, did you already have a specific school in mind where you wanted to request enrollment?



Note: This figure presents the proportion of parents who already had a preferred school, based on survey responses.

In this sample, approximately 75% of respondents indicated having a preferred school, and 73% included only one school in their application list, as shown in Figure A7. It is worth noting these large percentages may reflect sample bias, as survey respondents with a preference are likely more motivated than those without one. The bar distribution is similar between the treatment and pure control groups. However, parents in the latter group report higher rates of applying to only one school and lower rates of applying to two schools. This observation suggests that the treatment may have encouraged some parents to consider additional schools in their applications, a hypothesis that aligns with the findings in Figure A6, which show that parents in the treatment group had already decided upon a specific school at slightly higher rates than those in the pure control group.

Figure A7: Thinking about the schools you selected in the system for the student of whom you are a guardian, to how many schools did you choose to apply for a vacancy?

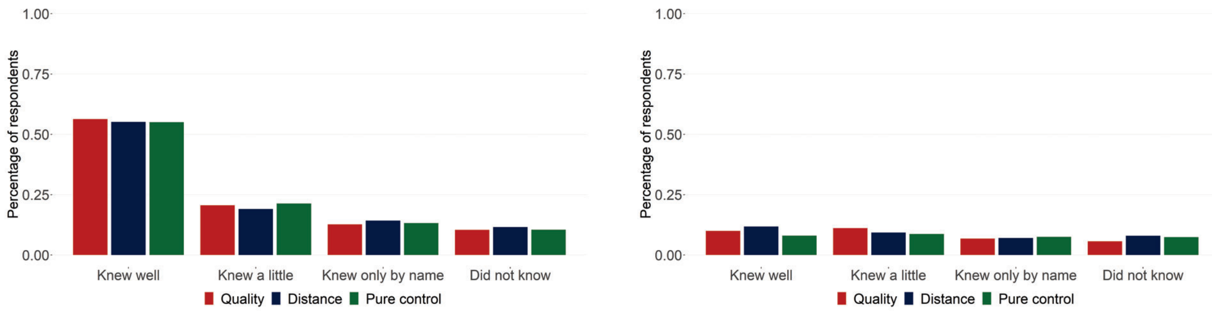


Note: This figure presents the number of schools that parents indicated they applied to, based on survey responses.

Finally, we analyze two responses to the same sort of question: one related to the first school chosen in the application, and another for the second school chosen.[14] Generally, parents report good or at least some knowledge of their first choice (Figure A8). However, Figure A9 shows that among those who selected a second school, knowledge is less pronounced, balanced between parents who are familiar with the school and those who are not. This pattern suggests that, as shown in Figure A10, parents tend to be more satisfied when they secure a spot in their first – and for many, only – choice. Among parents who indicated a second school, although satisfaction remains high for securing a spot at the latter, it is lower than for a first-choice school.

[14] Although the same question was asked for additional schools, such as the third school chosen, the number of respondents who selected a third or more schools and simultaneously responded to this survey is quite low, limiting our analysis.

Figure A8: Thinking about the school you selected, how would you rate your knowledge of this school?

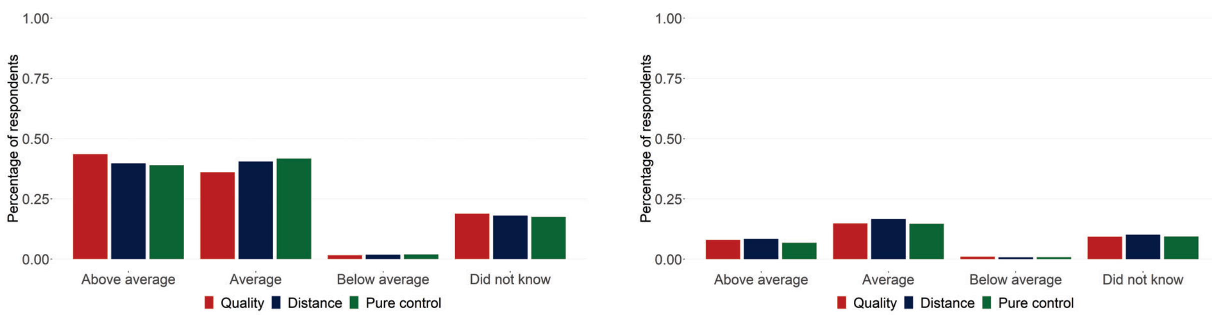


(a) First-choice school

(b) Second-choice school

Note: This figure presents the knowledge reported by parents about the school(s) applied to, based on the survey responses.

Figure A9: Thinking about the school you selected, how would you rate your perception of the students' learning outcomes compared to other public schools in Recife?

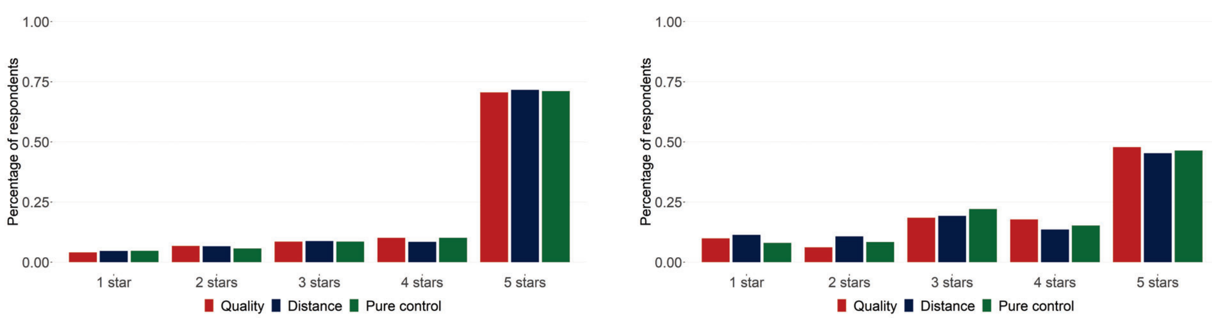


(a) First-choice school

(b) Second-choice school

Note: This figure presents the perception reported by parents about the school(s) applied to, based on the survey responses.

Figure A10: On a scale of 1 to 5 stars (where 1 star is very dissatisfied and 5 stars is very satisfied), how would you rate your satisfaction if you obtained placement at the school you listed?



(a) First-choice school

(b) Second-choice school

Note: This figure presents the knowledge reported by parents about the school(s) applied to, based on the survey responses.