Algorithmic College Admissions in the U.S.: Distances Between Vendors' Claims and Applicants' Perceptions

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The historically controversial U.S. college admissions process is increasingly shaped by algorithmic systems, exacerbating the potential for controversies over admissions and their fairness. Despite their increased use, questions remain about how vendors who provide algorithmic admissions technologies legitimize them and how applicants perceive these technologies. We report on 1) a qualitative content analysis of admissions technology vendor websites, and 2) interviews with college applicants, highlighting the distance between vendors' claimed benefits for universities (e.g., increased decision-making efficiency) and applicants (e.g., "unbiased" decisions) and applicants' perceived harms to themselves (e.g., undermining holistic review, hindering diversity, equity, and inclusion efforts). We consider the implications of algorithmic admissions decision-making, including privacy harms, discuss regulatory implications, and offer recommendations to guide algorithmic transparency efforts. However, we caution that transparency would not address some harms perceived by applicants, like inaccuracy and privacy violations.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: algorithms, AI, college admissions, higher education, fairness, bias, transparency, algorithmic harm, privacy harms

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1 Introduction

College admissions procedures shape access to higher education, which is integral to one's upward mobility [46], social capital [31], and social support [55]. College access is also integral to individual [156] and societal [150] economic success. Like other high-impact contexts (e.g., healthcare, hiring, child welfare) [4, 30, 127, 139, 140, 147, 148], college admissions offices globally [71, 133, 182] are increasingly using algorithmic systems. This includes the U.S. [63], where college admissions are historically controversial. Controversies stem from admissions policies like affirmative action[1] [13] or test-optional admissions [39, 96, 108], and scandals like Operation Varsity Blues[2], which unearthed a network of wealthy parents who bribed elite colleges for admission [109]. These

[1]Affirmative action is an umbrella term encompassing policies and practices designed to rectify past and present systemic discrimination in college admissions and employment. Over the years, people have questioned the rationale behind these policies, with some arguing against the prioritization of diverse schools and workforces [126]. Other controversies stem from how universities implement affirmative action practices, with legal opposition to racial quotas.
[2]Operation Varsity Blues refers to a highly publicized 2019 scandal involving a criminal conspiracy to influence undergraduate admissions at top U.S. universities by inflating test scores and bribing college officials, among other schemes.

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controversies undermine public trust in college admissions, exacerbating a legitimacy crisis for university admissions offices [1, 51].

At the same time, universities have begun deploying algorithmic systems in admissions and enrollment [63], promising more "standard" procedures that deflect public scrutiny. Machine learning [104] and predictive modeling [172] approaches assess application essays [98], rank and sort applicants for subsequent human review [95], and capture "demonstrated interest" [77, 99, 100], with underlying models often including sensitive attributes like race, income, and first-generation status [172]. Despite the promises of algorithmic college admissions, we lack empirical knowledge about how these technologies are legitimized, what problems they are purported to address, and how applicants – as an impacted group – perceive them. This is important because algorithmic college admissions technologies represent public-facing, "street-level" algorithms [9], affecting the work of admissions officers and applicants' experiences with college admissions.

Our examination of algorithmic systems' use in admissions is situated within prior Human-Computer Interaction (HCI) work in other high-impact contexts (e.g., criminal sentencing [142, 152], workplace monitoring [141], child welfare [33, 147, 162], hiring [4, 30, 140], student placement [102, 136], and school choice [120, 135, 164]), highlighting how algorithmic decision-making can create/perpetuate social inequities (e.g., [12, 75, 88]). Scholars have recently critiqued the "misplaced optimism" and lack of ethical scrutiny in the adoption of AI/algorithmic tools in higher education, including admissions [6], arguing that these tools reinforce existing biases (e.g., racial bias in student success predictions [76]). Further, despite higher education's implications for individuals and communities, and much scholarship dedicated to *building* algorithms and machine learning models to recommend or make admissions decisions [10, 71, 89, 98, 104, 133, 172, 182], exploration of the *social and ethical implications* of these systems remains sparse. Moreover, as policy in the U.S. begins to address algorithmic decision-making (e.g., [103, 171]), developers and vendors of algorithmic admissions technologies face increased pressure to 1) prove that they make accurate claims about these technologies' benefits and limitations, and 2) develop robust appeals and alternative human review processes. Against this background, we recognize a critical need to examine higher education technologies' ethical and social implications. We focus on algorithmic college admissions technologies with a growing presence in U.S. universities [34, 86, 87, 161, 163].

This paper reports on two studies examining 1) vendors' claims and 2) applicants' perceptions regarding algorithmic admissions technologies. We examine vendor claims because how algorithmic admissions technology vendors legitimize their products reveals their perspectives on problems plaguing "traditional" admissions processes, anticipated benefits of their technologies, and vendors' values [173]. Although vendor websites rarely communicate details of their technologies' functionality, they often provide insights into values that shape vendors' marketing [129, 140]. Analyzing claims made by vendors is also an act of "studying up" [17], or critically investigating those in power, like vendors whose technologies impact universities and applicants. Therefore, we conducted a qualitative content analysis of 52 admissions technology vendor websites to reveal what *problems* vendors position their products to solve and how.

Additionally, we have little empirical evidence of U.S. applicants' perspectives despite the impact algorithmic admissions could have on their futures. We investigate how applicants perceive the benefits and harms of these technologies and highlight the distance between their views and vendors' claims. Understanding applicants' perceptions is necessary in the development and deployment of any "ethical" admissions technologies; a relational ethics approach [6, 27, 28] emphasizes the need to center the perspectives of those most impacted by emerging technologies because these individuals can more readily identify ethical considerations that less impacted groups may miss. We conducted 18 semi-structured interviews with recent U.S. university applicants, using speculative verbal probes designed based on existing algorithmic admissions technologies assessing essays (e.g., [10, 14]), identity (e.g., [23]), and demonstrated interest (e.g., [177]), along with vendor descriptions.

Our analysis of vendors' claims about algorithmic admissions technologies reveals claimed benefits to admissions offices and applicants (e.g., increased decision-making efficiency). Interviews reveal that while applicants recognized some of these benefits, they also raised concerns about harms, including increased *applicant* labor, and algorithmic bias. Applicants did not view some of vendors' claimed benefits to admissions officers and applicants (e.g., "unbiased decisions") as benefits to them, instead citing potential harms like inaccurate, unfair decision-making and pressure for applicants to self-present in their application and online to appease the algorithms.

This work makes the following contributions:

- Reveals the distance between vendors' portrayals of algorithmic admissions technologies and applicants' perceptions
- Argues that despite vendors' claims, algorithmic admissions decision-making processes defy holistic review principles, possibly hindering rather than facilitating efforts toward diversity, equity, and inclusion
- Highlights perceived privacy harms stemming from algorithmic admissions technologies, emphasizing their significance in the college admissions context
- Provides design and regulatory considerations to foster more meaningful algorithmic transparency in the college admissions context

2 Related Work

We first draw from scholarship on U.S. college admissions to contextualize the uptake of algorithmic admissions technologies. Next, we review literature on the legitimization of algorithmic decision-making technologies to motivate our analysis of vendor websites. Finally, we review work on impacted groups' perceptions of algorithmic decision-making technologies to motivate our exploration of applicants' perceptions of algorithmic admissions technologies.

2.1 U.S. College Admissions and Algorithmic Admissions Technologies

The college admissions process is notoriously opaque and complex, hinging upon a university's institutional priorities in a given year [79, 153]. Despite varying university admissions processes, some criteria (e.g., grades, essays, extracurriculars) remain relatively standard [82]. Essays, for instance, help admissions officers assess the strength of students' narrative arguments [15].

To abide by federal and state-level policies banning affirmative action[3], regain public trust in light of admissions controversies, and achieve diversity goals, universities often engage in "holistic review" [22]. Holistic review processes in U.S. college admissions explicitly consider non-academic factors like students' background and school characteristics [82]. Other non-academic factors like "demonstrated interest" by a student in a university are increasingly measured through actions like campus visits or early applications [77] and digital traces from internet, email, and social media engagement [99, 100]. Many universities consider demonstrated interest, often as a factor that can "tip" an admissions decision one way or another [77].

Against this background, algorithmic technologies may (re)shape the process and public perception of college admissions. College admissions and enrollment technologies can perform descriptive, predictive, and prescriptive functions, not only describing the composition of an applicant pool but also making admissions recommendations [177]. Scholarship developing and assessing algorithmic

[3]In June 2023, the U.S. Supreme Court ruled the consideration of race in university admissions unconstitutional. This decision effectively overturned legal precedent dictating that race could be a factor in the admissions process because of a compelling interest (i.e., the benefits of diverse educational environments) [26, 84, 115, 158].

systems in college admissions focuses on machine learning [104] and predictive modeling [172] used for various admissions functions: assessing personal qualities in essays [98], ranking top applicants for human review based on quantitative metrics [95], and sensitizing human admissions officers to identity-related bias [10]. Models often include sensitive attributes like race, income, and first-generation status [172], but 2023 rulings rendering race-conscious admissions unconstitutional will likely change the attributes college admissions models are allowed to consider.

Like other contexts where algorithmic decision-making is increasingly used (e.g., hiring, child welfare), college admission is high-stakes. It intimately shapes applicants' access to opportunities, shaping their earning potential [46], social capital [113], and well-being [43, 44]. Unlike related contexts, college admissions require applicants to pay to apply, potentially shaping their expectations and attitudes toward algorithmic admissions. Additionally, the U.S. college admissions landscape is decentralized, making it difficult for applicants to understand whether algorithmic approaches and technologies are used, from which vendors, at which universities, and how they work. In a time where college admissions face a crisis of trust and legitimacy [1, 51], understanding any distances between vendors' portrayals and applicants' perspectives is crucial to understanding the implications of deploying algorithmic admissions technologies.

2.2 Legitimization of Algorithmic Decision-Making Technologies

Algorithmic decision-making is widespread in areas like criminal sentencing [142, 152], child welfare [33, 147, 162], hiring [4, 30], and student placement [136]. Vendors promote algorithmic systems by claiming benefits (e.g., accuracy, objectivity, transparency [148, 152]) in decision-making processes. Drawing upon computational notions of fairness [19], supporters argue that algorithms improve upon flawed human judgment [140, 152] and provide consistency [30], and claim that bias can be technically mitigated [76, 125].

Vendors, developers, governments, and policymakers, among others, legitimize algorithmic/AI technologies as solutions to supposed societal problems [56], contributing to the larger portrayal of these decision-making technologies as positive [8, 18]. These actors frame technology adoption as inevitable and progressive [94, 159], its benefits "unbounded" [36, 92], and its risks "limited and manageable" [85]. Scholarship at the intersection of technology and education describes "educational imaginaries" – "visions, policies, and projects" that "problematize, negotiate and ultimately govern citizens and citizenship at the intersection between technology and education" [130]. The "smart" (i.e., algorithmic/AI-enabled) university reflects pervasive educational imaginaries, prompted by the large-scale incorporation of online tools during the COVID-19 pandemic and discourses suggesting that universities must become "smart" to survive in a rapidly globalizing knowledge economy [69, 78]. These discourses suggest that without data-driven technologies, universities are outdated and risk failing [24, 78], a perspective aligning with the growing privatization and marketization of higher education, where institutions increasingly operate like businesses, not public services [78].

Yet, we know little about how vendors legitimize algorithmic admissions technologies. Past HCI work posits that analyzing claims made by AI vendor websites, specifically, is important to unearth industry trends, practices, and values and engage in ethical speculation about the implications of emerging technologies [32, 129, 140, 165]. We argue that studying claims made by vendors who provide and market college admissions technologies is an act of "studying up" [17], or critically investigating those in relative positions of power – in this case, vendors whose algorithmic systems impact universities and applicants. Therefore, we ask:

- *RQ1: How do vendors of college admissions technologies used in the U.S. describe the problems within college admissions, and how do they legitimize their technology products as solutions to these problems?*

2.3 Social Implications of Algorithmic Decision-Making Technologies

Critics of algorithmic decision-making tools highlight concerns about fairness/bias, privacy harms, and opacity. For one, they argue that many such systems can be biased and unfair in ways that compromise individuals' access to resources and opportunities. Impacted groups have critiqued recidivism prediction algorithms [152], child welfare algorithms [162], and algorithmic hiring systems [30] for facilitating and exacerbating bias, particularly against Black and Brown communities.

Research on the fairness of algorithmic admissions is limited and mixed. Keir et al. [90] suggest AI could standardize medical school admissions, but acknowledged potential biases like those present in human reviewers [90]. Bergman et al. [25] found algorithms better predict college readiness than standardized tests, while Gandara et al. [76] showed prediction accuracy varies by race, suggesting bias. Other scholars point to automated decision-making in higher education as embedding "old" forms of bias and inequality [164].

Algorithmic decision-making may also bear privacy harms [50], inclusive of economic, reputational, discrimination, psychological, and autonomy harms relevant to impacted groups. In higher education, algorithmic decision-making increasingly emphasizes the use of students' data and protected attributes as model inputs [106]. Scholars argue that the growing reliance on algorithmic decision-making in higher education can also exacerbate student surveillance [105]. Yet, it is unclear if and how applicants perceive algorithmic admissions technologies to confer privacy harms that shape their ability to access higher education. Prior work on K-12 school choice algorithms shows that fairness definitions and perceptions are informed by one's identities and positionalities [120]; our study adds to the debate over algorithms' implications in college admissions by ascertaining applicants' perceptions of algorithmic admissions technologies and their privacy implications.

Finally, opaque algorithmic decision-making stems from a combination of 1) intentional secrecy, 2) technical illiteracy, and 3) the gap between machine learning's mathematical logics and human reasoning [35], aligned with *organizational transparency* concepts of verifiability (i.e., information disclosure to build trust) and performativity (i.e., the challenges of making transparency work) [7]. Nissenbaum's contextual integrity framework [121] stresses the need for information disclosure – including about AI systems – to respect contextual norms of information flow.

Research on algorithmic opacity and transparency in K-12 education demonstrates these characteristics' influence on impacted groups' trust in automated decision-making [102]. Even transparency-focused algorithms can cause issues. San Francisco redesigned its student assignment algorithm after families found it frustrating, relying on modeling assumptions that clashed with real-world complexities [135]. While prior work has attended to perceptions of transparency and opacity with respect to algorithmic decision-making technologies in K-12 education, little work has focused on algorithmic admissions decision-making in U.S. higher education.

Scholars have begun to attend to impacted groups' perceptions (e.g., [11, 27, 28, 53, 72, 91, 123, 135, 136, 160, 181]) across a range of domains – demonstrating the importance of understanding such perceptions across contexts. Yet, few studies on algorithmic decision-making in higher education foreground students' perspectives. One exception is Marcinkowski et al. [101], who found that German students viewed algorithmic admissions decision-making as fairer than human decision-making. However, it is uncertain if U.S. students share this view, given controversial U.S. college admissions histories and policies like affirmative action. Additionally, since taxpayers partly fund U.S. universities, understanding applicants' views on these technologies is crucial to uphold the public service mission of many institutions. In a U.S.-based study of graduate school admissions with student participants, Zhang et al. [181] reported resistance to automated admissions decision-making and noted potential for non-technical improvements to admissions decision-making.

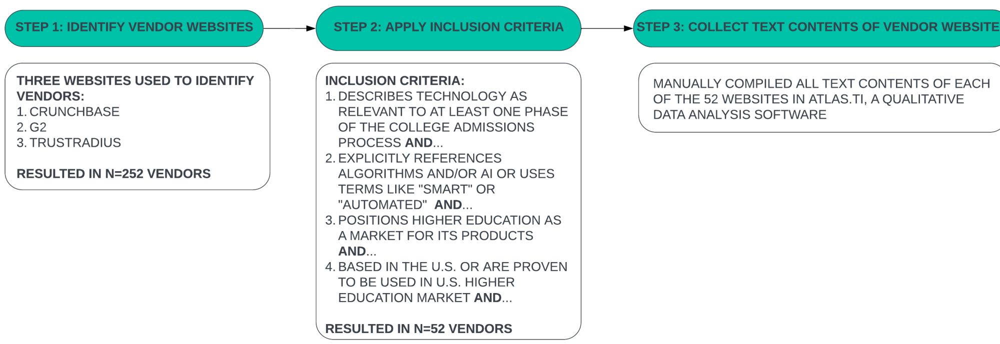

Fig. 1. Diagram detailing our qualitative content analysis data collection process

Our study focuses on algorithmic technologies used in *admissions decision-making*, given their significance for college access, career prospects, and overall well-being [67, 149]. Aligned with growing scholarship that centers impacted groups' perspectives on emerging technologies, we work directly with applicants, as they can most readily identify a range of reactions to these technologies that others (e.g., researchers, admissions officers) may miss [27]. Therefore, we ask the following research question:

- *RQ2: How do U.S.-based college applicants perceive algorithmic college admissions technologies, particularly concerning perceived benefits and harms?*

Together, RQ1 and RQ2 enable us to explore how closely aligned vendors' claims about algorithmic admissions technologies are with applicants' perceptions. Thus, our final research question asks:

- *RQ3: What distances exist, if any, between vendors' legitimization of college admissions technologies and applicants' perspectives?*

3 Methods

We conducted two studies involving 1) qualitative content analysis [83, 154] of the websites of 52 vendors whose technologies are used in U.S. college admissions and 2) semi-structured interviews with 18 recent college applicants.

3.1 Vendor Website Analysis

We identified commercially available college admissions technology vendors, reviewed their websites to determine eligibility for study inclusion, and collected *all* text contents of included websites for analysis. We opted to collect text data, not photo and video data, because of the limited visuals on vendor websites and the unique analytical approaches necessary to analyze them. We summarize the steps below, providing details in Figure 1. We consulted three websites (Crunchbase, G2, TrustRadius) used in related work [129, 140] to compile an initial list of 252 vendors. Next, we manually reviewed 252 vendor websites to determine eligibility for inclusion. Vendor websites had to 1) describe the technology as relevant to the college admissions process; 2) explicitly or implicitly (through terms like "smart" or "automated") reference algorithms/AI; 3) position higher education as a/the market for their product(s); 4) be based in the U.S. or used by U.S. universities. 52 vendors met these criteria and formed the final dataset. We manually compiled all text contents of the 52 websites in Atlas.ti, a qualitative data analysis software. Our appendix includes the 52 vendors whose websites we analyzed.

3.1.1 Data Analysis. The first author began the open coding process [52], developing an initial codebook. Next, both authors met and engaged in axial coding [52], finalizing a codebook comprising 15 parent codes (e.g., "characteristics of services/products") and 129 child codes (e.g., "efficiency"), which the first author then applied to the entire dataset. While we collected and analyzed all website text content, including about larger product suites beyond algorithmic admissions technologies (e.g., automated enrollment or marketing technologies), this paper draws on codes related to our research questions regarding algorithmic admissions.

3.1.2 Limitations and Opportunities. This study has several limitations. We may have missed vendors when developing and refining our database. Nevertheless, our findings reveal claims by popular vendors in this product space whose technologies are used at U.S. universities. Because of the proprietary, opaque nature of these technologies' workings, we rely on claims made on publicly available vendor websites, which we cannot verify firsthand. Future work may use algorithmic auditing [57, 145] methods to confirm or contest these claims, though auditing poses other challenges [54] and does not always produce actionable suggestions [131].

3.2 Semi-Structured Interviews with College Applicants

Next, we conducted semi-structured interviews to elicit applicants' perceptions of college admissions technologies. Our institution's IRB determined this study exempt from ongoing oversight. We compensated participants with a $25 gift card.

3.2.1 Participants and Recruitment. We interviewed U.S. students who applied to a four-year U.S. university and were 18 or older. Applicants we interviewed had recently completed college applications[4]. We attempted to recruit applicants of various races, ethnicities, genders, and socio-economic statuses, attributes shaping admissions experiences and outcomes [47, 48, 70, 107, 137]. We recruited by posting a flier on social media using college-related hashtags (e.g., #ApplyingToCollege) and asking administrator permission to recruit in popular admissions-related Facebook groups and Reddit communities. We received 772 screening survey responses, discarded 722 due to incompleteness or spam, and invited the remaining 50 respondents to complete the consent form. Of these 50, 36 completed the form and were invited to schedule an interview, which 18 completed. We stopped recruitment once we ceased identifying new themes after 18 interviews, signaling saturation [118]. Table 1 lists self-described participant socio-demographic information [5].

3.2.2 Data Collection. The first author conducted two-phase semi-structured interviews (41-73 minutes, average = 56 minutes) via Zoom. We provide our screening survey and interview protocols in the Appendix[6]. Semi-structured interviews elicit rich, contextualized data on participants' perspectives and experiences. In Phase 1, we asked participants about their experience applying to college and how they understand the admissions process, including how they expect technologies to be used within admissions decision-making. We asked students about their expectations regarding what components are evaluated, how, in what order, by whom, and whether technology shapes admissions decision-making.

[4]All had reported receiving admissions decisions, with nearly all admitted to a top-choice college, which is relevant as outcome favorability may shape perceptions of admissions algorithms [49, 176, 179].

[5]The screening survey allowed participants to self-describe as low-income rather than list their annual household income or select from income brackets. Asking for household income does not consider other factors (e.g., family size, location) relevant to one's lived experience with socio-economic status.

[6]We note that our screener survey and interview protocols include questions about social media and college admissions. The project we report on here was part of a broader inquiry that was also interested in discourses of algorithmic admissions on social media.

Participant	Gender	Race/Ethnicity	First-Generation?	Low-Income?
1	Female	White	X	X
2	Female	Vietnamese		
3	Woman	Asian		
4	Male	Asian		
5	Male	Asian (Viet & Cambodian)	X	X
6	Female	White		
7	Male	Vietnamese	X	X
8	Female	Hispanic/Latinx	X	X
9	Female	Asian		
10	Female	White (non-Latino and Latino)		
11	Female	White & Asian		
12	Male	White		
13	Female	Asian	X	X
14	Female	Asian		
15	Male	White		
16	Female	Black	X	X
17	Female	Chinese		
18	Male	Hispanic		

Table 1. Participant Socio-Demographics. First-generation = students for whom neither parent/guardian received a 4-year degree in the U.S. Participants self-reported gender in an open-ended text box, hence some using terms like "Female" while others used terms like "Woman."

In Phase 2, we asked participants to reflect on speculative verbal probes representing how algorithmic technologies may support admissions decision-making, designed based on vendor descriptions and news articles, along with reports about existing algorithmic admissions technologies. In response to each probe, we asked participants for their initial reflections as well as how they would feel if their college applications were assessed that way. We used four probes in interviews to represent algorithmic admissions technologies' possible data sources, centered on 1) grades and test scores, 2) essays, 3) identity facets, and 4) demonstrated interest. We report on the final three probes because they contend with data sources that are not inherently quantitative, yielding insights into how applicants perceive algorithmic admissions technologies handle qualitative demonstrations of merit within an application.

Probes [58] can generate rich, humanizing insights about participants, which is important given applicants' relative lack of power despite being most impacted by algorithmic admissions decisions [73]. HCI research has a rich history of using probes and other speculative tools (e.g., scenarios [42], critical design artefacts [110], vignettes [11, 74, 138]) in conjunction with interviews. Though speculative approaches – as opposed to those grounded in cognizant, direct experience with algorithmic technologies – have been critiqued, scholars point to their value for considering possible and preferable futures [62]. Speculative approaches are useful for investigating data work in organizations [81], making them apt to explore algorithmic admissions technologies' data sources.

Our speculative verbal probes map to Derix and Leong's [58] probe design framework, which considers four properties: 1) openness/boundedness, 2) materiality, 3) pace, and 4) challenge. Our probes were fairly *open* and explicitly described as an imaginative scenario. We ensured internal consistency by replicating language used in the first half of the prompt, providing sufficient context by introducing the probe activity and asking participants to imagine that the colleges they applied

Probe	Rationale
Probe 1: Among the factors the software would use to determine your admission status are your **written essays**.	We designed this probe based on existing scholarship on automated essay rating technology. Attali & Burstein [14] note that by the 1990s, several systems for automated essay scoring existed, including e-rater, used for graduate school admissions. Since then, automated educational grading systems have proliferated, relying on more advanced algorithmic approaches [80, 132, 157, 183].
Probe 2: Among the factors the software would use to determine your admission status are factors related to your **identity**, such as your zip code, household income, ethnic background, and whether you will be a first-generation college student.	We designed this probe based on the Environmental Context Dashboard [21], which uses neighborhood-level data, crime risk, family stability, educational attainment, housing stability, and median family income to create an "Overall Adversity Index" to contextualize applications. While the Environmental Context Dashboard is not algorithmic, its technological interface allows admissions officers to consider environmental contextual factors when making decisions.
Probe 3: Among the factors the software would use to determine your admission status are factors related to your **engagement** with the university, such as how often you visit school websites, open and read school emails, and attend on-campus recruitment events.	We designed this probe based on press pieces [61, 99, 100, 161, 175] and vendor documentation [41, 143] around technologies that track and weigh "demonstrated interest," or admissions officers' perceptions of a student's interest in attending a given college or university if admitted.

Table 2. Probe descriptions and rationales

to used software to inform their application's outcome. We used the phrase "among the factors" to allow participants to interpret the capabilities of the "software" and let interpretations shape their responses. Second, the dimension of *materiality* concerns the use of novel vs. familiar materials and references. While our probes themselves were novel, they were designed based on existing vendor documentation, press articles, and prior literature on admissions decision-making. We use neutral terms like "software" instead of "algorithm" to enhance interpretability and avoid bias from participants' preconceptions toward terms like "algorithm" or "AI." Third, regarding *pace*, probes were presented verbally in the context of a single interview. Although limiting extended reflection, the semi-structured interviews fostered dynamic exchanges that elicited rich data. Fourth, the dimension of *challenge* considers the level of commitment encouraged by probes. Our probes required moderate commitment; participants shared their thoughts in a one-hour virtual interview. Open-ended probes allowed applicants' understandings of college admissions and technology to freely inform their responses. Table 2 provides additional rationale for our decision to focus on data sources like essays (Probe 1), identity (Probe 2), and demonstrated interest (Probe 3).

3.3 Data Analysis

After each interview, the first author wrote memos identifying salient insights and used Otter.ai to transcribe interviews before manually checking transcripts for accuracy. She engaged in open coding [52, 144] of all 18 transcripts until reaching a saturation point [66], resulting in a provisional codebook. At this stage, codes included "fit," demonstrated interest, social identity/background, etc. The authors met to discuss and refine the provisional codebook. Then, the first author applied the finalized codebook to the entire dataset and engaged in axial coding, reorganizing the data, selecting representative codes, and developing themes [52, 144]. The authors met during the axial coding phase to refine the themes animating this paper.

3.3.1 Limitations and Opportunities. We focused on U.S. four-year universities, which differ from other national contexts' admissions processes (e.g., [119, 169]) and those at two-year colleges. We did not confine our study to a particular type of institution (e.g., public vs. private), which could affect applicants' perceptions. Additionally, our use of social media for recruitment may have biased our sample. Participants may have a deeper understanding of admissions processes stemming from their participation in admissions-related social media groups. Our exploratory interviews attempted to capture varying experiences and perceptions, not elicit representative or generalizable findings. We implore future work to use other recruitment strategies to reach students who are less active on social media and represent a broader range of identities than those represented here (e.g., Black and non-binary applicants).

Our probes were designed based on public documentation (e.g., [14, 23, 41, 86]) and focused on technologies' data sources (e.g., social media data, identity-related data) rather than other factors like automation levels [33] or human intervention [146], which may have influenced participants' responses. Additionally, while we focused on applicants' perceptions, we did not address the views of admissions officers, an area for future work. Finally, future work with applicants and admissions officers can consider speculative tools beyond probes, like design fictions [29] or speculative dashboards [81], for exploring perceptions about algorithmic admissions technologies.

4 Findings

Our analysis demonstrates how vendors legitimize algorithmic admissions technologies by claiming benefits like efficiency and accuracy. We reveal the distance (RQ3) between vendors' visions of algorithmic admissions technologies as efficiency-, ease-, and transparency-enhancing for admissions officers (RQ1) and applicants' perceptions of these technologies as encouraging more labor and providing less transparency for applicants (RQ2). Additionally, we illustrate the distance (RQ3) between vendors' portrayals of algorithmic admission technologies as bias-mitigating and accuracy-, diversity-, equity-, and inclusion-enhancing (RQ1) and applicants' perceptions of them as introducing algorithmic bias and new forms of inaccuracy (RQ2).

4.1 Efficiency & Ease for Admissions Officers vs. Increased Labor for Applicants

Our analysis revealed distance between vendors' articulated benefits of efficiency and ease and applicants' perceived harms of increased labor for applicants (i.e., lack of ease and efficiency).

4.1.1 Vendors' Claimed Benefits: Efficiency & Ease for Admissions Officers. The vendors in our data suggested their technologies would enhance efficiency for admissions personnel. For example, T1 promises that its technology *"empower[s] efficient review with a rich application reader experience."* Similarly, T9 states: *"Seamlessly collect and review applications. Use branded online portals to easily collect applications, coordinate reviews, and capture the feedback you need to make decisions."* In both cases, vendors implicitly articulate application collection and review as traditionally cumbersome, asserting that their products ameliorate efficiency-related challenges. Some vendors provide more specificity when describing how their products promote efficiency and ease, articulating algorithmic auto-scoring features as facilitating greater efficiency for admissions offices. For example, T12 provides *"auto-scoring: Generate scores or points for specific answers to help you quickly evaluate submissions,"* promising ease, efficiency, and speed.

Vendors invoked the notion of ease to describe how algorithmic admissions technologies automate low-level tasks, freeing time for employees to tackle more complex tasks. T26 argues that its technology helps admissions offices:

> *"Achieve more with less effort. Imagine how much more your team could achieve if your day wasn't taken up with tasks we label 'every day.' You could work more strategically, dedicate more time to the individual students who need the most help and, you know, complete your to-do list most days... It's your job to maximize your efficiency as much as humanly possible. But you're probably already doing that. Now, it's time to maximize your efficiency as much as technologically possible."*

T26 notes that the ease facilitated by its technology products can benefit admissions personnel *and* applicants, such as "*the individual students who need the most help.*" T26 also implies that techno-solutions such as their product provide a degree of efficiency and ease that is impossible to achieve without technology. Its website distinguishes between what is "*humanly possible*" and what is "*technologically possible.*"

4.1.2 Applicants' Perspectives: Workload Reduction for Admissions Officers vs. Increased Labor for Applicants. Applicants and vendors agreed that algorithmic admissions technologies could streamline the application review process, reducing admissions officers' workloads. Regarding technologies that would evaluate essays (Probe 1), P13 (Asian Female, FGLI) says, *"That would suck because I spent a lot of time on my essays... to just have it filtered and not read... but I do understand it. Because it's a lot of applications, and you can't read every single detail or read every single one of them."* P13 dedicated significant effort in applying to and being part of Questbridge, a college access program for low-income students, requiring substantial time and mentor-guided revisions on students' essays. This effort may have influenced her disappointment with algorithmic essay rating, though she acknowledged its efficiency benefits. Regarding admissions technologies that consider applicants' social identities (Probe 2), P15 (White Male) says:

> *"I think computers that flag underprivileged applicants or applicants that have shown interest are a great way to streamline processes... if a computer was able to flag underprivileged students like, 'Hey, this student is from a certain zip code, from a certain ethnicity, financial aid background, where they have absolutely been underprivileged... then I think that absolutely would benefit students... I think that would [also] absolutely aid some admissions officers in finding out which students have truly been held back."*

This participant notes the possible benefits of admissions technologies that *identify* and *flag* applicants who meet certain qualifications or embody specific characteristics, allowing admissions officers to sift through applications more efficiently. P15 did not come from social groups underrepresented in higher education and had access to the social capital necessary to meticulously craft his application, saying, *"I wrote a [university]-specific essay about how I had done a lot of diverse extracurriculars throughout my high school career... I also included a video portfolio that just took them to... a little spot near a local river, that got me interested in environmental science."* As such, his perceptions of the benefits of algorithmic admissions technologies are rooted in speculation on what *could* benefit underrepresented students, not lived experiences.

On the other hand, participants highlighted how tracking demonstrated interest (Probe 3) could encourage more labor and stress from applicants, even while it may make admissions officers' jobs easier. Describing a scenario in which she would try to "game" the system by engaging with a university online, P1 (White Female, FGLI) said:

> *"It was so irrational... My friend and I would go on different websites when it was close to the decision coming out... We would just click around and explore different things, which I*

> *guess was a plus because we got to know more about the school, but at the same time, we also had this fear if we didn't spend enough time on this website, then they're not going to take us. So I guess we just left our tab open for a few hours, and then we just clicked around to make sure that... it saw that we were actually active on the site."*

While there is always an element of stress and uncertainty in the application process, tracking of website traffic to factor into a demonstrated interest score – which existing systems do [116] – created undue stress for P1 and her friend, who engaged in additional *"irrational"* labor hoping to get the technology to work in their favor. As P1 notes, *"I found it really stressful just because I didn't know how much was too much and how much wasn't enough."* This stress may have been exacerbated by P1's underresourced high school context, which she said did not prepare her to apply to competitive universities; lower-resourced applicants may be more negatively impacted by demonstrated interest tracking algorithms than their more affluent counterparts.

4.2 Transparency for Admissions Officers vs. Opacity and Privacy Violations for Applicants

Second, our analysis showcased distance between vendors' vague claims of increased transparency for universities and applicants' perceptions of decreased transparency for them. While vendors and applicants both lauded transparency as a value, vendors primarily considered algorithmic admissions' transparency benefits to admissions offices. Applicants perceived these technologies to make the admissions process *less* transparent to them. This perceived opacity facilitated additional perceived harms for applicants, like violations of their privacy and expectations for admissions decision-making.

4.2.1 Vendors' Unsubstantiated Articulations of Transparency as a Benefit to Admissions Officers. Vendor websites promised transparency vis-a-vis their technologies, often vaguely describing their technologies' transparency benefits for admissions personnel – without substantiation – and rarely for applicants. T43 claims that its technologies *"provide transparency, control and increase productivity by providing the right people easy access to the right student and institution information."* Relatedly, T21 promises that its technology solution *"increases transparency, accountability, speed, and accuracy to help you make more strategic decisions and prepare for emerging enrollment trends."* Here, T43 and T21 articulate transparency as a benefit for admissions personnel, appealing to universities' values of organizational transparency [7] without the vendor describing *what* transparency entails and *how* it is achieved. While transparency is also important to applicants, vendors did not often address the implications of their products' algorithmic transparency for this group, which is likely a function of vendor websites serving as a marketing tool to universities.

4.2.2 Applicants' Perspectives: Opacity and Privacy Violations to Applicants. Opacity regarding whether and how algorithms are implemented into admissions processes, participants described how automated essay rating technologies (Probe 1) can feel disrespectful to applicants. P12 (White Male) said, *"I [spent] multiple days, probably weeks writing my essays. If all of that were to be judged instantly by [an algorithm], I would not feel too great. I would hate that. I'd want people to actually read my essay for me to get...the respect that my application deserves."* P12, who was rejected from his top-choice schools, may have found algorithmic rejection especially harmful. Lacking transparency about algorithmic admissions can feel disrespectful to the labor students put into their applications and invalidate the meaningful experiences shared in their essays.

In addition to being disrespectful, some participants perceived algorithmic admissions technology as violating their expectations regarding the admissions decision-making process. As P16 (Black Female, FGLI) says in response to Probe 1, *"I think the human should be the one reading the essay* *since the students wrote the essay intending for an admissions officer to read it."* The expectancy violation involved when students expect their essays to be written by a human and instead are evaluated by an algorithm may be heightened for P16, who reported engaging in significant labor to demonstrate fit through her admissions essay. She recalled, "*I reached out to admissions officers a lot... I wanted to know if my values align with the institution's.*"

Instead of being treated as a whole person with valuable ideas and a carefully crafted application, participants perceived that the introduction of automation quantified and dehumanized them, and violated their expectations, leading them to question why they sacrificed time and energy in a process that does not treat them with dignity and respect. When the presence of algorithms is opaque to applicants, they hold expectations of "traditional" admissions procedures. If such expectations are violated, participants perceive emotional harm in the form of disrespect.

Finally, participants perceived that demonstrated interest tracking technology (Probe 3) violated applicant privacy. P4 notes, *"It does seem a little bit intrusive if they're checking how often we open emails and visit the websites."* P4 locates demonstrated interest tracking via email and website engagement as an "intrusive" privacy violation, even *if* these metrics are accurate. Concerning technology monitoring applicants' social media engagement, P11 notes, *"I feel like when it comes to looking at whether or not you're engaging with [the university] on social media, that feels a little bit [like] an invasion to be tracking, 'Do you click on our profile? Do you like our post?' That feels like a bit much."* P11 and P4 use terms like "invasion" and "intrusive" to describe how demonstrated interest tracking via online engagement harms their privacy.

4.3 Bias Mitigation and DEI vs. Algorithmic Bias and Conformity

Our analysis also highlighted distance between vendors' articulated benefits of bias mitigation and diversity, equity, and inclusion (DEI) juxtaposed with applicants' perceptions of algorithmic bias and incentivization of conformity in applicants' self-presentation.

4.3.1 Vendors' Articulation of Bias Mitigation, and DEI as Benefits. Vendors noted that admissions officers' bias embedded in the decision-making process is a problem that their technologies would address by helping universities admit "best-fit," "qualified," or "the right" students objectively, truthfully, and consistently. As an example, T1 notes that its product *"uncover[s] biases"* in the admissions process and lets admissions offices *"work smarter with automated scoring,"* implying that admissions officers' bias is readily identifiable and straightforwardly mitigated via algorithmic scoring. Additionally, vendors referenced their products' bias-elimination approaches to promote equality. T27 notes that its product *"give[s] every applicant an equal opportunity by building a standardized assessment that will reduce bias in the admissions process,"* connecting claims about bias mitigation to larger discourses of equality and admissions, despite not providing evidence on how their products mitigate bias.

Vendor websites also describe other ways their products promote DEI. Regarding "diversity," T21 claims that their products help universities *"Build Better, More Diverse Classes"* with *"Liasion's Total Enrollment Approach"* that integrates algorithmic admissions technologies alongside products that manage other aspects of the student lifecycle (e.g., recruitment, enrollment). Similarly, T27 promises *"Equitable evaluation: Ensure consistency in the way your team interviews and assesses applicants for non-cognitive competencies, helping them reduce bias and make defensible decisions."* These examples highlight the assumption that vendors' techno-solutions can recruit, engage, and retain diverse student cohorts. Yet, many DEI-related claims are vague. It is unclear, for example, how vendors conceptualize and operationalize DEI regarding algorithmic admissions technologies.

4.3.2 Applicants' Perspectives: Algorithmic Bias and Conformity. While vendors claim their technologies enhance DEI efforts in admissions, applicants feared these technologies – particularly those that automatically evaluate applicants' essays – introduce algorithmic bias. P1 (White Female, FGLI) said:

> *"I feel like it's better if a human reads [essays] because they're able to empathize and just feel emotion towards a person and if an admissions officer feels like they truly connect with the applicant through their writing, I feel like that something that will make the student a great contribution to the school and I feel like only a human could be able to determine that."*

For P1, if an algorithm evaluates the essay, the connection one could make with admissions personnel through writing would be lost. Importantly, P1 reported feeling that one's ability to demonstrate fit for the university through their essays is a key factor for college admissions, which may have shaped her perceptions on algorithmic essay rating technologies. P5 (Asian Male, FGLI) expands upon this perception, saying: *"[Software] can analyze the feelings, but the emotions wouldn't work the same way... I feel like the computer would just look at how well you write your essay as opposed to how you can deliver your message to a human."* Like P1, P5 reported thinking that fit was a key admissions factor, noting that essays "*are the most important thing ever because that's the only part where admissions officers get to see who the applicant is as a person.*" These quotes reveal applicants' perceptions that algorithmic technologies are ill-equipped to comprehend admissions essays, which are designed to assess an applicant's writing abilities, *who* the applicant is, and the obstacles they have faced. Participants like P1 and P5 suggested that evaluating essays requires emotional expression on the applicant's side and empathy on the reader's side, which they do not perceive algorithms to possess. These participants preferred human adjudication despite noting that admissions officers' human bias exists, with P5 suggesting that an admissions decision "*depends on the mood of the admissions officer*" and P1 saying, "*if they didn't like their lunch that day, or if someone pissed them off on the way to work, that could affect whether or not a student gets in.*" Participants may have preferred human over algorithmic bias because they felt admissions officers' biases stemmed from their contextual knowledge about who would be good "fits" with a given college's values and priorities. P6 (White Female) said, *"I would trust [admissions officers] more than if a computer was doing it... at the end of the day, [admissions officers] have the best interest in school, and they know what they're looking for... They know the school better than me."* While technologies can be designed according to institutional priorities, participants like P6 perceive that human admissions officers still understand "fit" more thoroughly than an algorithm.

Although vendors claimed DEI benefits of their technologies, applicants highlighted how these technologies could instead homogenize cohorts, exacerbating disparities. P2 (Vietnamese Female, Transfer Student) notes how technology drawing from quantitative inputs (Probe 2) is unable to capture nuances of racial and ethnic minorities' lived experiences, saying:

> *"So even though it might be nice to consider a student's racial and ethnic identity, a computerized system could never understand a student's lived experiences and really make that distinction between 'Oh, these are the resources that the student may have had access to' or 'These are a lot of the struggles that a student may have had at home.' Maybe they can't give as much time in the classroom as they might have wanted because, culturally, what their family wants from them is to stay at home… or maybe they won't be able to graduate high school, and they'll spend all their time working and taking care of their family. I think that those are things that sometimes we fail to consider by just looking at what an applicant is checking off on a box."*

P2, the daughter of *"Vietnamese refugees who came to the U.S. right after the Vietnam War,"* interrogates the categorical inputs or checkboxes required for these tools to consider identity, arguing that they do not provide the necessary context for technologies to meaningfully assess an applicant's lived experiences. For P2, checking the "Asian" box in applications may obfuscate the precarity her family experienced as Southeast Asian refugees compared to other Asian groups better represented in higher education. While participants check boxes about their identities on college applications regardless of the (non)use of (algorithmic) technologies, P2 suggests that relying on these data in an admissions algorithm would be similarly reductionist and, contrary to vendors' claims, not enhance DEI.

Participants expressed how using technology to track demonstrated interest (Probe 3) in the admissions process could incentivize conformity in their self-presentations to universities and online interactions. As P18 (Hispanic Male) says:

> *"A person might really love a college, but they're not vocal about it in visiting the websites. But when [colleges] track engagement... [applicants] are going to act inauthentic to meet those requirements, [like] leave better reviews about a school to get a higher probability of being admitted. It forces people to be a certain way. It makes everybody into this one type of person... even though they don't really want to be that way."*

P18 argues that tracking demonstrated interest encourages a narrow set of online behaviors (e.g., website visits, social media interactions) to put on a good "face" for universities, mirroring P1's description of repeatedly refreshing university websites. This technology is perceived to violate applicants' autonomy, limiting authentic self-expression. He likens this to changing his self-presentation in classes that grade students for participation, noting that he *"act[s] really social"* despite naturally being *"not very vocal in how I learn."* Though not forced, students may be *coerced* into behaving a certain way online to attempt to maximize their likelihood of acceptance. As students develop folk theories [59, 60, 64] about how college admissions algorithms work, they mold their self-presentations to map to what they expect these algorithms to expect of them. In aggregate, applicants' homogenized and coerced self-presentation online and in their applications can hamper the very DEI efforts admissions technology vendors claim to promote.

Participants also described how technologies considering social identity (Probe 2) could unjustly truncate the review process for minoritized applicants. P11 (White and Asian Female) elaborates:

> *"It could be very easy for a college to just have it set to prioritize people who have a higher income because they're like, 'Then they'll give us more money... they might donate to us later'... Sometimes colleges are racist, and so then they discriminate against that because they have the [algorithm] there. You just say, 'Hey, if they're of this background, we don't want them.' And then fully deny it happening... As with anything, if you're setting it to accept certain types of people, there is going to be some automatic bias there."*

P11 notes how institutional goals like generating revenue could influence the technologies higher education institutions adopt in admissions, potentially exacerbating inequities for minoritized applicants. She also speaks to vendors' claims of efficiency and ease, critiquing how ease for the university can undermine DEI efforts, perpetuating and automating existing inequities. P11 noted that "*the country is built where Black people weren't allowed to go to college for a long time, women weren't allowed,*" explaining her expectation that the same biases underlying higher education's history could also bleed into algorithmic admissions technologies.

4.4 Accuracy vs. New Forms of Inaccuracy and "Gaming the System"

Our analysis surfaced distance between vendors' claimed accuracy benefits and participants' perceptions of inaccuracy as applicants may "game the system."

4.4.1 Vendors' Articulation of Accuracy as a Benefit of College Admissions Technologies. Vendors articulated accurate decision-making as a benefit of algorithmic admissions technologies, describing "*inaccuracies*" polluting traditional admissions workflows and positing their products as solutions for more accurate decision-making. T19 notes: *"Having quick access to clean, accurate, and secure data is critical to your organization's success. AdmissionPros has 25+ years [of] providing solutions that address the data needs across the university community."* T19 references *data* as the source and mode of "*inaccuracies*" without clarifying how exactly the product "*addresses the data needs across the university community.*" Vendors articulate that greater accuracy in data achieves greater organizational success, dismissing the importance of the admissions experience for applicants. By contrast, T50 notes that its product can *"support decision-making by enabling eligibility checks and candidate scoring. Identify and select your best-fit applicants with confidence and accuracy for one or more programs with the eligibility checklist feature and candidate scoring system."* T50 references decision-making outcomes as (in)accurate rather than individual data points that inform decisions. In both examples, vendors posit accuracy as a problem their technological products address, though what is inaccurate and how accuracy will be achieved technologically remain vague.

Vendors also referenced the accuracy of the data science techniques underlying their technologies' predictive analytics. T21 noted: *"Our models analyze four times the variables used in linear regression—and with greater accuracy—helping you make informed decisions and track your goals consistently and confidently... Gain a deeper understanding of the individual. Make decisions confidently, with strong data-backing."* T21 articulates the benefits of its statistical approaches for admissions personnel *and* for applicants who supposedly receive a more holistic review via more "accurate" computational techniques.

4.4.2 Applicants' Perspectives: New Forms of Inaccuracy and "Gaming the System". While vendors claimed accuracy as a benefit of algorithmic admissions technologies, applicants perceived that increased automation could create *new* inaccuracies. P10 (White Female) commented on how automated rating of admissions essays (Probe 1) may compromise accuracy:

> *"For example, the word devastated... people can use that in all contexts. One could be devastated at a family loss or devastated that their bag of chips fell on the ground. If people knew about this, they would exploit it... it may not be the time in technological advancement for us to judge student work by how they express emotion in their essays."*

P10 argues that an algorithmic essay rating technology could be more "game-able " than human review. While we highlighted participant concerns about admissions technologies' inability to comprehend emotion (Section 4.2.2), here we note how this shortcoming produces accuracy concerns. The "game-ability" of these systems may mean that applicants with algorithmically higher-rated essays are not necessarily the most qualified. P10's concerns over the game-ability of admissions essay rating technologies may stem in part from her perception that demonstrating fit through essays is a significant admissions factor. She said, *"Writing strong essays was probably my biggest part of making a strong application... my test scores were a bit middle of the road for a lot of high-ranking institutions, and it would probably put me out of the running if I did not have stronger essays."*

Participants also expressed reservations regarding the accuracy of algorithms that calculate students' demonstrated interest in a university (Probe 3). Several participants described how metrics of demonstrated interest are not valid measures of a student's underlying interest, resulting in questionable outcomes. In the case of algorithms using students' propensity for opening emails as a proxy for interest, P12 (White Male) reflects: *"There are probably people who just open emails because they hate their notifications. They don't read the email. Treating them better compared to people who may even scan over the email instead of clearing the notification... It'd be a misconception."* P12, who prioritized essays over demonstrating interest and was rejected from his top-choice schools, argues that email-opening behavior is a flawed, inaccurate measure of demonstrated interest [40, 100, 161, 175], yielding unjustifiable decisions and compromising the integrity of the admissions process. While his undesired admissions outcomes may have shaped his perceptions, he was open to demonstrated interest tracking, specifically aiming his critique at the use of online activities to measure interest.

Additionally, participants referenced opportunities for gaming the algorithm that could compromise the accuracy of admissions decisions. Responding to Probe 1, P14 (Asian Female) said, *"I think what happens is that as soon as it's publicized, as soon as somebody knows and the information gets out that if you include X amount of keywords, the computer will say, 'Oh, this is good'... At that point, I think it's just a competition of who can fit the most buzzwords."* Interestingly, P14 reported having access to resources like "*a private counselor*" and another "*counselor who specializes in art portfolios and arts admissions*" who helped her understand how to craft her essays. These connections who provided her tips for admissions may have shaped her expectations about these systems' gameability. Similarly, P2 (Vietnamese Female, Transfer Student) says:

> *"Nowadays, there are scanners that you can use on the Internet to look over your resume ahead of time to make sure it's not going [to be] flagged and rejected. If that had been a process more readily used in application processes, someone out there would create something very similar that would scan your application and pull out key factors about you as an applicant."*

P2 points to the technical prowess needed to build or reverse-engineer a system that would *"scan your application"* and assess it ahead of the actual submission, exacerbating inequities between those with varying levels of technical ability while compromising "accurate" decision-making, since those that algorithms deem most "qualified" may know how to "game" the algorithm but may not be the most qualified applicant.

In sum, we reveal the distance between vendors' claimed benefits and applicants' perceptions of algorithmic admissions technologies. First, vendors claim to promote ease for admission officers while applicants engage in increased labor. Second, vendors vaguely promise transparency to admissions offices, while applicants perceive exacerbated opacity. Third, vendors promise to remove human bias, while applicants fear algorithmic bias. Finally, vendors promise more accurate admissions decision-making, while applicants describe compromised accuracy.

5 Discussion

We contribute an empirical examination of algorithmic admissions technologies – namely, vendors' claims, applicants' perspectives, and distances between the two – reflecting enduring discrepancies [122] in implementing emerging technologies in higher education. Vendors claimed several benefits of their products, often for admissions offices and sometimes to applicants, including efficiency, transparency, bias mitigation, and accuracy (RQ1). However, interviews revealed applicants' perceived harms (RQ2). Findings highlight the distance between vendors' claimed benefits and applicants' perspectives (RQ3). We discuss our findings' implications for algorithmic admissions, regulation, and design.

5.1 Implications for Algorithmic Decision-Making: Human vs. Algorithmic Bias

Our findings highlight applicants' perceptions that algorithmic admissions may mitigate admissions officers' human bias, echoing prior work suggesting algorithms' potential to alleviate some human bias by providing standardized review [5, 25, 90, 101]. Applicants acknowledged human review could be fickle and based on an admissions officer's temporary emotional state. The notions that humans are subjective, emotional, and use decision-making heuristics underscore proponents' arguments about AI's potential to mitigate human bias [155, 167, 168].

Our findings around applicants' perceptions highlight how algorithmic admissions decision-making may *introduce* perceived algorithmic bias, corroborating prior work suggesting the existence of bias in student success prediction algorithms [76]. Participants perceived pre-existing biases [65] stemming from admissions' social contexts and practices (e.g., pre-existing racial and socio-economic bias given the exclusionary history of college admissions). Participants also perceived technical bias [65] (e.g., perceiving algorithms as unable to assess an essay's emotional content or glimpses of personal qualities). Finally, participants perceived emergent biases [65] arising from algorithms used in practice in college admissions, like participants' concerns over inaccurate and game-able proxies of demonstrated interest [77, 100] (e.g., email opens, website visits).

Some applicants described algorithmic biases as more harmful than human reviewers' biases alone. While human decision-making is complex and subjective [167, 168], subjectivity may facilitate healthy deliberation among an admissions decision-making team [174]. In our study, some participants questioned the importance of supplanting admissions officers' bias in the first place, noting that such bias may be valuable for decision-making due to the deep understanding of person-institution "fit"[7] that admissions officers hold. Importantly, applicants' preference for human over algorithmic bias (which encompasses developers' human biases) exists so long as human bias does not undermine diversity, equity, and inclusion (DEI) efforts. While we do not advocate *for* human decision-makers' bias, our findings challenge the notion that this bias is universally worse than algorithmic bias.

In sum, vendors frame algorithmic fairness and de-biasing as technical and mathematical, while applicants see it as deeply contextual, shaped by identity, understandings of college admissions, and historical factors. This distance reflects prior work [164] situating automated decision-making as part of the history of educational policy and governance, invoking complex relationships, biases, and power dynamics that shape experiences with fairness and bias. Our findings regarding applicants' perceptions of algorithmic versus human bias reflect an awareness of this complexity, which may be partly due to how algorithmic fairness perceptions vary across identity groups [120]. Next, we examine how vendors' commitment to techno-solutions obscures underlying issues in college admissions, undermines holistic review, and poses perceived privacy harms to applicants.

5.2 Vendors' Techno-solutionism Obfuscates Admissions Problems, Defies Holistic Review, and Poses Perceived Privacy Harms

5.2.1 The Significance of Techno-Solutionism in College Admissions. Vendors' claims that their products will solve long-standing admissions challenges reflect a commitment to "techno-solutionism" [117], which may exacerbate rather than resolve problems (e.g., lack of student diversity) vendors promise to address. Techno-solutionism assumes that current systems are flawed, change is inherently good, and technology's positive and negative impacts are straightforward and universally agreed upon. Past work, including in HCI, has critically analyzed techno-solutionism in domains including AI in hiring [140] and health care [53, 112]. We extend these works to argue that vendors' legitimization of their algorithmic admissions products indicates a commitment to techno-solutionism, overlooking power and inequality dynamics [112], deflecting attention away systemic failures [112], neglecting local adaptations of technologies [97], and failing to transparently communicate technologies' realistic benefits, harms, and limitations [111].

Techno-solutionism has particular implications for college admissions. Systemic failures in U.S. college admissions are illustrated by Operation Varsity Blues [178] as well as controversies around affirmative action [26, 84, 158] and test-optional admissions [38, 39]. Techno-solutionism's neglect of local technology adaptations is problematic given that college admissions practices and

[7] We note that the notion of "fit" has historically been used as an exclusionary mechanism [3, 37, 128, 134].

policies are highly idiosyncratic [153]. Finally, failure to inform the public, especially applicants, about technologies' realistic benefits and limitations may lead to distrust or misunderstanding of algorithmic college admissions, which our interview analysis demonstrates. In this context, techno-solutionism implies that technological interventions will work as expected for all impacted groups without considering power and identity-related dynamics in college admissions that may render these technological interventions harmful for some and beneficial for others. Vendors reinforce this idea by portraying traditional admissions as inefficient, biased, and resource-strained while positioning their products as solutions. However, as interviewees noted, algorithmic technologies may not be suited to assess identity-related aspects of application materials. The techno-solutionist impulse to ignore power and identity dynamics is significant here, revealing that marginalized applicants are neither the populations these technologies were designed "for" nor the populations who would benefit from them. At the same time, techno-solutionism shifts focus away from deeper crises of trust and legitimacy in admissions.

5.2.2 Algorithmic Logics Contradict Holistic Review. We argue that algorithmic admissions have the potential to fundamentally contradict principles of holistic review [20, 22, 82], wherein individual applicants' achievements are considered alongside non-academic factors like identity and availability of opportunities. We argue that the algorithmic admissions technologies that aim to increase efficiency for admissions personnel seem opposed to holistic review's goals of contextualized, individualized, and robust admissions decision-making. This opposition raises the question of whether algorithmic admissions will ameliorate or exacerbate admissions challenges like trust in university admissions offices and mounting legal challenges. Findings from our interviews suggest that techno-solutions may *not* ameliorate these crises (at least from applicants' perspectives) but *exacerbate* them. Participants' concerns around reductionist decision-making further question whether algorithms can adhere to holistic review processes in a way that feels sufficiently holistic and individualized to applicants, which is key to how trustworthy and acceptable they find algorithmic admissions technologies. While institutions often turn to techno-solutions to solve crises of legitimacy, trust, and resources, algorithmic admissions may further erode applicants' trust.

5.2.3 Perceived Emotional and Autonomy-Related Privacy Harms to Applicants. Additionally, our interview analysis demonstrates that some of the participants' reservations with algorithmic admissions are captured by Citron and Solove's privacy harms taxonomy [50], which contends with various tangible (e.g., economic, physical) and less tangible (e.g., reputational, autonomy) privacy-related harms. Participants noted how algorithmic admissions could confer emotional, autonomy, and more generalized privacy harms to them. These harms are especially salient for emerging adult applicants, significantly shaping identity development and well-being [16, 151]. Specifically, findings show how algorithmic admissions could increase distress and anxiety for applicants seeking to optimize admissions chances, much like the students and families who found themselves frustrated about New York City's opaque school admissions lottery algorithms [102] or San Francisco's school choice algorithms [135]. The labor of anticipating how to present oneself as a qualified applicant to opaque admissions algorithms and demonstrating interest via opening emails and refreshing web pages add stress and anxiety to an already uncertain process, signifying emotional harm – a privacy harm [50].

Our findings also suggest that vendors' claims to mitigate bias and promote fairness and DEI can backfire for applicants, harming their autonomy by creating the perception that they must conform in their self-presentation to maximize admissions chances. Particularly, given the increasing emphasis on "demonstrated interest" and digital tracking, applicants report engaging in self-presentation in application essays *and* personal digital communication. Conforming to self-presentational ideals can harm college applicants' autonomy during a developmental stage where the ability to explore and develop one's identity is critical [151]. Indeed, applicants' responses to demonstrated interest tracking technology probes revealed perceived harms at the nexus of emotional and autonomy harms, violating applicants' privacy by seeking information about them beyond the application and encouraging them to engage in stressful, potentially ineffectual self-presentation labor. Demonstrated interest tracking technologies may be met so negatively by applicants because the information flows they enable – the transmission of digital engagement data to admissions offices – violate the principle of contextual integrity [121], under which privacy is maintained when information flows conform to contextual norms but is eroded when those norms are violated. Contextual norms around college admissions facilitate applicants' expectations that certain aspects of themselves (e.g., their application materials, even aspects of their identity) can be considered fair game while others, like their social media use, are not. Together, algorithmic admissions – specifically demonstrated interest tracking technologies – can facilitate a range of troubling privacy harms for applicants. In the next section, we discuss how regulation can be used to address a number of these privacy harms.

5.3 Regulatory Implications: Addressing Privacy Harms Perceived by Applicants

Our analysis revealed how applicants perceive privacy harms associated with algorithmic admissions. While privacy harms are also relevant in other contexts (e.g., algorithmic hiring) [2, 4, 93, 129, 180], they are especially concerning here given the differences in the regulatory landscape between contexts like hiring, for instance, and college admissions. Like college admissions, algorithmic hiring shapes access to opportunities but is more attended to in existing U.S. regulations. It is a compelling example to learn from when considering our findings' regulatory implications.

5.3.1 Regulating "truth-seeking" about college applicants. Applicants pointed to the invasive nature of demonstrated interest tracking via online activity. While algorithmic hiring discrimination is under the purview of the Equal Employment Opportunity Commission [170], similar organizations do not exist for college admissions despite the salience of admissions to later employment opportunities. Employers [140] and universities both seek to discern the truthfulness of applicant self-presentations (e.g., via assessing demonstrated interest). Yet, while the hiring domain is accountable to the U.S. Employee Polygraph Protection Act forbidding invasive lie-detector tests [93], college admissions are not. We view demonstrated interest tracking as inherently concerned with flagging applicants who are not "truly" interested in attending a college – a form of identifying (dis)honest candidates. We take inspiration from workplace protections to suggest that policymakers may devise similar regulations in the college admissions context that severely limit – if not forbid – demonstrated interest tracking technologies given their invasiveness, opacity, and questionable efficacy regarding claims about discerning the "truth" about applicants.

5.3.2 Regulating unsubstantiated and potentially deceptive claims. Our analysis suggests that some of the vendors we analyzed may not be engaging in accurate descriptions of their products. For instance, while claims of transparency abound, they are vague and unsubstantiated. Further, applicants' perceptions often contrasted with vendors' claimed benefits, especially when vendors made claims about benefits to applicants. For instance, vendors suggested their products would facilitate diverse, equitable, and inclusive admissions processes, while applicants raised various DEI-related concerns. We show that, at the very least, these vendors do not substantiate how they achieve their claimed benefits, which may constitute deception. We argue that the Federal Trade Commission (FTC) could actively monitor vendor claims to ensure they market their products accurately, following truth-in-advertising legislation.

5.3.3 Regulating algorithmic decision-making. In the absence of transparency, applicants expected traditional human review and would experience expectancy violations if such technologies were used without their knowledge. Existing U.S. regulations, like the Freedom of Information Act (FOIA)[8], can empower the public, not just data subjects, to challenge opacity by requesting access to existing documentation about algorithmic admissions processes from universities [124]. Public universities may be compelled to provide information regarding the algorithmic admissions technology vendors and developers with whom they hold contracts.

In addition, broader attempts to regulate algorithmic decision-making can guide the regulation of algorithmic college admissions. In the U.S., the Blueprint for the AI Bill of Rights [171] outlines protections for algorithmic discrimination, data privacy, and human decision-making alternatives. Similarly, the AI Civil Rights Act [103], introduced in 2024 by U.S. Senator Markey, aims to make automated decision-making fair, transparent, and non-discriminatory in domains including admissions, requiring universities deploying algorithmic admissions to create robust human alternative review and appeals. However, these kinds of algorithmic regulation in the U.S. appear unlikely, at least in the near future, in light of Executive Order "Removing Barriers to American Leadership in Artificial Intelligence." This EO directs the Office of Management and Budget to revise memo M-24-10 regarding responsible and rights-impacting AI, ensuring consistency with the directive to deregulate the AI industry to "enhance America's global AI dominance" and create AI systems that are "free from ideological bias or engineered social agendas" [166].

In sum, this section considers ways policy interventions can regulate 1) universities' use of demonstrated interest tracking technologies, 2) unsubstantiated vendor claims across a range of algorithmic admissions technologies, and 3) the development of algorithmic decision-making technologies. Next, we consider design-oriented interventions that may address concerns regarding algorithmic transparency.

5.4 Towards Designing Transparent Admissions Technologies

Our analysis illustrates that vendors made vague, unsubstantiated claims that their products improve transparency over data and decision-making for admissions offices and rarely articulated transparency benefits for applicants, appealing to values of organizational transparency [7]. In contrast, applicants noted that introducing algorithmic technologies makes the admissions decision-making process *less* transparent to them than holistic human-review-based admissions, which also face transparency critiques. Algorithms can shape admissions decisions at scale, making it difficult, if not impossible, for applicants to understand who/what made the decision, or the rationale behind it. Such opacity stems from a combination of secrecy from developers, vendors, and universities, students' technological illiteracy, and negotiations in combining algorithmic logics and human reasoning in decision-making [35].

To help address these transparency tensions, vendors could use explainability principles to communicate technologies' benefits and drawbacks accurately instead of vague, unsubstantiated claims in marketing materials, as shown in the present study. Further, vendors could combine black-box (detailing the link between model inputs and outputs) and white-box (detailing the model's inner workings) explanations [45] to increase transparency to university clients, who can be better-positioned to communicate transparently about these tools to applicants. Full white-box explanations are unrealistic in high-stakes college admissions settings where there exists the ability for such algorithmic systems to be "gamed," as our findings highlight. Nevertheless, vendors must provide clear, accessible explanations for 1) the stage(s) in the application review process algorithmic

[8]The Freedom of Information Act (FOIA) is a U.S. law granting the public the right to access records from federal government agencies, which generally include public universities.

admissions technologies are used, 2) if/how they are used in conjunction with human review, and 3) model inputs and outputs, using tools like Model Cards [114] and Datasheets for Datasets [68]. Model Cards provide details of the model, its intended use, evaluation, ethical considerations, and caveats [114]. Datasheets inform individuals about the motivation behind the AI system, its composition, data collection, etc. [68]. These tools can be customized to fit the contextual norms of college admissions, tailoring to the information needs and algorithmic literacy of university clients, who can use these or similar tools to communicate about algorithmic admissions technologies to applicants in contextually appropriate ways [121]. Information about model inputs and outputs would particularly assuage participants' concerns about *what* admissions algorithms would consider (e.g., web activity in the case of demonstrated interest) and the extent to which algorithms are responsible for the admissions decision (e.g., algorithms that flag versus recommend applicants). Grounded in the contextual integrity framework [121], emphasizing tailoring the quantity and quality of information disclosed may address applicant concerns regarding expectancy violations, disrespect, and dehumanization, potentially ameliorating distrust toward algorithmic admissions decision-making technologies.

Model transparency could also promote equity in college admissions. Asymmetries in access to information have historically shaped college admissions through access to college counselors who provide niche essay tips and strategies for demonstrating interest to universities; the introduction of algorithms may exacerbate inequities in information as applicants must not only have information about college admissions but about algorithmic systems. Model transparency can ward off unfair advantages that affluent students may gain in learning how to "game" algorithmic admissions systems, as described by interviewees. However, model transparency approaches would *not* address concerns about decontextualized application review, increased labor from applicants, algorithmic bias, and inaccuracy issues.

6 Conclusion

U.S. college admissions is a controversial decision-making context increasingly reliant on algorithmic technologies. We conducted a qualitative analysis of college admissions technology vendors' websites and interviews with recent college applicants. Our analysis uncovers the distance between vendors' articulated benefits used to legitimize college admissions technologies and applicants' perceived harms and benefits of these technologies. In light of this distance, we argue that vendors' legitimization of these technologies represents a problematic commitment to techno-solutionism. We draw on distances between vendor claims and applicants' perspectives to interrogate whether holistic review and promoting DEI is possible with algorithmic admissions decision-making. In addition, we discuss how these technologies, from applicants' perspectives, can confer a range of privacy harms. As such, we call for reconsidering algorithmic technologies' use in admissions, particularly those used to track and measure "demonstrated interest." Finally, we consider our findings' regulatory implications and consider how algorithmic admissions may integrate more meaningful transparency. However, we maintain that doing so would not address other perceived harms of algorithmic admissions, like inaccuracy and privacy violations.

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A Interview Screening Survey

A.1 Basic Eligibility Criteria

- Are you at least 18 years old? (Y/N)
- Do you live in the United States? (Y/N)
- Did you apply to a four-year college or university (at the undergraduate level) in the 2021-2022 application cycle? A four-year university is a university that grants Bachelor's degrees (Y/N)
- Will you be attending a four-year university in the 2022-2023 academic year? (Y/N)

A.2 College Admissions Questions

- How confident are you that you understand how universities make decisions about who to admit or reject? (Not at all confident; Slightly confident; Somewhat confident; Fairly confident; Completely confident)
  - (if Not at all confident is NOT selected for the previous question) In a few sentences, explain how you think universities make decisions about who to admit or reject. (Free Response)
- Have you heard of the term "demonstrated interest" (or something similar) as it pertains to college admissions? (Y/N/Not Sure)

  - (If YES is selected for the previous question) Please briefly describe what demonstrated interest is. (Free Response)
  - (If YES is selected for having heard of demonstrated interest) How did you learn about the concept of demonstrated interest? Select all that apply. (A parent or guardian; A friend; A teacher or counselor; Social media or websites; University resources; Other (Open-Ended Text Box))

A.3 Social Media Questions

- Have you ever seen content on social media explaining how college admissions works? (Y/N/Not Sure)
  - (If YES is selected for previous question) Please briefly describe the content you saw on social media explaining how college admissions works. (Free Response)
- Have you ever produced content (e.g., a TikTok, a comment on Reddit, etc.) that describes how college admissions works? (Y/N/Not Sure or Don't Remember)
  - (If YES is selected for previous question) Briefly describe the content you produced related to college admissions and on what platform(s) you posted it. (Free Response)
- Have you ever seen social media content that focuses on "demonstrated interest" or other ways that colleges may assess your interest as part of college admissions decisions? (Y/N/Not Sure or Don't Remember)
  - (If YES is selected for previous question) Briefly describe the content you saw, and on what platform(s) you saw it. (Free Response)
- Have you ever produced content (e.g., a TikTok, a comment on Reddit, etc.) about the concept of "demonstrated interest" or other ways that colleges may assess your interest as part of college admissions decisions? (Y/N/Not Sure or Don't Remember)
  - (If YES is selected for previous question) Briefly describe that content, and on what platform(s) you posted it. (Free Response)

A.4 Demographics and Contact Information

- What gender(s) do you identify as? (Free Response)
- What racial and/or ethnic group(s) do you identify as? (Free Response)
- Do you identify as a first-generation student? First-generation students are any students whose parent(s) or guardian(s) did not earn a Bachelor's degree in the United Sates. (Y/N)
- Do you identify as a low-income student? (Y/N)
- What email address can I use to contact you if you are selected to participate in the interview study? (Free Response)

B Interview Protocol

B.1 Experience Applying to College

- To begin, can you walk us through your journey of applying to college?
  - What kinds of schools did you apply to and why?
  - What did you do to prepare your applications to make you stand out as an applicant?
  - Did you do anything outside of your application to make you stand out as an applicant?
  - How did technology play a role in your application and admissions process, if at all?
- How do you feel about the outcome of your application process?

B.2 Understanding of College Admissions

- Now I want to talk to you about your understanding of the college admissions process. In the screening survey you marked that you felt [X] level of confidence that you understand the process colleges go through to determine who to admit, waitlist, or reject. Can you tell me more about what makes you more or less confident about this?
  - How did you come to understand how college admissions works?
    - Who (or what) gave you this information?
    - Have you ever been presented with conflicting information about how college admissions works? If so, how do you decide what to believe?
- Aside from the typical components like your resumé, essays, transcripts, letters of recommendation, what other information do you think colleges use to make decisions about the applications they receive?
  - Who do you think is involved in making these decisions?
    - What made you think that these people are involved?
    - How do you feel about these people being involved?
  - Do you think information about your identity or background is important to colleges when they make admissions decisions?
  - Do you think anything else is involved in this decision-making process?
    - Do you think the people you described earlier use any tools or technologies to help them make these decisions?
  - What factors do you think they use to decide who to admit, waitlist, or reject? What made you think this?
    - Have you heard others talking about these factors or have you read about these factors anywhere?
    - How do you feel about these factors impacting admissions decisions?

B.3 Technology and College Admissions

- (If they HAD seen content on social media related to college admissions): In the screening survey you marked that you had seen content on social media related to college admissions.
  - Can you tell me more about the content that you saw related to college admissions?
    - On what platform did you view this content?
    - How did you come across this content on that platform?
    - Why do you think you saw that content on that platform?
    - What did you think about this content?
    - Did this content influence the way you thought about your own application process?
    - Did this content influence the way you prepared your application or any other actions you took to attempt to stand out as an applicant?
    - (If they mention "the algorithm" and not covered earlier:)
      - What benefits do you think using these approaches provide to applicants?
      - What harms do they provide to applicants?
      - What benefits and harms do you think these approaches provide to you, specifically?
      - How do you think these approaches impact colleges?
- (If they HAD seen content on SM related to demonstrated interest): In the screening survey you marked that you had seen content on social media specifically related to the term "demonstrated interest" or other ways colleges assess your interest during the application process.

  - Can you tell me more about the content that you saw related to demonstrated interest or a related topic?
    * On what platforms did you view this content?
    * How did you come across this content on that platform?
    * Had you heard of the term demonstrated interest (or related term) before? If so, how were you first introduced to it?
    * What did you think about this content?
    * Did this content influence the way you prepared your application or any other actions you took to attempt to stand out as an applicant?
    * (If not covered earlier in the interview)
      · How would you describe "demonstrated interest" to someone who doesn't know what it is?
      · How do you think colleges assess demonstrated interest? Why do they do that this way?
      · What benefits do you think measuring demonstrated interest in this way provides to applicants?
      · What harms does it provide to applicants?
      · What benefits and harms do you think colleges' use of "demonstrated interest" provide to you, specifically?
      · How do you think the use of "demonstrated interest" metrics impacts colleges?
- (If they HAD produced content on social media related to admissions): In the screening survey you marked that you had produced content on social media related to college admissions.
  - Can you tell me more about the content that you produced related to college admissions?
    * What made you want to produce this kind of content?
    * How did you obtain the information you shared in these posts?
    * On what platform did you post this content?
    * Who was your intended audience?
    * How did the audience react to your content?
    * What impact, if any, do you think this content had on your audience?
- (If HAD produced content on SM related to demonstrated interest): In the screening survey, you marked that you had produced content on social media specifically related to "demonstrated interest" or similar ways that colleges assess your interest during the application process.
  - Can you tell me more about the content that you produced related to demonstrated interest or a related topic?
    * What made you want to produce this kind of content?
    * How did you obtain the information you shared in these posts?
    * On what platform did you produce this content?
    * Who was your intended audience?
    * How did the audience react to your content?
    * What impact, if any, do you think this content had on your audience?

B.4 Probes

- Imagine that the colleges you applied to used software to help inform your application's outcome; in other words, whether you would be accepted, waitlisted, or rejected.
  - Among the factors the software would use to determine your admission status are academic factors, such as standardized test scores and high school GPA
    * What do you think about this?

    * Would you feel comfortable having your own application assessed this way? Why or why not?
- Among the factors the computer software would use to determine your admission status are your written essays.
    * What do you think about this?
    * Would you feel comfortable having your own application assessed this way? Why or why not?
- Among the factors the computer software would use to determine your admission status are factors related to your identity, such as your zip code, household income, ethnic background, and whether you will be a first-generation college student
    * What do you think about this?
    * Would you feel comfortable having your own application assessed this way? Why or why not?
- Among the factors the software would use to determine your admission status are factors related to your engagement with the university, such as how often you visit school websites and open and read school emails, as well as how often you attend on-campus recruitment events
    * What do you think about this?
    * Would you feel comfortable having your own application assessed this way? Why or why not?

C List of Analyzed Vendor Websites

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Vendor Number	Vendor Name	Vendor Number	Vendor Name
1	Admission Connect Technology - Salesforce	27	OneWorldSIS
2	Finalsite's SchoolAdmin EMS	28	SimpleApply
3	Enrollsy	29	Unibuddy
4	Slate by Technolutions	30	Virtue Analytics
5	Digitstorm Funnel	31	Jenzabar ONE
6	OpenEduCat	32	Mainstay
7	Blackbaud Enrollment Management System	33	E2SRecruit
8	AcademiaERP by Serosoft	34	Embark Campus
9	SurveyMonkey Apply	35	STARS
10	TargetX	36	Shape
11	Submit.com	37	EMPOWER SIS
12	Anthology	38	Ynot
13	CustomViewbook	39	CampusGroups
14	Diamond ADM	40	Full Fabric
15	Azorus	41	ToucanTech
16	Enrollment Rx	42	Classe365
17	AchieverCRM	43	Campus Cafe
18	AdmissionsPro CRM	44	Creatrix Campus
19	Adventus.io	45	Unit4 Student Management
20	Centralized Application Service	46	Intersect by EAB
21	Centurus ONE	47	DegreeSight
22	Edular	48	Collegix
23	Element451	49	MoveIN
24	Fireworks CRM	50	iSchool 360
25	GeckoEngage	51	MAESTRO SIS
26	Kira Talent	52	ModernCampus Suite

Table 3. List of algorithmic admissions technology vendors whose websites we analyzed