

# EEPA, CF

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## 1 Background: The Student List Business

### 1.1 Situating Student Lists Vis-a-vis Recruiting

Student lists are a match-making intermediary connecting universities to prospective students. The U.S. higher education market can be conceived as a national voucher system, whereby tuition revenue – composed of household savings and grants and loans from federal, state, and private sources – follow students to whichever institution they enroll in. Students want to attend college but do not know all their options, where they would be admitted, and how much it will cost. Universities have a financial incentive to provide access to students. Additionally, universities pursue some mix mix of broad enrollment goals (e.g., academic profile, racial diversity), while also meeting the needs of various campus constituencies (e.g., College of Engineering needs majors, marching band needs players) (Stevens, 2007). Universities cannot realize these goals solely from prospects who contact the university on their own. They must find prospects who can be convinced to apply. However, universities don't know who they are, where they are, or how to contact them. Student lists overcome the problem faced by universities, providing the contact information of prospects who satisfy their criteria.

The “enrollment funnel” – depicted in in Figure 1 – is a conceptual model used in the enrollment management industry to describe stages in the process of recruiting students. The funnel begins with a large pool of “prospects” (i.e., prospective students) that the university would like to convert into enrolled students. “Leads” are prospects whose contact information (or “profiles”) has been purchased. “Inquiries” are prospects that contact your institution and consist of two types: first, inquiries who respond to an initial solicitation (e.g., email) from the university; and second, “student as first contact” inquiries who reach out to the university on their own (e.g., by sending ACT scores). Applicants consist of inquiries who apply plus “stealth applicants” who do not contact the university before applying.

The funnel narrows at each successive stage in order to convey the assumption of “melt” at each stage (e.g., a subset of “inquiries” will apply). Practically, the enrollment funnel informs interventions that increase the probability of “conversion” from one stage to another (Campbell, 2017). For example, financial aid packages are used to convert admits to enrolled students (e.g., McPherson & Schapiro, 1998).

At the top of the enrollment funnel, universities identify leads by buying student lists. The sum of purchased leads plus student-as-first-contact inquiries (e.g., taking a “[virtual tours](#)” that records IP address) constitutes the set of all prospects the university has contact information for, who can receive targeted recruiting interventions via mail, email, social media, etc. The majority of BA granting public and private non-profit institutions purchase student lists annually. Based on data provided by university clients, Ruffalo Noel Levitz (2020) reported that 28% of public universities purchased less than 50,000 names, 44% purchased 50,000-100,000 names, 13% purchased 100,000-150,000 names, and 15% purchased more than 150,000 names. 34% of private institutions purchased fewer than 50,000 names, 24% purchased 50,000-100,000 names, 23% purchased 100,000-150,000 names, and 18% purchased more than 150,000 names. Ruffalo Noel Levitz (2018) asked clients to rate different “first contact” interventions (e.g., off-campus recruiting visit) as sources of inquiries and enrolled students. For the median public university, student list purchases were the highest source of inquiries, accounting for 26% of inquiries, and accounted for 14% of enrolled students, which ranked fourth after “application as first contact” (19%), campus visit (17%), and off-campus visit (16%). For the median private non-profit university, student list purchases were the highest source of inquiries, accounting for 32% of inquiries and were tied with off-campus recruiting visits as the highest source of enrolled students, accounting for 18% of enrolled students.

## 1.2 The Market for Student List Data

Although the student list business has historically been dominated by College Board and ACT, in the 21st century student lists have been central to a surprising level of dynamism in the enrollment management industry. Drawing from Jaquette, Salazar, & Martin (2022), this section summarizes key dynamics that have shaped the contemporary market for student list data.

The first dynamic is the centrality of enrollment management consulting firms to the student list business. Although universities are the paying customers of student list products, many universities outsource student list purchases to enrollment management consulting firms.

Furthermore, student lists are an essential input to the predictive models and recruiting interventions (e.g., emailing prospects) the consultancies provide.

The second dynamic is competition followed by concentration. In the 2000s, advances in technology yielded new sources of student list data, creating opportunities for new vendors. Start-up firms entered the student list market by creating college search engines, which asked students to submit information in order to receive recommendations about colleges and scholarships. Another new source of student list data comes from college planning software that is sold to high schools and used by high school students and guidance counselors. In the 2010s, the enrollment management industry experienced a surge in horizontal followed by vertical acquisitions. Horizontal acquisitions occurred when one enrollment management consulting firm acquired a competitor (e.g., e.g., RuffaloCODY acquired Noel-Levitz in 2014) [CITE]. Vertical transformations transformed the student list business. For example, the K-12 information system provider PowerSchool entered the student list business by acquiring the edtech/enrollment management firm Hobsons, which operated the Naviance college planning software and Intersect student recruiting software. EAB entered the market for student list data through acquisitions (e.g., Cappex college search engine) and by becoming the exclusive reseller of the Intersect recruiting platform.

Third, incumbents College Board and ACT attempted to retain their competitive advantage – through new products and features – amidst the test-optional movement. Both organizations conspicuously embraced data science by developing new search filters based on statistical models that promise to help universities make “efficient” name buys that target “right-fit” students. For example, ACT allows universities to filter prospects based on their predicted probability of enrolling, while College Board developed “geodemographic” search filters that target prospects based on the characteristics/behavior of their high school and their neighborhood. While EAB has become a supplier of names, both College Board and ACT leveraged their oligopoly position in the student list business to sell enrollment management consulting, offering clients information about prospects that is not included in purchased lists. However, the test-optional movement poses an existential threat to the college entrance exam. As fewer prospective students take College Board and ACT assessments, their competitive advantage in the coverage of college-going high school students will erode. Several for-profit firms are positioned to acquire market share ceded by College Board and ACT.

## 2 Literature Review

We position our scholarly contribution as a bridge between two literatures in sociology. First, we review scholarship that engages with the recruiting side of enrollment management (Cottom, 2020; Megan M. Holland, 2019; e.g., Stevens, 2007). Second, we review scholarship from the sociology of race that focuses on the nexus between structural racism and the digital economy (e.g., Cottom, 2020; Hirschman & Bosk, 2020; Norris, 2021) [THIS OPENING PARAGRAPH NEEDS TO BE REVISED]

### 2.1 Platform Studies in Education

An emerging literature examines digital platforms in education (Kerssens & Dijck, 2022; Janja Komljenovic, 2022a; e.g., Nichols & Garcia, 2022; B. Williamson, 2021), drawing from a broader multidisciplinary, transnational set of literatures around “platform studies” (Benjamin, 2019; e.g., Noble, 2018; Sadowski, 2019, 2020). Digital platforms (e.g., Uber, Coursera, Naviance) are intermediaries for exchange coordinate market transactions and create new markets (Sadowski, 2020). Platforms are also the “ground on which all the user activity happens, allowing the platform to record everything happening in it” (J. Komljenovic, 2021, p. 322).

One thread of platform studies deconstructs “platform capitalism,” the business models utilized to generate profit from digital platforms. Platform capitalism (often called “rentier capitalism”) generates profit by charging customers “rent” – as in the rent a tenant pays a landlord – for the right to use the platform without transferring ownership rights to the customer (Sadowski, 2020). Monetary rent refers to money a customer pays to an organization for access to digital products, for example a university pays annual subscription fees to Elsevier for access to academic journals (J. Komljenovic, 2021). Data rent refers to “digital traces” that platform users create by interacting with the platform (e.g., personal information they submit, interactions on the platform) (J. Komljenovic, 2021). Digital platforms gain ownership over user data via terms-of-use agreements. drawing from Marx (1978), Sadowski (2019) develops the concept “data as capital,” to describe how platforms monetize user data, which may be used to improve the platform or may become the basis for a new platform.

Another thread of platform studies examines how digital platforms reproduce structural inequality (Benjamin, 2019; e.g., Noble, 2018; O’Neil, 2016). Noble (2018) shows that the results of search algorithms reflect racist ideologies of people on the internet and the

profit imperative of advertisers that capitalize on these ideologies. Benjamin (2019) develops *race critical code studies* and attendant concepts. “Discriminatory design” is the process embedding structural inequality in platform algorithms, for example, by scoring customers based on an input that people of color have been excluded from. Through “technological determinism,” the usage of these biased algorithms affects society, often amplifying the effects of structurally racist inputs. Because targeting by race is profitable, platforms capitalize on residential segregation by using geography as an input to circumvent laws prohibiting race as an input. As Benjamin (2019, p. 147) writes, “racialized zip codes are the output of Jim Crow policies and the input of New Jim Code practices.”

Student list products are exemplars of platform capitalism that reproduce structural inequality. Student list data are extracted from the user-data of students laboring on platforms to prepare for college (e.g., taking the SAT) or search for college. Terms-of-use agreements grant platforms ownership over these data. Following Sadowski (2019), College Board monetizes this commodity by licensing names to universities for roughly \$0.50 per prospect. New entrants to the market (e.g., EAB, PowerSchool) wrap proprietary databases of prospects within software-as-service products that recruit these prospects (e.g., Intersect, Enroll360), which are then sold to universities for an annual subscription. Student list products reproduce structural inequality because the search filters used to target particular prospects are themselves products of historical inequality in educational opportunity. Examples of problematic search filters include zip code, AP test scores, and whether a prospect indicated an interest in a “peer” university.

The Summer 2022 special issue of *Harvard Educational Review* sets the commitments and direction of the nascent “platform studies in education” literature. Nichols & Garcia (2022) reviews extant scholarship on technology within education research, observing that most scholarship focuses on technical questions about student learning outcomes and instructional practice. Napier & Orrick (2022, p. 207) states that, “platform studies scholars urge us to go beyond pedagogical and technical questions toward social, political, and economic critiques. Consistent with this call, a growing transnational literature examines the economic business models of platform capitalism in the education sector (e.g., Janja Komljenovic, 2022b, 2022a; B. Williamson, 2021). Big tech and edtech companies profit by developing software systems – sold for an annual subscription – that perform core functions of education systems [E.G., ]. Other studies observe that, as education systems outsource core functions, digital platforms exert influence on organizational governance and education policy (Napier & Orrick, 2022; e.g., Ben Williamson, Gulson, Perrotta, & Witzenberger, 2022).

In contrast to the robust scholarship on discrimination within critical data studies (e.g.,

Noble, 2018), the nascent literature on platform studies in education does now show how platforms that structure educational opportunity exclude along racial and class dimensions. Additionally, while scholarship argues that digital platforms influence education policy, extant scholarship does not conduct concrete empirical analyses that show how platforms should be regulated. Thus, our analyses contributes to platform studies in education literature, first, by showing how College Board student list products discriminate and, second, by showing how problematic search filters can be regulated by existing federal policy.

## 2.2 Sociological Scholarship on Recruiting

[NOW THAT THE FIRST PART OF LIT REVIEW IS NOT JUST ABOUT SOC OF ED, IT IS LESS DEFENSIBLE TO ONLY REVIEW SOCIOLOGY OF RECRUITING. YOU MIGHT BE ABLE TO GET AWAY WITH IT BY SAYING THAT MOST RESEARCH ON RECRUITING COMES FROM WITHIN SOCIOLOGY AND WHAT WE SAY ABOUT WHERE THE SOC OF ED LITERATURE FALLS SHORT IS ALSO TRUE OF ECON AND INTERDISCIPLINARY RESEARCH IN HIGHER ED] Considering the “enrollment funnel” depicted in Figure 1, scholarship from the sociology of education has focused more on the latter stage of which applicants get admitted (Killgore, 2009; e.g., Posselt, 2016) [and financial aid? check] than earlier “recruiting” stages of identifying prospects, acquiring leads, and soliciting inquiries and applications. However, a growing body of research substantively analyzes recruiting from the perspective of students, high schools, and postsecondary institutions (e.g., Cottom, 2020; Megan M. Holland, 2019; Posecznick, 2017; K. G. Salazar, Jaquette, & Han, 2021; Stevens, 2007), often utilizing ethnographic or case-study designs and often as part of a broader analysis of college access or enrollment management.

Holland’s (2019) analysis of pathways from high school to college exemplifies scholarship that engages with recruiting from the perspective of high school students [e.g., McDonough (1997)][CITE]. First-generation students and underrepresented students of color often reported that “school counselors had low expectations for them and were too quick to suggest that they attend community college” (Megan M. Holland, 2019, p. 97). This trust vacuum created an enrollment opportunity because these students were drawn to colleges that made them feel wanted. Megan M. Holland (2019) found that high school recruiting visits — including college fairs, instant decision events, and small-group representative visits — influenced where students applied and where they enrolled, but this finding was strongest for first-generation students and underrepresented students of color. By contrast, affluent students with college-educated parents were less taken by such overtures and more concerned with college prestige.

Several studies analyze connections between colleges and high schools from an organizational perspective. These studies often conceptualize off-campus recruiting visits as an indicator of enrollment priorities and a network tie indicating the existence of a substantive relationship (Jaquette, Han, & Castaneda, forthcoming). Stevens (2007) provides an ethnography of enrollment management at a selective private college that depends on revenue from tuition and donations and is sensitive about acceptance and yield rates. The College valued recruiting visits to local high schools as a means of maintaining relationships with guidance counselors at feeder schools and tended to visit the same set of largely affluent private and public schools year after year. Analyzing the other side of the coin, Khan (2011) shows how private school guidance counselors exploit colleges' desire for trustworthy information about applicant enrollment intentions to get less-qualified students into top colleges. K. G. Salazar et al. (2021) analyzed off-campus recruiting visits by public research universities. 12 of the 15 universities made more visits to out-of-state schools than in-state schools, and these out-of-state visits concentrated focused on affluent public and private schools located in predominantly white communities. K. G. Salazar (2022) analyzes recruiting visits to Los Angeles and Dallas by out-of-state public research universities, finding that universities engage in "recruitment redlining – the circuitous avoidance of predominantly Black and Latinx communities along recruiting visit paths" [p. X]. Thus, in contrast to branding by about the commitment to racial diversity (M. M. Holland & Ford, 2021), scholarship consistently finds that the recruiting efforts of selective institutions prioritize affluent, predominantly white schools and communities.

A smaller set of studies analyze recruiting at open-access institutions that target working adults [E.G., CITE]. Cottom's (2017) analysis of the for-profit sector is simultaneously an ethnography of enrollment management and a work of political economy. For-profits found a niche in Black and Latinx communities because traditional colleges and universities disregarded these communities. They systematically sold low-quality programs to women of color, generating profit by encouraging these students to take on federal and private loans. This business model exemplifies "predatory inclusion," the logic of "including marginalized consumer-citizens into ostensibly democratizing mobility schemes on extractive terms" (Cottom, 2020, p. 443)

[MODIFY THIS PARAGRAPH/SECTION SO THAT IT ARGUES THAT SCHOLARSHIP ON RECRUITING HAS NOT TAKEN THE LEAD OF CRITICAL DATA STUDIES/PLATFORM STUDIES IN FOCUSING ON PLATFORMS/PRODUCTS RATHER INSTEAD OF ASSUMING THAT RECRUITING IS BASED ON INDIVIDUAL ORG BEHAVIOR] Upon reflection, scholarship assumes that recruiting is something done by

individual colleges and universities. But university enrollment management behaviors are increasingly structured by software and services purchased from third-party vendors. Scholarship on enrollment management must analyze the products being sold to universities and the vendors that create these products. For most universities, student list purchases largely determine which prospective undergraduate students will receive recruiting interventions. Although universities make choices about which names purchase, these choices are structured by the algorithmic architecture of student list products — which prospects are included in the product, the targeting behaviors allowed by the product, and the targeting behaviors encouraged by the product. Cottom (2020) argues that algorithmic products are not race neutral. Rather, scholarship on the sociology of race shows that algorithmic products reproduce racial inequality by incorporating seemingly neutral inputs that systematically exclude non-white people. Therefore, we review key advances from the sociology of race in order to conceptualize how student list products reproduce racial inequality.

## 3 Conceptual Framework

### 3.1 Structural Racism and Algorithms

#### 3.1.1 Structural Racism

Contemporary sociology is largely concerned with a structural analysis of race. Bonilla-Silva (1997) argues that most social sciences define racism as an ideology held by individuals (e.g., explicit or implicit racial bias). This approach measures societal racism by examining the attitudes of individuals and excludes the possibility that institutions can be racist. Bonilla-Silva (1997) argues for a focus on the underlying social structure rather than the ideology associated with it. He defines “racialized social systems” as “societies that allocate differential economic, political, social, and even psychological rewards to groups along racial lines” (p. 474). Racial groups are a social construction of a racialized social system. For example, in the U.S. “black people” is a construct that emerges from the slave trade and its legacy. “Racial ideology” – commonly known as racism – is the ideological component of a racialized social system, which includes individual bias and also institutions that that benefit dominant racial groups. Bonilla-Silva (1997, p. 476) argues “that the only way to ‘cure’ society of racism is by eliminating its systemic roots.” As the practices that produce racial inequality become increasingly covert, the utility of the concept racialized social system is drawing attention to the systemic roots of seemingly neutral institutions and practices that produce racial inequality.



The sociology of race defines structural racism as a “a form of systematic racial bias embedded in the ‘normal’ functions of laws and social relations” (Tiako, South, & Ray, 2021, p. 1143), whereby processes viewed as neutral or common-sense systematically advantage dominant groups and disadvantage marginalized groups (Bonilla-Silva, 1997). The sociology of race is influenced by historical scholarship from Du Bois (1935) and Robinson (2000), which defines capitalism as a system whereby the source of profit is exploitation based on the social construction of race (in contrast to Marx (1978), who argues that capitalism is defined by exploitation of the working class. Analyses of racial capitalism that build on Robinson (2000) tend to focus on structural racism in the production side of the economy (labor), for example, the “gig economy” (Cottom, 2020). By contrast, this article is concerned with structural racism on the consumer side of the economy, whereby people of color experience systematic discrimination in credit market, housing markets, and education markets – including products that help universities identify prospective students.

### **3.1.2 Algorithms, Actuarialism, and Micro-targeting**

Burrell & Fourcade (2021) (215) define algorithms as “sets of instructions written as code and run on computers.” Algorithmic products are attractive to investors because of the way these products scale. On the cost side, the marginal costs of adding more users is low. On the revenue side, each new user contributes new data to cull, improving the accuracy of the product and creating opportunities for new products.

Algorithmic products utilize actuarial methods and are based on the logic of actuarialism (Burrell & Fourcade, 2021; Hirschman & Bosk, 2020; Simon, 1988). Pioneered by the insurance industry, actuarial methods proceed in two steps. First, apply statistical techniques to previous cases in order to identify factors positively and negatively associated with an outcome of interest. Second, apply these results to future cases in order to make predictions and to assign levels of risk to each case. Actuarialism is the ideology that equates fairness with risk, as determined by predicted probabilities. Under the logic of actuarialism, individuals or businesses that have characteristics associated with loan default should be charged higher interest rates.

Burrell & Fourcade (2021) observes that the adoption of actuarial methods across many industries was buoyed by concerns about racial equity following antidiscrimination legislation in the 1970s. Amidst mounting evidence about the explicit and (more recently) implicit biases of individual decision-makers, actuarial products removed individual discretion and promised standardized, “procedural fairness” based on objective data. Hirschman & Bosk

(2020) argues that actuarial methods can promote racial equity when the prejudice of individual decision-makers is the source of racial inequality. For example, the analysis of residential real estate exchange by Korver-Glenn (2018) found that homes in predominantly white neighborhoods received higher appraisal values than those in non-white neighborhoods because appraisers have discretion in selecting similar comparison homes (“comps”) for the valuation. When appraising homes in predominantly white neighborhoods, appraisers tended to restrict “comps” other white neighborhoods – regardless of geographic proximity to non-white neighborhoods, whereas homes from non-white neighborhoods were appraised against homes in non-white neighborhoods.

However, scholarship from the sociology of race argues that actuarial methods often reinforce structural racism. We highlight two mechanisms. Fourcade & Healy (2013) discuss “classification situations,” defined as the use of actuarial techniques by organizations to categorize consumers into different groups. Historically, classifications were binary; consumers with “good” credit were offered loans and consumers with bad credit were not. Advances in data analytics (e.g., the calculation of individual credit scores) and the profit imperative led finer classifications. Fourcade & Healy (2013) (p. 566) offer a quote from a banking trade publication: “Stop trying to lend at low margin to accountants, lawyers and civil servants who are reliable but earn the bank peanuts. Instead, find the customers who used to be turned away; by using modern techniques, in credit scoring and securitization, they can be transformed into profitable business.” Thus, the emergence of classifications that categorize consumers into many groups, or along a continuum, is associated with the emergence of tiered products targeting different consumer groups with different benefit levels. For example, the “payday” loan industries targets consumers groups that were previously denied credit altogether, but charges excessive interest rates. Cottom (2020) defines “predatory inclusion” as the inclusion of “including marginalized consumer-citizens into ostensibly democratizing mobility schemes on extractive terms.” Predatory inclusion is exemplified by the for-profit college industry, which systematically targeted women of color and generated profit by encouraging these students to take on loans (Cottom, 2017). Other examples include sub-prime mortgage schemes targeted at minorities and the “gig economy” Cottom (2020).

A second source of structural racism in actuarial methods – central to student list products – is the use of structurally racist inputs. Actuarial products predict future outcomes by modeling the determinants of the outcome using historical data. Even when these models do not explicitly include race, they often include inputs that are correlated with race and that minorities tend to score poorly on because they have been historically excluded from this input. For example, Obermeyer, Powers, Vogeli, & Mullainathan (2019) found that

a commercial algorithm used by hospital systems under-predicted the health care needs of Black patients because the algorithm used health care costs as a proxy for health needs, but Black patients tend to receive less care relative to their health needs than other patients. Thus, Burrell & Fourcade (2021) (p. 224) state that “predicting the future on the basis of the past threatens to reify and reproduce existing inequalities of treatment by institutions.” Within the College Board suite of student list products, “geodemographic segment” filters classify each high school and neighborhood based on past college-going behaviors. The classification – based on cluster analysis – is highly correlated with race because communities of color that have been historically excluded from higher education are more likely to be lumped together.

As an example, Norris (2021) reconstructs Moody’s algorithm for credit ratings of city governments, which assigns credit scores to cities based on determinants thought to predict the probability of loan default. When cities issue bonds, these credit scores affect bond interest rates. Norris (2021) models Moody’s city credit rating score as a function of the criteria included in Moody’s rating system. Norris (2021) introduces the concept “racialized input” to describe the use of inputs that appear race-neutral, but actually disadvantage people of color due to historical exclusion. Furthermore, the inclusion of racialized inputs masks structural racism within actuarial systems because racialized inputs “explain away” the relationship between race and the outcome. The use of “median household income” by Moody’s rating system is a racialized input because earning differentials are a function of historical discrimination. When Norris (2021) excludes household income from the model, having a larger share of Black residents is negatively associated with city credit rating. When analyses include this racialized input in the model, share of Black residents is no longer associated with city credit rating, thereby masking structural racism within city credit ratings

### **3.1.3 Micro-targeting and Market-Segments**

Scholarship within the tradition of critical data studies has observed the growth of micro-targeting and market segmentation in algorithmic products that target prospective customers (e.g., Benjamin, 2019; Cotter, 2022; Cotter, Medeiros, Pak, & Thorson, 2021; Noble, 2018). Micro-targeting approaches promise to reach granular segments of society with great precision. For example, Cotter et al. (2021) state that “Facebook microtargeting is driven not by a goal of making all users available to advertisers, but of making the ‘right’ individuals available” and that “Facebook advises that advertisers ‘Implement a targeting strategy that focuses on reach and precision and eliminates waste.’” Student list products in the digital era develop filters that increase precision in targeting desired prospects and market them-

selves on micro-targeting. College Board Student Search promises to “create a real pipeline of best-fit prospects” College Board (n.d.) while ACT Encoura uses the tag-line “find and engage your best-fit students” Encoura (n.d.). Enrollment management consulting firms promise precision when marketing list buying services. For example, Ruffalo Noel Levitz states the “RNL Student Search and Engagement” product enables universities to “target the right students in the right markets” by making “the most efficient name purchases using predictive modeling” (Ruffalo Noel Levitz, 2021).

Scholars of critical data argue that racial exclusion is a predictable consequence of micro-targeting and market segmentation (Benjamin, 2019; Cotter et al., 2021; Noble, 2018). The process of developing a classification system requires software developers and companies to make a series of inherently subjective decisions (e.g., who is in the dataset, which measures to utilize, which categories to identify), creating opportunities for individual biases of developers and structurally racist inputs to enter the algorithm. Cotter et al. (2021) (p. 3) argues that most classification systems are developed to optimize profit and “audiences are treated as a commodity to be bought and sold. When audience segments are under-valued in the market, demand among advertisers for the ability to reach them will be relatively low, which decreases the likelihood that a corresponding segment will be produced.” A theme from scholarship on micro-targeting in politics is that these technologies *could* be used to to increase outreach to marginalized groups, but in practice they are not. Rather, micro-targeting practices raise concerns about “political redlining,” whereby “Campaigns routinely ‘redline’ the electorate, ignoring individuals they model as unlikely to vote, such as unregistered, uneducated, and poor voters (Kreiss, 2012, p. X)[QUOTED FROM COTTER 2021].

### 3.1.4 Conceptualizing student-list products

We conceptualize student list products vis-a-vis scholarship from the sociology of race and critical data studies. Scholarship from the sociology of race argues that the emphasis on explicit and implicit bias of individual decision-makers masks structural racism. Algorithmic products – particularly products that generate a “score” for each customer – reproduce racial inequality when these products utilize structurally racist inputs. Consistent with these ideas, student list products offer search filters that enable universities to target prospective students. Several search filters can be conceptualized as structurally racist inputs, for example zip code, AP score, and PSAT/AP score. While products (e.g., city credit ratings) that that utilize structurally racist inputs and lead to a numeric score are deterministically discriminatory, users of student list products may elect to not use structurally racist search filters – or use these filters thoughtfully – such that purchased lists do not exhibit problem-

atic racial inequalities. At the same time, student list products offer customers discretion in choosing filters that introduces the possibility of individual-level racial bias (explicit or implicit) (e.g., excluding predominantly non-white zip codes) that is not possible in purely algorithmic scoring products.

Student list products share commonalities with micro-targeting and market segmentation products offered by Facebook, Google, and political consulting firms. Rather than assign a single global score, these products classify potential customers into groups in order to target each group efficiently. However, classification systems are not neutral because they are created by people to maximize particular outcomes. To the extent that customers of student list products (universities) value the ability to target students from affluent, predominantly white schools and communities, then student list products incorporate filters that enable universities to do this with great efficiency. Additionally, like classification products, student list products are limited by who is included in the underlying data. Student list products offered by College Board and ACT exclude students who do not take their standardized assessments.

To summarize, student list products exhibit systematic racial and socioeconomic disparities due to disparities in who is included in the underlying database and due to the inclusion of structurally racist search filter inputs to select prospects from the underlying database. When purchasing student lists, universities may be thoughtful about avoiding structurally racist search filters. However, individual discretion also raises the possibility of racial disparities due to explicit/implicit prejudice and also due to lack of understanding about the products they are using.

## 3.2 Predicting Exclusion

K. Salazar, Jaquette, & Han (2022) categorize the filters available in the College Board Student Search Service product into the four buckets of geographic, academic, demographic, and student preferences (e.g., desired campus size, intended major). Table X describes filters by category. Drawing from the sociology of race, we conceptualize particular student list filters as “structurally racist” or “racialized inputs” if they have the appearance of neutrality but are correlated with race due to historic exclusion from this input. This section develops predictions about the relationship between filters and exclusion, focusing on racial and socioeconomic exclusion.

### 3.2.1 Geographic filters

Geographic search filters (e.g., state, zip code, “geomarket,” CBSA, geodemographic market segment) enable universities to target prospects based on where they live.

The concepts of “space” and “place” from critical geography (Agnew, 2011; Bell, 2007) describe two alternative approaches to conceptualizing geographic location. Place refers to a holistic understanding of a geographic location that incorporates the “history, peoples, and purposes within the political, social, and economic landscape” (Bell, 2007, p. 317). By contrast, space simply refers to a physical location which can be described in terms of quantifiable spatial features (e.g., distance, demographics, economic activity) and geospatial research adopts a view of space “as a location on a surface where things ‘just happen’” (Agnew, 2011, p. 318).

Marketing practices conceive of geography as space. Market research exploits racial segregation as a means to identify and target prospective customers (Benjamin, 2019; Noble, 2018). Benjamin (2019) (p. 147) states that “racialized zip codes are the output of Jim Crow policies and the input of New Jim Code practices.” Geodemography (now referred to as “spatial big data”) is a branch of market research that estimates the behavior of consumers based on where they live. College Board (2011b), which describes the development of geodemographic segment filters, illustrates the underlying assumptions of geodemography: The basic tenet of geodemography is that people with similar cultural backgrounds, means, and perspectives naturally gravitate toward one another or form relatively homogeneous communities; in other words, birds of a feather flock together (p. 1).

Scholarship on racial segregation conceives of geography as place. Contemporary segregation is a function of historic (Harris, 1993; e.g., Rothstein, 2017) and contemporary [e.g., Korver-Glenn (2018); RN4800] structurally racist laws, policies, and practices promoting residential segregation. Geographic filters are built on the back of racial segregation. We argue that targeting prospective students based on geographic location (space) without consideration to the history (place) that produces its unique patterns of residential segregation is likely to reinforce historical race-based inequality in educational opportunity.

**EXPECTATIONS** We expect that utilizing smaller geographic filters is associated with greater racial and socioeconomic disparities in student list purchases because American residential segregation occurs at fine-grained geographic levels [CITE]. Prior research on recruiting finds that selective private universities and also public research universities – particularly in out-of-state recruiting efforts – target affluent schools and communities (Jaquette et al., forthcoming; K. G. Salazar, 2022; K. G. Salazar et al., 2021; Stevens, 2007). These

results suggest that universities may filter on affluent zip codes when purchasing student lists. We expect that filtering for affluent neighborhoods is positively associated with racial exclusion because people of historical and contemporary practices that exclude people of color from living in many affluent neighborhoods

“Geomarkets” are created by by College Board Enrollment Management Services using information about score senders from previous admissions cycles (College Board, 2011a) . For example, CA10 is the “City of San Jose” and CA11 is “Santa Clara County excluding San Jose.” We expect that geomarket filters positively associated with racial exclusion because geomarket borders are drawn to reflect historic geographic disparities in educational opportunities.

## SOMETHING ABOUT GEODEMOGRAPHIC FILTERS?

### 3.2.2 Academic filters

College Board academic filters include high school graduating class, SAT score, PSAT score, AP score by subject, high school GPA, and high school class rank.

Broadly, the first source of racial and socioeconomic exclusion is that the underlying student list database excludes students who have not taken College Board assessments (SAT, AP, PSAT). Prior research shows that test-taking rates differ by race and class. Thus, we expect that who is included in the underlying database exhibits racial and socioeconomic exclusion prior to conditioning on a particular assessment or a particular score.

A related source of exclusion within the population of test-takers is who takes which assessment. Students attending schools in affluent communities tend to have better access to AP curricula. Research shows that students from underrepresented populations are less likely to take the PSAT [CITE] or AP tests [TRUE? CITE?] [note that CB did not release AP participation rates by race]. Therefore, conditioning on these assessments may increase exclusion. Additionally, College Board Search enables universities to target high school students early in the search process (e.g., sophomore PSAT takers) but students from underrepresented populations are more likely to take assessments later in high school (e.g., take SAT senior year). We expect that filtering for prospects early in high school is positively associated with racial and socioeconomic exclusion.

A second broad source of exclusion comes from test score thresholds utilized on filters. Test scores differ by race and class as a function of differential access to test preparation and . . . . [READ SOME STUFF AND THEN WRITE; STUFF FROM STRUCTURAL RACISM IN STANDARDIZED TESTING BY TIAKO AND RAY?]. We expect a positive relationship

between test score thresholds and racial and socioeconomic exclusion. As an alternative to test scores, universities may filter on high school GPA or high school class rank [RESEARCH BY TIENDA AND FOLKS?]. We expect a weaker relationship between these filters and racial/socioeconomic exclusion.

### 3.2.3 Demographic filters

Demographic filters include race, ethnicity, gender, low SES, and first generation status. We focus on filtering by race, which was the most commonly used demographic filter in K. Salazar et al. (2022).

Drawing from critical legal scholarship (Harris, 1993; Leong, 2013), we argue that race/ethnicity filters tend to exclude students from communities of color even when they are used to target non-white prospects. Harris (1993) conceptualizes “whiteness as property” as tangible, legally sectioned economic benefits that accrue to white people because of four “property functions of whiteness (rights of disposition, right to use and enjoyment; right to reputation and status; right to exclude). Whiteness and non-whiteness also define the “reputation and status” ascribed to localities, whereby “‘the inner city,’ ‘the ghetto,’ and ‘urban’ are linked to communities of color” (K. G. Salazar, 2022, p. X). The “absolute right to exclude is exemplified in exclusionary zoning ordinances prohibiting multi-family units) historically used to discourage Black residents from living in predominantly White areas” (K. G. Salazar, 2022, p. X).

Whereas “nonwhiteness” was historically “used as a basis for withholding value by denying nonwhite people legal rights and privileges” (Leong, 2013, p. 2155), nonwhiteness now confers social and legal value as a function with society’s preoccupation with diversity. The commodification of nonwhiteness – a “commodity to be pursued, captured, possessed, and used” (p. 2155) – encourages organizations to prioritize representational diversity, which Leong (2013) argues is exemplified by universities enrolling and marketing a diverse student body as a marker of status and prestige. However, selective universities pursue representational diversity while simultaneously privileging characteristics associated with whiteness (e.g., a “good high school”, “interesting extracurricular activities”, “good scores”) (Jack, 2019; Stevens, 2007; Thornhill, 2019). By combining race/ethnicity filters with academic achievement (e.g., AP test score range), geographic, and/or geodemographic filters, universities can screen for Students of Color who have characteristics perceived to be associated with whiteness, often as a function of living in a predominantly white community or attending a predominantly white school.



Building from these ideas, we expect that filtering for underrepresented students of color in combination with racialized inputs (e.g., AP scores, PSAT scores, affluent zip codes) systematically excludes students of color who live in predominantly non-white communities and attend predominantly non-white schools.

#### **3.2.4 Student preference filters**

#### **3.2.5 ? exclusion due to multiple racialized inputs?**

Figure 1: The enrollment funnel



## 4 References

- Agnew, J. A. (2011). Space and place. In J. A. Agnew & D. N. Livingstone (Eds.), *The SAGE handbook of geographical knowledge* (pp. 316–330). Los Angeles: SAGE.
- Bell, C. A. (2007). Space and place: Urban parents' geographical preferences for schools. *The Urban Review*, 39(4), 375–404. <https://doi.org/10.1007/s11256-007-0059-5>
- Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new jim code*. Medford, MA: Polity.
- Bonilla-Silva, E. (1997). Rethinking racism: Toward a structural interpretation. *American Sociological Review*, 62(3), 465–480. <https://doi.org/10.2307/2657316>
- Burrell, J., & Fourcade, M. (2021). The society of algorithms. *Annual Review of Sociology*, 47, 213–237. Journal Article. <https://doi.org/10.1146/annurev-soc-090820-020800>
- Campbell, A. (2017). *Higher education marketing: How to master your admissions funnel*. Hop Online. Retrieved from <https://hop-online.com/blog/higher-education-marketing-admissions-process/>
- College Board. (n.d.). College board search solutions. The College Board. Retrieved from <https://cbsearch.collegeboard.org/solutions>
- College Board. (2011a). Enrollment planning service. The College Board. Retrieved from

<https://collegeboardsearch.collegeboard.org/pastudentsrch/support/licensing/college-board-search-services/enrollment-planning-service>

- College Board. (2011b). *Segment Analysis Service: An educationally relevant geodemographic tagging service*. College Board. Retrieved from <https://secure-media.collegeboard.org/mSSS/media/pdf/segment-analysis-service-overview.pdf>
- Cotter, K. (2022). Selling political data: How political ad tech firms' discourses legitimate microtargeting. In *17th international conference on information for a better world - shaping the global future (iConference)* (Vol. 13192, pp. 195–208). CHAM: Springer International Publishing Ag. [https://doi.org/10.1007/978-3-030-96957-8\\_18](https://doi.org/10.1007/978-3-030-96957-8_18)
- Cotter, K., Medeiros, M., Pak, C., & Thorson, K. (2021). "Reach the right people": The politics of "interests" in facebook's classification system for ad targeting. *Big Data & Society*, 8(1), 16. <https://doi.org/10.1177/2053951721996046>
- Cottom, T. M. (2017). *Lower ed: The troubling rise of for-profit colleges in the new economy*. New Press, The.
- Cottom, T. M. (2020). Where platform capitalism and racial capitalism meet: The sociology of race and racism in the digital society. *Sociology of Race and Ethnicity*, 6(4), 441–449. <https://doi.org/10.1177/2332649220949473>
- Du Bois, W. E. B. (1935). *Black reconstruction: An essay toward a history of the part which black folk played in the attempt to reconstruct democracy in america, 1860-1880* (1st ed., p. 746). New York: Russel & Russel.
- Encoura. (n.d.). Encoura. ACT. Retrieved from <https://encoura.org/>
- Fourcade, M., & Healy, K. (2013). Classification situations: Life-chances in the neoliberal era. *Accounting Organizations and Society*, 38(8), 559–572. Journal Article. <https://doi.org/10.1016/j.aos.2013.11.002>
- Harris, C. I. (1993). Whiteness as property. *Harvard Law Review*, 106(8), 1707–1791. <https://doi.org/10.2307/1341787>
- Hirschman, D., & Bosk, E. A. (2020). Standardizing biases: Selection devices and the quantification of race. *Sociology of Race and Ethnicity*, 6(3), 348–364. <https://doi.org/10.1177/2332649219844797>
- Holland, Megan M. (2019). *Divergent paths to college: Race, class, and inequality in high schools*. Rutgers University Press. <https://doi.org/10.36019/9780813590288>
- Holland, M. M., & Ford, K. S. (2021). Legitimizing prestige through diversity: How higher education institutions represent ethno-racial diversity across levels of selectivity. *Journal of Higher Education*, 92(1), 1–30. <https://doi.org/10.1080/00221546.2020.1740532>
- Jack, A. A. (2019). *The privileged poor: How elite colleges are failing disadvantaged students* (p. 276). Cambridge, Massachusetts: Harvard University Press,. Retrieved from

- Restricted to UCLA. Limited to three concurrent users. Try again later if unavailable.  
[http://openurl.cdlib.org?sid=UCLA:CAT&genre=book&\\_\\_char\\_\\_set=utf8&isbn=9780674239647](http://openurl.cdlib.org?sid=UCLA:CAT&genre=book&__char__set=utf8&isbn=9780674239647)
- Jaquette, O., Han, C., & Castaneda, I. (forthcoming). The private school network: Recruiting visits to private high schools by public and private universities. In S. Burd (Ed.), *Lifting the veil on enrollment management: How a powerful industry is limiting social mobility in american higher education*. Book Section, Cambridge, MA: Harvard Education Press.
- Jaquette, O., Salazar, K., & Martin, P. (2022). *The student list business: Primer and market dynamics*. Washington, DC: TICAS. Retrieved from [https://ticas.org/wp-content/uploads/2022/09/The-Student-List-Business\\_-Primer-and-Market-Dynamics.pdf](https://ticas.org/wp-content/uploads/2022/09/The-Student-List-Business_-Primer-and-Market-Dynamics.pdf)
- Kerssens, N., & Dijk, J. van. (2022). Governed by edtech? Valuing pedagogical autonomy in a platform society. *Harvard Educational Review*, 92(2), 284–303. <https://doi.org/10.17763/1943-5045-92.2.284>
- Khan, S. R. (2011). *Privilege: The making of an adolescent elite at St. Paul's school* (p. 232). Princeton, N.J.: Princeton University Press.
- Killgore, L. (2009). Merit and competition in selective college admissions. *Review of Higher Education*, 32(4), 469–488. Retrieved from <Go to ISI>://WOS:000266737500002
- Komljenovic, J. (2021). The rise of education rentiers: Digital platforms, digital data and rents. *Learning Media and Technology*, 46(3), 320–332. <https://doi.org/10.1080/17439884.2021.1891422>
- Komljenovic, Janja. (2022a). The future of value in digitalised higher education: Why data privacy should not be our biggest concern. *Higher Education*, 83(1), 119–135. <https://doi.org/10.1007/s10734-020-00639-7>
- Komljenovic, Janja. (2022b). Where is value in digital higher education: From commodities to assets. *International Higher Education*, (111), 9–11.
- Korver-Glenn, E. (2018). Compounding inequalities: How racial stereotypes and discrimination accumulate across the stages of housing exchange. *American Sociological Review*, 83(4), 627–656. <https://doi.org/10.1177/0003122418781774>
- Leong, N. (2013). Racial capitalism. *Harvard Law Review*, 126(8), 2151–2226. Retrieved from <Go to ISI>://WOS:000320488400001
- Marx, K. (1978). Capital. In R. C. Tucker (Ed.), *The marx-engels reader* (second). New York: W.W. Norton; Company.
- McDonough, P. M. (1997). *Choosing colleges: How social class and schools structure opportunity* (pp. xi, 174 p.). Albany: State University of New York Press.
- McPherson, M. S., & Schapiro, M. O. (1998). *The student aid game*. Princeton, NJ: Princeton University Press.

- Napier, A., & Orrick, A. (2022). The economic, social, and political dimensions of platform studies in education. *Harvard Educational Review*, 92(2), 206–208. <https://doi.org/10.17763/1943-5045-92.2.206>
- Nichols, T. P., & Garcia, A. (2022). Platform studies in education. *Harvard Educational Review*, 92(2), 209–230. <https://doi.org/10.17763/1943-5045-92.2.209>
- Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York: New York University Press.
- Norris, D. (2021). Embedding racism: City government credit ratings and the institutionalization of race in markets. *Social Problems*. <https://doi.org/10.1093/socpro/spab066>
- O’Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy* (First edition., pp. x, 259 pages). New York: Crown.
- Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447–453. <https://doi.org/10.1126/science.aax2342>
- Posecznick, A. (2017). *Selling hope and college merit, markets, and recruitment in an unranked school*. Ithaca ; London: Cornell University Press. Retrieved from <https://muse.jhu.edu/book/52616>
- Posselt, J. R. (2016). *Inside graduate admissions: Merit, diversity, and faculty gatekeeping* (pp. x, 250 pages). Cambridge, MA: Harvard University Press.
- Robinson, C. J. (2000). *Black marxism: The making of the black radical tradition* (pp. xxxiii, 436). Chapel Hill, N.C.: University of North Carolina Press. Retrieved from [Table of Contents http://lcweb.loc.gov/catdir/toc/99030995.html](http://lcweb.loc.gov/catdir/toc/99030995.html)
- Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.
- Ruffalo Noel Levitz. (2018). *2018 marketing and student recruitment report of effective practices*. Ruffalo Noel Levitz. Retrieved from [http://learn.ruffalonl.com/rs/395-EOG-977/images/RNL\\_2018\\_Student\\_Recruitment\\_Marketing\\_Report\\_EM-19.pdf](http://learn.ruffalonl.com/rs/395-EOG-977/images/RNL_2018_Student_Recruitment_Marketing_Report_EM-19.pdf)
- Ruffalo Noel Levitz. (2020). *2020 marketing and recruitment practices for undergraduate students report*. Ruffalo Noel Levitz. Retrieved from [https://learn.ruffalonl.com/rs/395-EOG-977/images/2020\\_Marketing\\_Recruitment%20Practices\\_Undergraduate\\_Students.pdf](https://learn.ruffalonl.com/rs/395-EOG-977/images/2020_Marketing_Recruitment%20Practices_Undergraduate_Students.pdf)
- Ruffalo Noel Levitz. (2021). RNL student search and engagement. Retrieved from <https://www.ruffalonl.com/enrollment-management-solutions/building-demand/student-search-and-engagement/>
- Sadowski, J. (2019). When data is capital: Datafication, accumulation, and extraction. *Big Data & Society*, 6(1), 12. <https://doi.org/10.1177/2053951718820549>

- Sadowski, J. (2020). The internet of landlords: Digital platforms and new mechanisms of rentier capitalism. *Antipode*, 52(2), 19. <https://doi.org/10.1111/anti.12595>
- Salazar, K. G. (2022). Recruitment redlining by public research universities in the los angeles and dallas metropolitan areas. *The Journal of Higher Education*, 1–37. <https://doi.org/10.1080/00221546.2021.2004811>
- Salazar, K. G., Jaquette, O., & Han, C. (2021). Coming soon to a neighborhood near you? Off-campus recruiting by public research universities. *American Educational Research Journal*, 58(6), 1270–1314. <https://doi.org/10.3102/00028312211001810>
- Salazar, K., Jaquette, O., & Han, C. (2022). *Geodemographics of student list purchases: A first look*. Washington, DC: TICAS. Retrieved from [https://ticas.org/wp-content/uploads/2022/09/Geodemographics-of-Student-List-Purchases\\_A-First-Look.pdf](https://ticas.org/wp-content/uploads/2022/09/Geodemographics-of-Student-List-Purchases_A-First-Look.pdf)
- Simon, J. (1988). The ideological effects of actuarial practices. *Law & Society Review*, 22(4), 771–800. Journal Article. <https://doi.org/10.2307/3053709>
- Stevens, M. L. (2007). *Creating a class: College admissions and the education of elites* (p. 308). Cambridge, MA: Harvard University Press.
- Thornhill, T. (2019). We want black students, just not you: How white admissions counselors screen black prospective students. *Sociology of Race and Ethnicity*, 5(4), 456–470. <https://doi.org/10.1177/2332649218792579>
- Tiako, M. J. N., South, E., & Ray, V. (2021). Medical schools as racialized organizations: A primer. *Annals of Internal Medicine*, 174(8), 1143–1144. <https://doi.org/10.7326/m21-0369>
- Williamson, B. (2021). Making markets through digital platforms: Pearson, edu-business, and the (e)valuation of higher education. *Critical Studies in Education*, 62(1), 50–66. <https://doi.org/10.1080/17508487.2020.1737556>
- Williamson, Ben, Gulson, K. N., Perrotta, C., & Witzemberger, K. (2022). Amazon and the new global connective architectures of education governance. *Harvard Educational Review*, 92(2), 231–256. <https://doi.org/10.17763/1943-5045-92.2.231>