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Selling Student Success: A Critical Analysis of Predictive Analytics Vendors in Higher Education

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Abstract

As predictive analytics become increasingly embedded in higher education, commercial vendors offering these tools play a growing role in shaping institutional decision making, particularly through identifying students deemed “at risk.” In this qualitative study, we analyzed 132 publicly available materials from 15 vendors to examine these companies’ marketing of predictive analytics. Drawing on Snow and Benford’s (1988) framing theory, we investigated how they construct the problem of student success and how they portray students in these constructions. Findings from our thematic analysis are: (1) the primary problem vendors purport to address is the lack of data insights to support student success, including due to data silos, capacity constraints, and the exclusion of student behavioral and engagement data; (2) vendors largely frame the problem their products address as one of institutional finances; and (3) vendors acknowledge structural barriers but rarely recognize students’ strengths. Although vendors frequently invoke equity-oriented language to position their tools as student-centered, our analysis reveals an emphasis on financial value for institutions and a limited engagement with students’ assets, ultimately narrowing pathways for supporting students’ success.

Introduction

Predictive analytics is widely used in higher education for various purposes. A 2018 survey across three higher education associations found that 89% of respondents reported using predictive analytics (Parnell et al., 2018). A primary use of predictive analytics in higher education is to predict the likelihood of students' success, drawing on demographic, behavioral, and academic data (Attewell et al., 2022; Bird et al., 2025; Gándara et al., 2024; Muscanell, 2024). With the use of prediction algorithms in machine learning to identify patterns in data, colleges and universities aim to identify students deemed as "at risk" so that they can intervene to improve students' outcomes.

Although predictive analytics can help institutions target support for students, observers have raised concerns about their underlying assumptions and potential consequences (Ekowo & Palmer, 2016; Feathers, 2021; Jarke & Macgilchrist, 2021). Educational institutions' growing use of prediction algorithms has prompted increasing scrutiny over issues of transparency, algorithmic bias, and the potential amplification of existing inequities (Baker & Hawn, 2022; Bird et al., 2025; Gándara & Anahideh, 2025; Gándara et al., 2024; Kizilcec & Lee, 2022; Selwyn, 2019; Whitman, 2020). Moreover, scholars have noted that these tools frame historically underserved students as "at risk" based on deficit-oriented logics (Madaio et al., 2022). Such logics blame individuals, or their proximal environments, such as their families or communities, for their failure, often without accounting for systemic barriers or recognizing students' strengths (Davis & Museus, 2019).

These concerns are heightened by institutions' increasing reliance on commercial vendors for predictive analytics tools. Because these products are often proprietary, it is challenging to evaluate their performance or underlying logic. According to one estimate, as of 2019, approximately one third of U.S. 4-year institutions had contracted with for-profit vendors for predictive analytics services, with over 30 companies operating in this space (Barshay & Aslanian, 2019). Among public 2-year and private for-profit institutions, the rates were estimated to be 19% and 15%, respectively (Barshay & Aslanian, 2019). Yet despite the prevalence of this outsourcing, vendors of predictive analytics tools have received relatively little scholarly attention.

In this study, we contribute to the growing literature on predictive analytics in higher education by focusing on the role of predictive analytics vendors, actors that are often overlooked but increasingly prevalent within higher education institutions. Prior research has focused primarily on technical model performance or institutional implementation, with relatively little attention paid to the commercial providers who develop, market, and shape how predictive tools are understood and adopted (e.g., Attewell et al., 2022; Bird et al., 2025; Gándara et al., 2024; Klempin et al., 2019; Rossman et al., 2021). In examining how vendors market predictive analytics tools to colleges and universities, we thus shift the analytic focus from algorithmic performance to discourse. In this study, we asked the following questions:

1. How do vendors of predictive analytics for higher education construct the problems their products are designed to address in their public-facing materials?
2. How do they portray students in the construction of student success problems and proposed solutions?

To address these questions, we examined 132 public-facing materials from the websites of 15 vendors that market predictive analytics tools for college student success. We analyzed these qualitative data both inductively and deductively using thematic analysis (Braune & Clarke, 2006, 2021). We anchored the analysis in Snow and Benford’s (1988) framing theory, which outlines three core framing tasks: diagnosing problems, proposing solutions, and providing rationales for action (e.g., purchasing predictive analytics products). Using this framework, we examined how the problem of college student success is framed, including to whom the problem is attributed to (e.g., students, institutions, or others) and how vendors position their products as solutions.

To deepen our analysis of how vendors frame students in their predictive analytics marketing materials (addressing the second research question), we drew on Yosso's (2005) community cultural wealth (CCW) framework, which foregrounds: (1) structural and systemic barriers to student success, and (2) the strengths of historically underserved students, who are disproportionately labeled "at risk" by predictive models (e.g., Bird et al., 2025; Gándara et al., 2024; Yu et al., 2021; Yu et al., 2020). Guided by CCW, we investigated whether and how vendors (1) acknowledged structural barriers and (2) recognized students' assets in their framings of student success.

Related Literature on Predictive Analytics in Higher Education

Educational technology companies proliferate in higher education (Mirrlees & Alvi, 2019). A market research firm predicted that the education and learning analytics market would be worth nearly $35 billion by 2027, with higher education comprising a substantial share of the market due to "the increasing spending capacity of higher education institutions on data-driven solutions" (Meticulous Market Research Pvt, 2021, p. 10). One major category of educational technology in higher education is predictive analytics, which includes tools used to estimate students' likelihood of success, commonly measured as course passing, persistence, or graduation, or failure, construed as the absence of those outcomes (The Ada Center, n.d.).

Most scholarly attention to predictive analytics has focused on the technical aspects of the statistical models underlying these products (e.g., Bird et al., 2021; Yu et al., 2020; Zhidkikh et al., 2024). Much of this work has emphasized statistical fairness, or the extent to which student success prediction models perform equitably across social groups, finding that commonly used predictors tend to overestimate failure for racially minoritized and other marginalized students (Baker & Hawn, 2022; Bird et al., 2025; Gándara et al., 2024; Lee & Kizilcec, 2020; Yu et al., 2021; Yu et al., 2020). The extent of this bias depends on model design, including the types of variables used (Bird et al., 2025; Yu et al., 2021). These findings point to potential barriers to university admission, access to rigorous coursework, or receipt of institutional supports for students who are predicted to fail (Gándara & Anahideh, 2025). Concerns about fair treatment in decisions supported by predictive analytics are compounded by institutions' reliance on vendor-developed tools, whose underlying algorithms are proprietary and opaque, preventing meaningful evaluation of their accuracy, equity, or appropriateness for the task (Baker & Hawn, 2022; Bird et al., 2021; Gardner et al., 2023).

A smaller body of work has examined how predictive analytics are used in practice. Research shows that institutions often use predictions to identify "at-risk" students for targeted interventions, such as advising or coaching (Hall, 2017; Klempin et al., 2019; Rossman et al., 2021). For instance, Hall (2017) described how predictive analytics informed student success coaching, directly shaping student support decisions. Other studies have illustrated how colleges and universities use predictions from statistical models to guide advisor and faculty interventions (Klempin et al., 2019; Rossman et al., 2021).

However, the effectiveness of such interventions is mixed. Hall (2017) found that proactive coaching informed by predictive analytics did not significantly improve students' GPA, concluding that identification alone is insufficient; student outcomes depend on institutions' capacity to act on predictive insights. Similarly, Rossman et al. (2021) evaluated a large-scale proactive advising intervention based on predictive analytics at 11 large public universities. Across the sample, they did not find statistically significant improvements in credit accumulation or retention, except at Georgia State University, where outcomes improved significantly. These findings support the contention that prediction alone is not enough to improve student outcomes without humanistic approaches to supporting students, particularly those historically underserved in higher education (Acosta, 2019; Dowd et al., 2018).

Critical scholars have noted that these systems often operate from the assumption that students, not institutions, need to change to enhance student outcomes (Jarke & Macgilchrist, 2021; Whitman, 2020). Based on limited research, the designs of at least some student success prediction models appear to be aligned with this logic, including largely individual (student)-level predictors, such as academic, demographic, and behavioral variables, including data from ID card scans (e.g., gym or library visits) and activity in Learning Management Systems, such as Blackboard or Canvas (Ram et al., 2015; Whitman, 2020; Yu et al., 2020). For example, a Freedom of Information Act (FOIA) request revealed that one vendor, EAB's, predictive models, which differ across higher education institutions, often include demographic variables (i.e., age, gender, race, veteran status, first-generation status, legacy status), academic records, and test scores, all of which are individual-level predictors. Predictors beyond the student level listed in the FOIA-obtained documents were scantly used, and limited to high school size, ZIP code-level income, and average performance of students in the same major (Feathers, 2021). While some of these variables (e.g. aggregate performance by major) potentially point to systemic departmental issues, models described in existing literature appear to treat the student as the primary site for intervention.

Through an ethnographic case study, Whitman (2020) demonstrated that university administrators categorize these individual-level predictors into immutable attributes, on one hand, and behaviors students can change, on the other (Whitman, 2020). As Whitman explains, “The institutional reframing of success in terms of ‘what students can change’ enables the institution to transfer the burden of success away from itself and keep the tacitly held knowledge of inequality out of the university’s visions for predictive modeling” (p. 2). The embedded theory of change in such predictive systems thus locates responsibility at the individual (student) level, ignoring how structural conditions, such as a hostile classroom environment, may influence student behaviors like attendance or purported engagement and, ultimately, their academic outcomes. This approach contrasts with other strategies to supporting student success that focus on transforming institutional structures, cultures, and climates to support students from diverse backgrounds (e.g., Museus, 2014).

Notwithstanding these examples, the degree to which vendors reinforce a framing that overwhelmingly places the responsibility for success on the student likely varies, with that variation missing from existing literature. For instance, some vendors may design predictive analytics products that account for supra-student factors. Through their marketing materials, they may also convey to institutions that they have agency, and perhaps a responsibility, to improve its students’ outcomes. Doing so would recognize the potential for institutional improvement in supporting the success of all students.

To our knowledge, no study has explored the broader ecosystem in which these tools are developed and marketed. While nonprofit organizations like New America offer guides on vendor contracts, highlighting concerns about data ownership, acquisitions, and data breaches, there is limited research on the vendors themselves (Palmer, 2018). This study contributes to filling that gap by examining how vendors of predictive analytics frame student success problems and market their solutions to higher education institutions.

Framing Theory

Our analysis of how student success problems are framed is guided by Snow and Benford's (1988) framing theory, which is focused on ideology, frame resonance, and participant mobilization. Framing theory originated in social movement research and has primarily been applied to that field, although its reach has expanded in recent decades (Benford & Snow, 2000; Snow & Benford, 1988). In the theory's formulation, the authors recognized that one of the core actions of social movements is to frame, or to "assign meaning to and interpret relevant events and conditions in ways that are intended to mobilize…" (Snow & Benford, p. 1988). In that work, they outlined four categories of variables that affect the strength of a social movement, including core framing tasks, such as problem and solution definition; the constraints of belief systems; phenomenological constraints, or how the frames relate to participants' worlds; and cycles of protest.

Given our interest in how predictive analytics vendors frame problems of college student success and proposed solutions, we focus on two of Snow and Benford's framing tasks diagnostic framing and prognostic framing (p. 200). Specifically, this theory anchors our investigation of how predictive analytics vendors frame problems (diagnostic framing) and name solutions (prognostic framing) (Benford & Snow, 2000; Snow & Benford, 1988). The theory also draws attention to problem attribution, noting that while there may be consensus on defining a problem (e.g., college student success rates are inadequate), there may be less consensus on who to blame for the problem (Benford & Snow, 2000; Snow & Benford, 1988). Marketing discourse from predictive analytics vendors may blame students, institutions, or other entities for the problem of college student success.

Community Cultural Wealth

To deepen our analysis, we supplement Snow and Benford's (1998) framing theory with Yosso's (2005) CCW framework, rooted in critical race theory, to examine how vendors of predictive analytics frame students, including their outcomes and the reasons for them. The CCW framework challenges dominant deficit-oriented interpretations of students' outcomes, particularly for those from communities of color, as a result of individual shortcomings. Deficit logics include those that blame the students or their immediate communities for not persisting in higher education, rather than identifying broader oppressive and hegemonic structures that have maintained social hierarchies by privileging certain groups (Davis & Museus, 2019). In contrast, CCW highlights the strengths and assets students bring with them, especially those cultivated through familial, communal, and cultural experiences.

Although conceptualized as a framework that centers communities of color, CCW has been applied to the study of various historically underserved populations in higher education, including first-generation students and students from rural communities (Gannon, 2023; Garriott, 2020). This framework is apt for the present study because students from historically underserved communities are overrepresented by risk indicators in student success prediction models (e.g., Gándara et al., 2024; Yu et al., 2021; Yu et al., 2020). Thus, we are interested in how "risk" in student success prediction models, which is disproportionately associated with historically underserved communities, is portrayed in vendors' public materials.

Yosso (2005) identified six interrelated forms of capital that historically underserved students draw upon in educational settings: aspirational, familial, social, linguistic, navigational, and resistance. Aspirational capital refers to the "ability to maintain hopes and dreams for the future, even in the face of real and perceived barriers" (Yosso, 2005, p. 77). Familial and social capital are, respectively, the "cultural knowledges nurtured among *familia* (kin)" and the "networks of people and community resources" (Yosso, 2005, p. 79). Linguistic capital includes the "intellectual and social skills attained through communication experiences in more than one language and/or style" (p. 78); it can include storytelling, art, and various communication skills. These forms of capital include the family, and community supports that help sustain students from underserved communities in formal school settings. Turning to student traits, navigational capital includes the "skills of maneuvering through social institutions" (Yosso, 2005, p. 80), especially ones not created for marginalized groups. Last, resistance capital comprises "knowledges and skills fostered through oppositional behavior that challenges inequality" (Yosso, 2005, p. 80). These include resisting and persisting in hostile environments, and teaching others how to do the same. These various forms of CCW challenge institutional assumptions about what counts as valuable knowledge, and they underscore how historically underserved students succeed, not despite their backgrounds, but in part because of them (Yosso, 2005).

A growing body of research suggests that acknowledging these forms of wealth is vital to the success of historically underserved populations (Arámbula Turner, 2021; Araujo, 2011; Benson et al., 2023; Brooms & Davis, 2017; Del Real Viramontes, 2021; Johnson et al., 2020; Kouyoumdjian et al., 2017). Research has also highlighted how CCW can inform institutional decision making and the design of environments and student support systems that recognize and leverage students' strengths. For example, Araujo (2011) and Del Real Viramontes (2021) examined programs serving farmworker and transfer students, respectively, showing how these initiatives succeeded when they recognized and leveraged the cultural wealth students brought with them. Their findings also echo those of Luedke (2017) on the important role of staff of color in supporting students of color.

Collectively, these studies highlight how understanding the array of cultural resources students possess can guide the development of programs and practices to support college students' success. Instead of exclusively pursuing remedial or deficit-oriented interventions based on "risk" identification, institutions might also implement initiatives that leverage students' motivations, as well as familial, social, and linguistic capital, such as family mentorship programs or culturally led advising models (Luedke, 2017).

The CCW framework not only highlights student assets but also calls attention to supra-student factors, including structural and institutional conditions that shape students' success. These include access to financial aid, inclusive campus climates, and the presence of culturally responsive practices. In this context, CCW helps reframe dominant notions of "risk" embedded in predictive analytics tools and in higher education more broadly (Ekowo & Palmer, 2016). Rather than attributing risk to individual students, CCW prompts us to understand risk as produced by institutional environments, including, for racially minoritized students, the persistent risk of racism (Acevedo & Solórzano, 2023). This framework thus helps illuminate how institutional practices either amplify or mitigate these risks.

Thus, CCW turns our analytic gaze to the factors (what might be considered "variables" or "features" in predictive models) that exist beyond the student. It invites us to interrogate whether and how these structural "risk" factors are acknowledged by vendors of predictive analytics in the ways they frame problems and propose solutions in their public materials.

Rooted in Snow and Benford’s framing theory, supplemented by the CCW framework, we analyzed how vendors define the problems they purport to solve, how they situate their proposed solutions, and how they portray students. We investigated whether and how predictive analytics vendors (1) recognize students’ CCW as an essential resource for their success, and (2) acknowledge systemic and structural barriers that historically underserved students must navigate. In doing so, we depart from most studies employing CCW, which tend to focus on students’ own perspectives and experiences. Instead, we shift our analysis to the commercial organizations (vendors) that provide predictive analytics tools, which may both reflect and shape how institutional actors conceptualize risk and students’ success. We investigate how the discourse embedded in predictive analytics marketing aligns with or diverges from asset-based educational practice that affirms the cultural wealth of historically underserved students and recognizes the structural barriers that impede their success.

Research Design and Methods

Data Collection

The dataset for this study included 132 publicly available documents collected from the websites of 15 predictive analytics vendors between October and December 2024. These data represent a range of materials, including marketing content, case studies, podcast transcripts, and blogs, all of which reference predictive analytics tools related to college student success.

Identifying Vendors

The first author produced an initial list of vendors through a Google search using the following terms: “predictive analytics,” “early warning,” “early alerts,” “prediction”, and “forecast,” combined with “success” and related terms, including “persistence” and “graduation”; this list included 53 vendors. After reviewing the list, members of the research team collaboratively developed a set of inclusion and exclusion criteria. First, vendors had to be for-profit entities that provide predictive modeling services, excluding those that merely provide a platform for institutions to develop their own predictive tools. This ensured a focus on vendors that retain proprietary control over model design. Second, vendors had to define students' success in terms of their educational outcomes such as persistence, degree completion, or deficit-based counterparts (e.g., stop-out, dropout). Vendors that focused exclusively on institutional outcomes, such as yield prediction (predicting whether an admitted student would accept an offer) or tuition revenue optimization were excluded from the analysis.

Two researchers independently reviewed the list against the inclusion and exclusion criteria, resulting in a final sample of 15 vendors. To enhance the reliability and completeness of the dataset, the third author independently reviewed the websites of all 15 vendors. This review served to verify that vendors in the initial dataset met the inclusion criteria. Vendors were excluded if they were acquired by or merged under a different company (e.g., Hobsons, Rapid Insight, Blackboard Analytics, TargetX), focused solely on enrollment management (e.g., Ellucian Analytics, Kuali, Education Dynamics, RNL), exclusively offered self-service platforms for predictive analytics (e.g., Oracle, Microsoft, SAS Visual Analytics), or did not provide college student success predictive modeling services (e.g., iData, Jenzabar Analytics, Retention 360, Canvas). These exclusion decisions ensured that the final sample reflected vendors most relevant to student success prediction. A complete list of the 15 vendors in the final sample appears in Appendix A.

Sourcing Online Materials

After identifying vendors, the first author systematically visited each vendors' website to identify content that met two conditions: (1) the material referred to quantitative prediction modeling (i.e., predictive analytics), and (2) it focused on college students' success. Webpages meeting these criteria were saved as .pdf files and imported into Dedoose research software for qualitative analysis. These materials included product descriptions, institutional case studies, podcast transcripts, vendor-hosted blogs, customers' testimonials, and publicly posted materials related to algorithmic transparency and implementation. This process yielded the total of 132 documents stored for analysis.

Data Analysis

Our analysis of predictive analytics vendors' marketing materials proceeded in six stages. First, following Braun and Clarke's (2006, 2021) thematic analysis approach, the first two authors familiarized ourselves with the data by reading the documents from each vendor's websites. Second, we engaged in inductive coding, identifying concepts directly from the data. Examples of inductive codes include *algorithmic bias, barriers to student success, data sources*, *defining student success*, *economic value proposition, intervention strategies,* and *theory of change*. Third, following inductive coding, we coded the data with codes aligned with the six forms of capital from the CCW framework, which was our initial theoretical framework, before adding framing theory. These codes were scantly applied throughout the data, an observation we elaborate on in the Findings.

We encountered Snow and Benford's framing theory after completing this CCW-driven deductive analysis. This new framework aligned closely with our research questions and allowed us to focus more specifically on how the problem of student success was framed, how solutions were presented, and to whom blame was attributed. As such, in the fourth phase of analysis, two members of the research team undertook an additional round of coding using this new framework. For this round, we developed and applied codes aligned with key concepts in framing theory: *diagnostic* and *prognostic framing*, *problem attribution*, and given our interest in the framing of students, *asset- or deficit-based framing of students*. Across both rounds of coding, the researchers involved in coding produced memos on notable findings. In addition, through peer debriefing sessions, we resolved coding discrepancies, including those related to overlap across multiple forms of CCW capital.

In the fifth phase of analysis, one of the authors identified preliminary themes based on the prevalence of codes applied (e.g., *organizational/data silos, economic value proposition, efficiencies, insufficient/inadequate data insights, institution's finances*, *framing of students, problem attribution,* and *theory of change*), their co-occurrence, and absences in the data (recognition of students' CCW). In the sixth and final phase of analysis, the research team reviewed the themes against the full corpus of data, following Braun and Clarke's (2006) thematic analysis procedures. Specifically, guided by the research questions, each author read the proposed themes, revisited the coded data, and produced memos on the following: (1) How well do the data support the themes? (2) Are there data that complicate, challenge, or contradict the themes? Are there disconfirming examples or tensions in the data we need to account for? (3) Is each theme internally coherent and distinct from the others? (4) Are there other data excerpts that best illustrate the essence of each theme?

Through a debriefing meeting guided by analytic memos, the authors discussed and refined the preliminary themes. For instance, we removed a fourth theme capturing problem and solution (mis)alignment, because it was not sufficiently analytically distinct from the first theme or supported by the data. Relevant evidence originally grouped under that theme was incorporated into the first theme. Peer debriefing during this phase also helped us clarify important analytic distinctions among deficit-based language, blame attribution, and responsibility for solutions. These distinctions informed revisions to the presentation of the second theme and are taken up more directly in the Discussion. The findings presented below reflect the outcome of this multi-step analytic process.

Findings

We identified three themes, each addressing a dimension of how vendors construct the problem of student success and how they portray students in this construction. The first two themes capture the primary problems that student success prediction aims to address: limited data insights and institutions' finances. The third theme turns to the portrayal of students, who are painted largely as deficient and whose strengths, which could be leveraged to enhance their success, are seldom acknowledged. Predictive analytics vendors' materials (and, accordingly, their algorithms and proposed interventions) vacillated between blaming students and blaming structures for student failure.

"Data rich yet information poor:" Insufficient Data Insights

The first two themes address the first research question: How do vendors of predictive analytics for higher education construct the problems their products are designed to address in their public-facing materials? Our analysis revealed that the primary problem predictive analytics vendors identified in their marketing materials was the lack of adequate data insights within higher education institutions. As described on one vendor, Zogotech's, website, "It's not uncommon for colleges to be data rich yet information poor." Three primary reasons for limited data insights were identified: fragmented data systems, capacity constraints, and the exclusion of relevant variables for predicting student success.

Data Silos. One of the primary reasons for insufficient data insights cited in vendors' marketing materials was "fragmented data systems," frequently referred to as "data silos." As described in a case study by ZogoTech, Pete Belk, the Director of Admission and Recruitment at JCCC, stated, “We struggled with fragmented data systems and delayed access to critical information. It was like trying to navigate in the dark.” Case studies or testimonies like the one quoted here were rampant throughout the data, employed to demonstrate prior success as a form of empirical credibility. In another example, Ocelot describes their solution in reference to such silos, “Ocelot breaks down the silos of existing campus systems to more effectively get students and staff the information they need, when they need it, to be most successful.”

Capacity Constraints. A second frequently cited cause of insufficient data insights was institutional capacity. As noted on an EAB webpage describing a product called Rapid Insight, “Too often, access and capacity issues keep staff from using data to make fast and effective decisions.” The company then positioned its product as a solution: “Rapid Insight puts reliable data in decision-makers’ hands with simplified predictive modeling, a code-free data workspace, and cloud-based dashboards.” In this context, capacity issues encompass both staffing constraints and deficits in technical expertise, including programming skills. As another example, a ZogoTech post describes the problem of “Limited Resources,” “both in terms of finances and staff.” The post adds that “Combined with limited data, these institutions find it impossible to prioritize the interventions, support services, and other initiatives that will have the biggest impact on graduation rates.” Both data silos and capacity constraints are problems located at the institutional (structural level). In contrast, the third data-related problem identified by vendors, described next, indicates the need for more data on individual (student) behaviors, suggesting a problem attribution at least partly located at the student level.

Not Enough Behavioral Data. Beyond data silos and capacity constraints, vendors also emphasized the limitations of excluding certain types of data from predictive models. First, vendors highlighted the shortcomings of relying on "historical analytics that reveal past trends and patterns," rather than incorporating "real-time" and "actionable" data. Civitas Learning, for instance, offers examples of actionable analytics, including "LMS engagement relative to peers, changes in persistence within the term, and the ability to identify exactly which student success initiatives are making a difference and benefitting specific student groups." Similarly, a ZogoTech use case on empowering community college faculty and staff identifies the problem of "Lack of Real-Time Data," noting that "Timely data is crucial for decision-making." Another Civitas blog post likewise argues for the inclusion of real-time data: "While these metrics are helpful for long-term planning and assessment of overall institutional effectiveness, they're not great diagnostic tools. To improve student outcomes, leaders like you need metrics to help determine which students need support now."

Vendors such as EAB also stressed the importance of incorporating what they term "engagement" or "behavioral" data, in contrast to "frozen" data, or "things that are set in stone about a student, like their homework, ethnicity, age." They instead advocate including data on "tiny interactions and transactions," such as information drawn from learning management systems (LMS) and service appointment records. Although many vendors emphasized the importance of such dynamic data (e.g., behavioral and engagement metrics), they offered little explanation of how these data could be used in practice. For instance, if a student is flagged for visiting the library infrequently, logging in to the LMS irregularly, or low student usage of meal plans (e.g., Othot), it is unclear what intervention follows.

In another example, Civitas argues for emphasizing "real-time behavioral data such as classroom engagement, enrollment patterns, academic performance, and degree alignment... factors that students can actually change." While the author seeks to move beyond demographic (fixed) variables, they continue to place blame on individuals by focusing on those factors they "can actually change," rather than institutions.

In these examples, vendors emphasized individual behaviors (symptoms) without clearly interrogating root causes. These causes might include inaccessible pedagogy, hostile or non-inclusive learning environments, or scheduling challenges (e.g., related to family or work obligations), none of which were included in models. Therefore, these factors were largely absent from proposals for solving the challenges surrounding student success. Whether due to data infrastructural challenges, capacity constraints, or the omission of certain types of data from predictive models, this finding underscores the primary problem vendors identified through their marketing materials: inadequate data insights.

"Optimized Student Lifecycles, Healthier Revenues:" Institutional Finances

The second theme captures vendors' framing of student success in financial terms, linking improvements in student outcomes to institutional return on investment (ROI). Vendors commonly position predictive analytics as a tool to help institutions retain more students, reduce recruitment costs, and improve financial stability. Students' success is thus portrayed largely as a business strategy.

In some cases, students' success was explicitly cast as an opportunity, namely, a means to enhance the institution's bottom line. For instance, Othot stated that their products "will enable greater success for students and thus the institutions that serve them," a claim of mutual benefit for students and institutions echoed by Ad Astra in their proposition, "Enhance student success while achieving better financial outcomes" and Helio Campus in their heading, "Optimized Student Lifecycles, Healthier Revenues." For Helio Campus, the "student lifecycle" encompasses the full process from initial student interest in the institution through enrollment, retention, and graduation. On that same website, Helio Campus describes how their products will improve the institution's finances by increasing student success. Titled, "Revenue Growth & ROI in Higher Ed," the website notes,

> Target the right students, offer the necessary financial aid, and properly assess individual retention risks with timely insights to help you impact student success, while increasing revenue streams.

Here, Helio Campus outlines the mechanisms by which their products will increase revenue--broadly, by improving student success.

Ad Astra reinforced this framing with an unattributed quote on its website: "We want and need to be better stewards for the students we have, especially in [a] time of decreasing enrollments. We need to grab additional students wherever we can. We cannot afford not to." This quote underscores the perception that students represent revenue, given the additional funding that accompanies student enrollments, primarily through tuition revenue (net of institutional discounts) and governmental appropriations.

Whereas in this study we focus on the prediction of students' success, most vendors offer products that span the student lifecycle, supporting the broader goal of enrollment and revenue optimization. In a blog post about a partnership between the vendors Othot and RNL, Fred Weiss tied student success directly to financial outcomes: "There is no doubt that there is a financial component to this. Many states now have outcomes-based funding, and the cost of retaining a student is lower than the cost of recruiting a new student." Likewise, Zogotech appeals to community colleges' incentives under performance-based funding models. On one website, they quote the Chief Information Officer at North Central Texas College noting that, "In 2023, alone, Pathways Analytics [a Zogotech product] helped us find 706 credentials, which is estimated to be

$1M+ in performance-based funding." These quotes reflect responses to state financing policy incentives to improve measured outcomes, as well as vendors' self-positioning as tools to maximize revenues under such financing policies.

The emphasis on ROI was pervasive. Terms such as "revenue" or "ROI" appeared on the websites of nearly every vendor in the dataset, with the exceptions of Qlik, Slate, and Watermark. For example, Civitas advised institutions to "adjust services to achieve a greater return on investment (ROI)" for student success programs and services. Another post by Civitas asserted, "Including persistence as an evaluation metric is essential to an ROI-driven approach to student success." EAB similarly stated that "Student retention leads to ROI."

Vendors also quantified the financial value of their products, including statistics to support their framing of the student success problem (or opportunity) and proposed solutions. For instance, Civitas Learning offered an "ROI Guide" titled "How to Shift to an ROI-Generating Student Success Strategy," citing results such as a $150K ROI in a Single Term" for a "four-year public partner" and "$1.2M in net tuition revenue" for University of Central Oklahoma. Modern Campus quantified the consequences of not retaining students: Citing an Education Policy Institute study in the article "Improve Student Retention," they noted that "universities lose an estimated $100,000 in tuition, fees and potential earnings for each student who does not graduate."

Overall, institutionally centered language dominated the dataset, suggesting that vendors primarily speak to institutions' business models and financial concerns. This institutional-finance centered framing both reflects and reinforces institutional priorities, treating student retention as a revenue-enhancing strategy. This institutional framing sets the stage for how students themselves are portrayed.

“At-Risk” Logic in Student Framing

The third theme more directly addresses the second research question asking how vendors portray students in the construction of student success problems and proposed solutions. Our analysis found that students are often framed as “at-risk.” Students were positioned as problems to be solved, often in the service of protecting an institution’s bottom line. The term “risk” appeared in roughly half of vendors’ materials (8 of 15), typically referring to students at risk of not persisting or graduating. This risk was portrayed as something that predictive models can detect and help resolve, if an institution intervenes in time.

Focused on Deficiencies. Across the vendor documents analyzed, vendors frequently described the causes of attrition or underperformance in terms of what students lacked (e.g., motivation, preparedness, or engagement), implicitly adopting a deficit view of students. For instance, IBM’s case study on the University of Florida highlighted “study habits” as predictors of success, noting that with learning management systems, it is now possible to “monitor how long students spend watching video lectures, reading course literature, and working on assignments.” This quote attributes the blame for student success on students, implying their “study habits” are inadequate. While study habits almost certainly relate to student success outcomes, such a focus overlooks other factors associated with student success (e.g., financial constraints and campus climate), including the root causes of the observed disengagement (e.g., poor pedagogy and extracurricular responsibilities, such as caregiving or the need to work while enrolled).

A document from Watermark also highlights student deficiencies as predictors of student success, proposing that “Low grades or self-confidence can lead students to drop out.” Likewise, Othot, referring to findings from Civitas, claimed that, “Root causes for why a student doesn’t graduate may include academic issues, lack of support, finances, family, or general immaturity." Among the myriad individual-level factors that place responsibility for a lack of student success on students themselves, this quote identifies family as a potential hindrance. This framing turns the concept of familial capital from CCW on its head. Defined as the emotional, moral, and practical support systems that students draw from their families and communities, it was operationalized by Othot (and presumably through the original Civitas Learning source[1]) through a deficit lens. Rather than acknowledge the sustaining and motivational role that families, particularly in marginalized communities, play in students' persistence, familial influence was framed as a liability. This reductive portrayal blaming family for students' success was further evident in the way one vendor, EAB, employed a family-related financial proxy, a parent's method of payment, as a predictive input to determine whether a student might be identified as "at-risk." This example is also noteworthy given the prospect of algorithmic bias; using methods of payment could lead these models to overpredict failure for students from low-income backgrounds.

In another example arguing for the importance of "sufficient exploration of student variables," a Civitas white paper on algorithmic bias asserts:

> For example, members of a small minority group might have a strong affinity towards each other, resulting in cliques outside school speaking in their native tongue, which can slow cultural assimilation and language-skill development. In such a case, it's not the group membership that is interfering with student success, but the group behaviors.

That excerpt from the Civitas white paper advances a deficit narrative by shifting attention away from structural conditions and onto the supposed liabilities of minoritized

[1] The referenced document was unavailable at the time of data collection.

students' social and linguistic practices. The author's distinction between "group membership" and "group behaviors" purports to avoid bias but it simply relocates it. By naming "clique" formation, native-language use, and limited "cultural assimilation" as risks to student success, the text pathologizes forms of community belonging that may in fact sustain students academically and socially.

The language across these documents reinforces an image of students as inherently vulnerable or deficient. Terms such as "at-risk students," "students in need," "struggling learners," and "students lacking support" appear throughout the dataset, underscoring the notion that certain students are predisposed to poor outcomes unless proactively helped. The very premise of many predictive products is to create early alerts for those who are failing to thrive on their own.

Acknowledging Assets: An Exception. Although deficit logic proliferated, we found disconfirming evidence from Ocelot. In an article from Ocelot titled "Recognizing Different Student Identities as Assets to Increase Sense of Belonging," the unnamed author wrote,

> A problem with a term like "achievement gap" … is that it suggested a deficiency among students in the lower-performing group. This implies that the solution entails augmenting the students' existing skills and identities somehow to help them succeed in the institution. We now understand that higher education institutions were not designed for the diverse array of students they currently serve, pointing to a more likely scenario where the gaps result from the institutions' inability to effectively support, retain, and graduate the students they enroll.

The author further asserted, "In addition to removing institutional barriers to success, we can also reframe students' diverse identities as assets, not deficits. Research shows that supporting students through asset-based practices can boost a host of important student metrics, including belonging, engagement, and success." Although the author did not provide concrete examples of students' cultural wealth (e.g., family and community support, aspirations, or resilience), the article moved blame away from students and aligned with CCW principles. Its proposed solutions, all effectuated through "human-centered AI", included using "culturally responsive communication" and "treat[ing] each student as an individual".

Risk-Framing without Student-Blaming. Deficit framing of students, including using the term "at-risk" did not necessarily mean students were exclusively to blame, however, as numerous vendors acknowledged structural barriers to student success. For instance, a Civitas blog post stated that "At NSU, students are only at-risk if there is no one at the institution proactively working to support them." Vendors also acknowledged other structural barriers to student success, including course availability, inadequate communication with students, and burdensome policies. For instance, in a post titled, "How Mohawk Valley Community College Used Leading Metrics to Improve Time to Complete," Ad Astra described,

> The institution sought a way to identify where issues existed and the resulting financial impacts of those issues on the community college. Lynch hypothesized if the institution could better define its pathways, students would find it easier to follow their degree maps and the institution could reduce stop outs.

In this quote, Ad Astra identified the structural challenge students face following their degree maps, a challenge that is attributed to the institution. Consistent with the second finding presented above, this problem is tied to institutions' finances, with the vendor promising to improve the institution's bottom line by addressing this student-success problem.

As another example, as Ocelot noted, “So many traditional policies and processes miss the mark by not thinking about how students will navigate them. Too often, they create unnecessary friction and a continual ‘bounce from office to office to get the help they need.” Referencing course scheduling, Ad Astra also identified a structural barrier to student success, noting, “Those without scheduling flexibility are often left with the choice of either switching majors or stopping out altogether.”

These statements acknowledge that student success can be constrained by institutional design rather than by student factors (e.g., motivation or ability) alone. This theme therefore complicates a simple reading of “at-risk” discourse as necessarily deficit-framed. It shows that deficit-oriented language, such as references to “risk,” does not always entail blaming students for their circumstances or assigning them primary responsibility for improving their outcomes.

Discussion

Guided by framing theory (Snow & Benford, 1988), this study examined how predictive analytics vendors in higher education frame the problem of students’ success and how they portray students. Drawing on 132 public-facing documents from 15 vendors, we identified three primary findings. First, the primary problem predictive analytics vendors purport to address is one of limited data insights, which are attributed to data silos, limited financial resources, and the exclusion of student engagement and behavioral variables from prediction models. Second, students’ success is often framed as a financial issue, with vendors positioning their products as a means to optimize institutional revenue through improved retention. Third, although structural barriers are acknowledged, students are overwhelmingly depicted through a deficit lens, often labeled “at-risk” with little acknowledgment of their strengths or cultural assets.

The vendor narratives reveal a fundamental tension between a student-deficit-based, institution-centered model of students' success and an asset-based, equity-centered vision such as that offered by the CCW framework. CCW theory argues that students from marginalized communities bring with them an array of valuable knowledge, skills, networks, and resilience, which are forms of capital that traditional educational institutions often overlook (Yosso, 2005). These include aspirational capital (dreams and ambitions), linguistic capital (multilingual skills and styles of communication), familial capital (community and kin support), social capital (peer and mentor networks), navigational capital (skills to maneuver through institutions), and resistance capital (abilities to challenge injustice). Our findings show that the vendors' documents, by and large, do not operate with an asset-based paradigm. Across the dataset, vendors rarely acknowledged, let alone leveraged, such forms of student capital. Rather than recognizing students as resourceful agents navigating educational institutions, students were overwhelmingly portrayed as passive or lacking. Acknowledgements that students' community ties or lived experiences are resources to build upon in the pursuit of academic success were largely absent from the dataset, reinforcing a deficit narrative that stands in stark contrast to CCW's call to recognize and value those very attributes.

Although the term "at-risk" implies deficit framing, it does not always entail overt student-blaming. The findings from this study suggest the need to distinguish among three related but analytically separate dimensions: (1) whether students are described through asset- or deficit-based language; (2) whether the causes of student success or failure are attributed primarily to students or to institutions; and (3) whether responsibility for addressing barriers to success is placed on students or on institutions. Some examples do reproduce student-blaming assumptions, either explicitly or implicitly, by suggesting that students must change their behavior in order to improve their outcomes. However, other examples use deficit-oriented terms, such as “risk,” while locating both the source of the problem and the responsibility for intervention at the institutional level. In these cases, “risk” language does not simply individualize failure; it can also function as a way of naming institutionally produced barriers that require institutional action. Nevertheless, vendors’ materials also advanced numerous solutions focused on modifying students’ behavior (i.e., via alerts, nudges, advising), fixing students via systems, without altering the systems that produce risk in the first place. In doing so, predictive analytics platforms risk reinforcing systemic inequities. As argued by Davis and Museus’s (2019), “the emphasis on individual and cultural deficiencies perpetuates assumptions that our system should seek a quick fix to remedy disparate experiences and outcomes... rather than focus on addressing core systems of oppression and systemic inequities that permeate social and educational institutions” (p. 124).

Implications for Practice

The deficit framing prevalent in predictive analytics vendors’ materials can actively shape the interventions that colleges choose to implement. If students are viewed primarily as lacking or “at risk,” institutions might gravitate toward solutions that monitor, surveil, and remediate, while neglecting approaches that empower and validate students’ identities. One critical implication is that interventions driven by these vendor tools may inadvertently reinforce the idea that students fail because of their own shortcomings, diverting attention from necessary institutional reforms. As Ruha Benjamin, as quoted in Oetting (2021), has noted, data can serve as “even greater fuel for pathologizing and blaming people who are most affected”. If a predictive system flags a first-generation student as high risk, a deficit framing could prompt more intensive advising for that student, which is not inherently bad, but it might preempt a review of the institution's own bureaucratic hurdles or unwelcoming climate that contribute to the struggles of students who are also the first in their families to attend college.

In light of the CCW framework, our findings also reveal a dearth of recognition of the strengths of historically underserved students that could be leveraged to enhance their success. CCW would encourage institutions to design success initiatives that recognize students' cultural strengths, such as drawing on familial knowledge or community support as assets in mentoring, campus activities, and curriculum design. Yet few documents suggested leveraging these kinds of assets. There was no mention of partnering with families, no feature that identified students who succeed against the odds to learn from them, no discussion of building on student activism or peer networks. If institutions rely heavily on such narratives and tools, they will likely continue to pursue a technocratic approach to students' success, one that becomes efficient at identifying problems but not adept at recognizing root causes, designing strategies that address those root causes, or leveraging students' community cultural strengths.

Limitations and Delimitations

As with all research, this study has limitations and delimitations. First, we relied exclusively on publicly available materials due to the proprietary nature of predictive analytics tools and services. As a result, we were unable to examine the internal data sources, modeling choices, or algorithmic decision rules that vendors use in practice. Access to such materials would offer a more comprehensive understanding of the extent to which vendors recognize students' strengths, adopt holistic definitions of student success, or account for structural and systemic barriers, rather than reinforce deficit-based logics that attribute failure to students themselves.

Given our research interests, we analyzed what vendors chose to make visible to external audiences, which may not fully capture how predictive analytics products or services are discussed in other venues. These publicly available documents represent the most accessible and visible representations of vendors' narratives, and they were therefore well suited to answering our research questions. Since we are interested in framing of products and services that could persuade potential clients (institutional leaders), focusing on outward facing narratives is appropriate for understanding how vendors frame the problem of student success and proposed solutions, including ones they purport to offer. These materials offer insight into how vendors frame the problem of students' success and how they align their proposed solutions with that framing.

In addition, our data are limited to a snapshot in time. Because websites are dynamic, the framing of vendors' predictive analytics products may have shifted since data collection. Our analysis therefore captures how vendors were publicly positioning predictive analytics at one moment in time, rather than offering a longitudinal account of how framings evolve, which could be the subject of future research.

Conclusion

In sum, predictive analytics vendors present a compelling business case for promoting students' success: by identifying risk and intervening early, one can improve outcomes and enhance revenue. But the narratives embedded in vendors' materials reflect and reinforce a narrow view of students and their success, grounded in deficit assumptions and institutional self-interest. This view is in tension with a framework of CCW, which centers students' assets and advocates for systemic change.

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Appendix A

Vendors, Relevant Service Description, and Sample Size

Vendor	**Relevant Service Description**	**Documents Collected**
Ad Astra	"Forecast demand by Completion Path to ensure your schedule progresses every student in their path."	8
Brightspace Insights by D2L	"Discover how Brightspace uses data and personalized learning features to find and support students who may be at-risk."	4
Civitas Learning	"AI-powered, institution-specific models surface predictive insights, not just patterns from the past, but timely indicators of what's likely to happen next."	14
Degree Analytics	"Combine LMS, SIS, and Campus Utilization Data to create a single pane view of all student activities. Identify risk factors unique to each university related to its student behavior by cohort."	3
Education Advisory Board (EAB/Starfish)	"The Starfish platform brings insight to student data, allowing campuses to take action and serve students proactively."	12
HelioCampus	"Advanced analytics & AI capabilities: Predict patterns, detect at-risk students, and enable data-informed decisions through AI-driven insights."	10
Hanover Research	"Evaluates comprehensive data through a Graduation Early Warning Dashboard to identify which student profiles are at risk for not graduating, key triggers that may contribute to failures to graduate, and possible intervention points for improving graduation rates."	5
IBM	"IBM SPSS Modeler is a leading visual data science and machine learning (ML) solution designed to help enterprises accelerate time to value by speeding up operational tasks for data scientists. Organizations worldwide use it for data preparation and discovery, predictive analytics, model management and deployment, and ML to monetize data assets."	6
Modern Campus (Signal Vine)	"Gain insights into how students are engaging with campus activities and use that data to inform decision-making. Modern Campus Involve's powerful analytics platform allows administrators to identify trends, intervene with at-risk students, and continuously improve the student experience.."	7
Ocelot	" AI-powered predictive analytics and data-driven models can analyze various factors, such as academic performance, financial hardship, and personal	9

	circumstances, to identify students who may need additional support .”	
Othot Predictive Analytics (Liaison)	“Othot delivers predictive analytics for higher education enrollment and student success.”	20
Qlik	“Optimize student success rates using predictive analytics.”	2
Slate by Technolutions	“Slate is the most comprehensive system to meet the needs of admissions, student success, and advancement offices—all from within a single unified interface. We seek to empower higher education with transformative technologies.”	6
Watermark	“Get early alerts when students veer off course. With predictive models for persistence and course completion, you can offer support before it’s too late.”	11
ZogoTech	“By examining historical data, ZogoTech can help colleges predict which students might face academic challenges, allowing for proactive interventions and support.”	15