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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 161 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 position their products as solutions. Findings from our thematic analysis are: (1) vendors primarily frame the problem their products address as one of institutional finances; (2) vendors acknowledge structural barriers but rarely recognize students' strengths; (3) proposed solutions to challenges to students' success do not always align with problem framing. 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; EDUCAUSE, 2024; Gándara et al., 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 analyzed how vendors construct the problems their products are designed to solve and how these framings align with the solutions they are selling. Specifically, 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 their proposed solutions align with these problem framings?
3. How do they portray students in the construction of student success problems and proposed solutions?

To address these questions, we examined 161 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); the solutions proposed; and how vendors position their products.

To further guide our analysis of problem definition and proposed solutions, 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 support decisions at the individual student level. 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, as some models predominantly include 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 Navigate'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. They may also convey to institutions that they have agency, and perhaps a responsibility, to improve its students’ outcomes through their marketing materials. 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, marketed, and adopted. 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 study is guided primarily by Snow and Benford's (1988) framing theory focused on ideology, frame resonance, and participant mobilization. Benford and Snow's framing theory originated in social movement research and has primarily been applied to that field, although its reach has expanded in recent decades. 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 Snow and Benford's three core framing tasks diagnostic framing, prognostic framing, and motivational framing (p. 200). Specifically, this theory anchors our investigation of how predictive analytics vendors frame problems (diagnostic framing), name solutions (prognostic framing), and catalyze action (motivational framing) (Benford & Snow, 2000; Snow & Benford, 1988). While the motivational framing task focuses on calls for mobilization vis à vis social movements, we adapt this frame to examine how vendors' marketing discourse connects diagnostic and prognostic framing with their products. In this way, the call to action that vendors seek to motivate is procurement of their products.

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. As articulated by Benford & Snow (2000), problem definitions are not always aligned with proposed solutions; we investigate their consistency in our study.

Lastly, while we are primarily guided by the core framing tasks in Snow and Benford's framing theory, we also draw insights from its set of factors described as phenomenological constraints. These variables, hypothesized to be related to the strength of a social movement, refer to the extent to which the "framing strike[s] a responsive chord with those individuals for whom it is intended" (p. 207). The individuals for whom predictive analytics marketing materials are intended are college and university leaders. As such, we glean how vendors are targeting their marketing language to resonate with the target audience, including through three elements outlined by Snow and Benford. The first is empirical credibility, or the strength of the evidence for the framing. The second is experiential commensurability, or how the frame aligns with the experiences of the target audience. The last is narrative fidelity, that the framing "rings true with existing cultural narrations" (Snow & Benford, 1988, p. 210). In this study, cultural narrations within higher education may include field-level logics, such as academic, market, professional, commercial, and managerial logics (Cai & Mountford, 2021).

## Community Cultural Wealth

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' success. 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, 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 oppositional behavior and teaching others how to resist and persist in hostile environments. 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 defaulting to remedial or deficit-oriented interventions based on "risk" identification, institutions might 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 proposed 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 portray students, and the extent to which their proposed solutions: (1) align with their problem definition and (2) reflect or contradict an asset-based view of students' success. 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 161 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, student success prediction; this list included 53 vendors. After reviewing the list, the research team established 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 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), offered self-service platforms (e.g., Oracle, Microsoft, SAS Visual Analytics), or did not provide predictive modeling services for "at-risk" student classification (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: (a) the material referred to quantitative prediction modeling (i.e., predictive analytics), and (b) it focused on college students' success. Webpages meeting these criteria were saved as .pdf files and imported into Dedoose mixed-methods 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 161 documents stored for analysis.

**Data Analysis**

Our analysis of predictive analytics vendors' marketing materials proceeded in five 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 *data sources*, *defining student success*, *theory of change*, and *intervention strategies*. We also coded for categories of variables (or features) included in prediction models: *academic*, *activity*, *behavioral*, *belonging*, *climate*, *demographic*, *engagement*, and *financial*, in cases where they were outlined.

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. As part of this analysis process, we developed a meta-matrix that mapped each type of capital against each of the following codes: *defining student success*, *barriers to student success*, *student success interventions*, and *student framing*. The matrix allowed us to capture the co-occurrence of different forms of CCW with student success framing. Once the meta-matrix was developed, two researchers independently coded the data to enhance reliability. The meta-matrix showed an overwhelming absence of CCW throughout the data and across the other major codes (i.e., *defining student success*, *barriers to student success*, *student success interventions*, and *student framing*), 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 offered promising analytical purchase. 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, phenomenological constraints, and given our interest in the framing of students, asset- or deficit-based framing of students.

Across both rounds of coding, the three researchers involved in coding across both stages of 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 and, applying framing theory, differences between narrative fidelity and experiential commensurability.

In the fifth phase of analysis, one of the authors identified preliminary themes based on the prevalence of codes applied (e.g., *economic value proposition*, *structural/systemic barriers to student success*, *framing of students*) their co-occurrence, and absences in the data (recognition of students' CCW). In a subsequent phase of analysis, the research team will review the themes against the full corpus of data, following Braun and Clarke's (2006) thematic analysis procedures.

## Findings

We identified three themes, each addressing a dimension of how vendors construct the problem of student success, portray students, and align their proposed solutions with their problem framing. The first theme captures how the problem that student success prediction aims to address is ultimately one of institutions' finances. The second 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. The final theme elucidates the theory of action and how proposed solutions do not always follow from the problem framing.

**"Optimized Student Lifecycles, Healthier Revenues"**

The first 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. This type of framing exemplifies experiential commensurability, by which vendors are appealing to college and university leaders' experiences and dominant (financial) concerns.

In some cases, students' success was explicitly cast as an opportunity, namely, a means to enhance the institution's bottom line. This phenomenon is captured in a heading from Helio Campus: "Optimized Student Lifecycles, Healthier Revenues." Here, the "student lifecycle" encompasses the full process from initial student interest in the institution through enrollment, retention, and graduation. 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." This quote reflects a response to state financing policy incentives to improve measured outcomes, as well as vendors' self-positioning as a tool 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, Watermark, and ZogoTech. For example, Civitas advised institutions to "adjust services to achieve a greater return on investment (ROI)" for student success programs and services. EAB similarly stated that "Student retention leads to ROI." 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. These figures illustrate empirical credibility, the use of evidence to lend further credence to their framing of the student success problem (or opportunity) and proposed solutions.

Vendors explicitly tied student attrition to financial loss. For instance, Modern Campus cited an Education Policy Institute study in the article "Improve Student Retention," noting that "universities lose an estimated $100,000 in tuition, fees and potential earnings for each student who does not graduate." One Civitas post asserted that "Including persistence as an evaluation metric is essential to an ROI-driven approach to student success." This framing both reflects and reinforces institutional priorities, treating student retention as a revenue-enhancing strategy. Overall, institutionally centered language dominated the dataset, suggesting that vendors primarily speak to institutions' business models and financial concerns. This institutional framing sets the stage for how students themselves are portrayed.

**"At-Risk": Deficit Logic in Student Framing**

The second theme is that students are overwhelmingly framed through a deficit lens, most commonly via the term "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 materials from eight (of 15) vendors, 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.

Across the 161 vendor documents analyzed, student success was predominantly framed as a problem located at the level of the individual student. Vendors frequently described the causes of attrition or underperformance in terms of what students lacked (e.g., motivation, preparedness, 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 LMS it is now possible to "monitor how long students spend watching video lectures, reading course literature, and working on assignments." 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."

The language across these documents reinforces an image of students as inherently vulnerable or deficient, awaiting institutional salvation. Terms such as "at-risk students," "students in need," "struggling learners," and "students lacking support" appear frequently, 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. Even positively sounding roles like "empowering students" are often framed in deficit terms. A platform (EAB) might claim to "empower students to take charge of their own success," but in practice this translates to prompting students with system-generated nudges or resources, implying that students would not or could not take charge without those prompts.

Although deficit logic dominated, we found disconfirming evidence from one vendor, Ocelot. In an article titled "Recognizing Different Student Identities as Assets to Increase Sense of Belonging," the unnamed author wrote that

> 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

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[1] Now unavailable

> 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". While these practices are consistent with an asset-based perspective, they are somewhat vague and impersonal, despite attention to personalization. It is also unclear whether and why AI is necessary to address the problems of deficit orientations towards historically marginalized groups posed in this blog post. This example notwithstanding, the portrayal of students in predictive analytics vendors' materials was heavily skewed toward victims of circumstance or subjects to be managed, with minimal recognition of students as active agents or contributors to their own success story.

Deficit framing of students did not 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 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.’” Though their connection to the vendors’ predictive analytics products is unclear, these stated problems reflect important acknowledgments that student success may be thwarted by institutional design, not purely individual motivation or ability.

**Theory of Action: From Prediction to Success**

The third theme concerns vendors’ theories of action: how they claim predictive analytics leads to improved student outcomes. Generally, such action consists of identifying students who are at risk of failure by predicting their likelihood of success, understanding predictors of risk, and intervening to change their trajectory. Common interventions include automated alerts to advisors, personalized outreach, and financial support. In many cases, however, vendors focus only on symptoms (e.g., limited engagement) rather than root causes, without a clear path to improving outcomes.

In some cases, this logic is clear and concrete: for example, with predictive analytics, one identifies students at risk of attrition and reaches out with advising or emergency aid. These are relatively straightforward applications with an observable link between a problem and a proposed solution. Another common example, albeit not directly connected to predictive analytics, consists of identifying issues regarding course availability to optimize scheduling so students can enroll in the classes they need.

Other examples displayed more tenuous connections between their problem framing and proposed solutions, lacking a clear theory of action for solving the problem. For example, ZogoTech identified causes of student attrition, including low "engagement." Regarding engagement, its online materials stated that "Keeping students engaged and enrolled is a significant challenge. Analyzing data on student engagement and retention can help colleges develop targeted strategies to improve these areas." However, what those targeted strategies are, and how they are informed by the data products and services they offer, remained unspecified.

Although many vendors emphasized the importance of 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 or logging in to the LMS irregularly, it is unclear what intervention follows. In this way, vendors emphasized individual behaviors (symptoms) without always interrogating root causes. These causes might include inaccessible pedagogy, racially hostile learning environments, or conflicting family obligations, none of which were included in models. Therefore, they were all absent from proposals for solving the challenges surrounding student success.

Other examples included solutions that align with the problem but are disconnected from the vendors' products and services. These include reducing higher education jargon (Ocelot) and improving campus climate (Hanover). While these solutions, which recognize structural barriers to student success, have potential to improve student outcomes, it is unclear how the vendors' products are services are needed to, or able to, support them.

## Discussion

Guided by framing theory (Snow & Benford, 1988), we have examined how predictive analytics vendors in higher education frame the problem of students' success, how they portray students, and how their proposed solutions align with their framing of those problems. Drawing on 161 public-facing documents from 15 vendors, we have identified three primary findings.

First, students' success is often framed as a financial issue, with vendors positioning their products as a means to optimize institutional revenue through improved retention. Second, 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. Third, vendors' theories of action (i.e., how predictive insights are expected to lead to improved outcomes) are frequently vague, misaligned with stated problems, or focused narrowly on individual students' behavior rather than institutional responsibility.

Together, these findings illuminate what vendors believe matters most to their institutional clients, especially ROI. This finding aligns with prior critiques that analytics tools serve to benefit institutions, not the individuals within them (Selwin, 2019). Our study shows that vendors appeal directly to institutions' financial interest in their public materials, exhibiting a form of experiential commensurability (Snow & Benford, 1988). While they reflect institutions' priorities, vendors may actively influence how colleges and universities define problems, prioritize interventions, and operationalize students' success. In this way, vendors' discourse becomes a mechanism through which institutional values are both mirrored and shaped.

**Community Cultural Wealth: Tensions and Absences**

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—forms of capital that traditional 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. Notably, an acknowledgement 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.

This absence of students' assets exists alongside another pattern: although vendors acknowledged some structural barriers (e.g., inadequate course availability), most solutions were not tied to those structural conditions. Instead, the responsibility for overcoming barriers was typically assigned to students themselves. For example, if a student was predicted to be "at-risk" due to disengagement, the solution might be a flag or alert prompting outreach, not an inquiry into the root causes of disengagement (e.g., poor pedagogy, unwelcoming classroom environments, family caregiving burdens). One exception was the use of predictive analytics to optimize course scheduling, an intervention that addresses a structural barrier directly. But in most cases, vendors offered solutions intended to fix students via systems, rather than fixing the systems themselves, reflecting a mismatch between problem framing and intervention design.

Of course, although the term "at-risk" implies deficit framing, it does not always entail overt student-blaming. Several vendors acknowledged that institutions bear responsibility for intervening early or removing administrative burdens. Nevertheless, the bulk of 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 by negating a core tenet of cultural capital: that students' familial and community-based knowledge consists of sources of strength rather than liabilities. Our findings echo Davis and Museus's (2019) argument that "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 "in need," 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 has noted, data can serve as "even greater fuel for pathologizing and blaming people who are most affected" (Oetting, 2021). 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. With the exception of course availability, vendor materials overwhelmingly neglected to frame their products or services as catalysts or tools to examine or change institutional practices (such as a lack of culturally relevant pedagogy). The responsibility for success remained squarely on identifying “risky” students and fixing them.

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 (and by extension, the vendors that serve them) 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 only one of the vendors’ 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 achieving students' success: by identifying risk and intervening early, one can improve outcomes and protect revenue. But the narratives embedded in their 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, acknowledges structural barriers, and advocates for systemic change. Without intentional efforts to align predictive analytics with culturally responsive, equity-minded practice, institutions risk adopting tools that manage students, framing them as risk, rather than empower them. For colleges and universities committed to equity, the challenge they face is whether and how they are willing to interrogate the assumptions embedded in the predictive analytic tools they adopt.

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**Appendix A**

Vendors, Relevant Service Description, and Sample Size

| **Vendor** | **Relevant Service Description** | **Documents Collected** |
|---|---|---|
| Ad Astra | "Predicts progress in future semesters and time to completion." | 9 |
| Brightspace Insights by D2L | "Brightspace helps identify at-risk students and support their success in four key ways: by personalizing the learning experience with release conditions, automating check-ins using intelligent agents, turning data into actionable insights through the Data Hub, and offering rich visualizations in the Class Progress tool." | 5 |
| Civitas Learning | "By providing a wider variety of insight into student outcomes, Multi Outcome Insights enhances the understanding of different aspects of the student experience. Prediction Change Tracking: Monitor shifts in student predictions over time to quickly identify emerging trends, risks, or opportunities—and assess the impact of interventions." | 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. Identify, track, and engage students with the resources aligned to their specific needs while examining institutional capacity to support students." | 19 |
| HelioCampus | "Our world class data infrastructure and innovative machine learning models enable you to draw connections across academic, financial, and student data to precisely identify areas of action and opportunity." | 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." | 6 |
| IBM SPSS Modeler | "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 | 11 |

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| | management and deployment, and ML to monetize data assets.” | |
| Modern Campus (Signal Vine) | “Modern Campus Pathways is more than just a software solution; it’s a transformative approach to higher education that puts students at the center of their learning journey. By leveraging data-driven insights, predictive analytics and personalized support, institutions can proactively identify and address barriers to student success, ensuring that every student reaches their full potential.” | 16 |
| Ocelot | “Ocelot: Higher Ed’s trusted partner for AI-Driven Student Lifecycle Engagement.” | 10 |
| Othot Predictive Analytics (Liaison) | “Othot delivers advanced analytics tailored to enrollment management and student success. By utilizing artificial intelligence (AI) and machine learning (ML), Othot enables you to make data-driven decisions throughout the entire student lifecycle, from recruitment to graduation.” | 19 |
| Qlik | “Shift to an active system that leverages AI/ML to help you bring data together, make sense of it, trust it, analyze it, and take action. Qlik provides proven solutions, including data integration, data quality, analytics, and AI/ML. You can finally close the gap between your data and your business outcomes.” | 5 |
| 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. Find, track, and solve early alert situations as soon as they appear—or before they even pop up. See all alerts at a glance, communicate to groups or individuals, track interactions, and keep the data locked down to only those who should know.” | 8 |
| Watermark | “Student Success & Engagement flagged at-risk students, enabled easy communication between student and success coach, provided an early alert system, and used predictive analytics for student success.” | 10 |
| ZogoTech | “ZogoTech brings your institutional data into several core Data Models within the product. These Data Models are constructed around the most commonly needed student success data.” | 16 |