



The AIR Professional File

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Supporting quality data and
decisions for higher education.



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COMMENTS FROM THE EDITORS

In *Institutional Influences on Graduate Student Debt in U.S. Public Higher Education Institutions*, Melanie Jenkins-Simpson, Anne Oxenreider, SangAh Oh, M. J. Kim, and Megan Bogia provide an empirical look at how institutional financial structures, pricing, and geographic contexts shape federal graduate student borrowing across public higher education. Rather than simply analyzing individual student demographics or borrowing choices, the authors document an institution-level approach by merging available program-weighted loan data from NACIQI with financial and outcome metrics from IPEDS and the College Scorecard for public institutions. And while shifting the focus from individual to institutional factors, the authors provide empirical evidence on pricing and revenue as well as providing initial exploration of differences between master's and doctoral debt.

The article is particularly relevant for higher education researchers, institutional leaders, and policymakers who need to understand how institutional resource allocation and pricing strategies impact graduate affordability. The authors demonstrate how federal datasets can be

effectively combined for degree-level debt analysis while also raising important questions about state appropriations, tuition dependency, financial aid transparency, and equity in graduate education.

Mary Ann Coughlin
Guest Editor

In *Higher Education Workforce Artificial Intelligence Skill Development: A Policy Consideration Analysis Through the Applied Lens of Practical Conversational Coding*, Michael Littrell and Andrea Arce-Trigatti provide a practical look at how generative AI can expand the technical capabilities of higher education professionals. Rather than simply discussing the potential of AI-assisted coding, the authors document the development of a functional survey and dashboard application created through natural-language prompts. They provide the prompts, describe the development process, and illustrate the resulting application, offering readers a concrete example that can be examined and replicated.

The article is particularly relevant for higher education professionals whose data-collection needs



extend beyond the capabilities of standard survey platforms but who may not have programming expertise. The authors demonstrate how conversational coding can help practitioners develop and test customized solutions while also raising important questions about workforce development, technical collaboration, and the democratization of AI skills in higher education.

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Institutional Influences on Graduate Student Debt in U.S. Public Higher Education Institutions

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This study extends work that originated through the 2025 National Center for Education Statistics Data Institute, where the authors' initial contributions helped shape the project's focus, data approach, and early analysis. Dr. Jenkins-Simpson contributed additional development, refinement, and revisions to the study following the Data Institute.

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Abstract

This study examines how institutional finance and structure influence graduate student debt in U.S. public higher education institutions. Using newly available institution-level data from the National Advisory Committee on Institutional Quality and Integrity, the Integrated Postsecondary Education Data System, and the College Scorecard, we estimate a series of cross-sectional regression models for master's and doctoral program completers. The models assess relationships between graduate tuition levels, institutional revenue measures, and geographic context.

Results indicate that in-state graduate tuition is the most consistent and significant predictor of higher borrowing among master's program completers. Geographic differences also emerge, with U.S. institutions in the Midwest and Northeast exhibiting lower borrowing levels relative to those in the South. Absolute levels of institutional revenues per full-time equivalent student are associated with borrowing patterns, whereas proportional revenue composition shows weaker and less-consistent relationships. Models of doctoral borrowing exhibit limited explanatory power, reflecting smaller analytic samples and heterogeneous funding structures, but demonstrate the feasibility of cross-institutional analysis using emerging federal data.

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Overall, our findings underscore the importance of institutional pricing, financial resources, and geographic context in shaping graduate student debt outcomes; findings also highlight directions for future policy and research focused on financial aid transparency, clearer communication of expected borrowing, and affordability in graduate education.

INTRODUCTION

Rising levels of graduate student debt have drawn increasing attention from policymakers, institutional leaders, and researchers seeking to understand how institutional factors shape students' borrowing outcomes. Although prior studies have examined student-level borrowing patterns, far less is known about the institutional characteristics and financial structures that influence borrowing at the graduate level. This study addresses that gap in understanding by integrating data from the National Advisory Committee on Institutional Quality and Integrity (NACIQI), the Integrated Postsecondary Education Data System (IPEDS), and the College Scorecard to assess how institutional resources and geographic context relate to graduate borrowing across public institutions in the United States (Institute of Education Sciences, 2025; National Advisory Committee on Institutional Quality and Integrity [NACIQI], 2024; U.S. Department of Education, 2025a, 2025b, 2025c, 2025d).

Specifically, this study seeks to examine the following questions:

- 1| How do institutional characteristics relate to median borrowing amounts among graduates (with a master's or doctoral degree) at public institutions with borrowing greater than zero?
- 2| How do these relationships vary across U.S. Census regions?

These two questions guided our development of a series of multiple regression models that incorporated institutional traits, institutional revenue structures, and geographic differences. The results contribute to a broader understanding of how institutional finance and geographic context shape graduate student debt burdens and offer implications for institutional planning, financial aid policy, and future research.

Significance of Study

The relationship between institutional resources and graduate student debt is an important issue for policymakers, institutions, and students. Research suggests that an institution's financial health can shape students' financial burden, with more-affluent institutions better able to offset tuition costs through grants, assistantships, and other forms of subsidized aid (Taylor & Cantwell, 2019). In contrast, institutions with fewer financial resources may rely more heavily on tuition revenue, increasing students' reliance on loans to finance graduate education. Prior research shows that institutional characteristics, including levels of state and institutional aid, selectivity, and institutional wealth, are associated with variation in student debt outcomes (Craig & Raisanen, 2014; Monks, 2014). Miller (2020) further notes that, as tuition costs rise, a growing percentage of graduate students turn to loans, increasing long-term financial burdens.

At the same time, much of the existing literature has focused on student-level borrowing, with less attention to how institutional and structural factors shape aggregate debt levels. As Hillman (2015) observes, there remains a gap in understanding how colleges and state policy contexts influence borrowing patterns across institutions. This gap in the literature raises important questions about the

financial sustainability of graduate education and the implications for equity among students from different socioeconomic backgrounds. While prior studies have examined borrowing using student-level datasets, few have analyzed graduate student debt at the institutional level.

Problem Statement

This study investigates how institutional type defined by sector, Carnegie Classification, and other structural characteristics relates to the median borrowing amounts of graduate students pursuing master's and doctoral degrees. It seeks to understand how variations in institutional financial resources influence graduate students' reliance on federal, state, institutional, and private loans. The research posits that students attending resource-limited institutions, such as master's-level and regional public universities, may depend more heavily on loans due to limited access to institutional aid, assistantships, or other funding mechanisms. By examining borrowing patterns across institutional types, this study aims to illuminate the financial pressures faced by graduate students and to contribute to broader discussions about funding disparities, equity in graduate education, and policy strategies to mitigate student debt burdens.

To situate this inquiry within the broader field of higher education finance, the next section, Literature Review, reviews existing research on student loan dependency, institutional resources, and financial aid policy, and highlights the persistent gaps that this study seeks to address. Literature provides important context for understanding how institutional characteristics and resource structures shape graduate student borrowing behavior, yet few studies have examined these relationships at the institutional level. Building on this foundation,

the Theoretical Framework section draws on human capital theory, institutional stratification theory, and loan aversion theory to guide the study's analytical approach. The subsequent section, Methodology, details the empirical strategy, data sources, and variables used to examine patterns of borrowing across institutional types and regions. The Results and Discussion section presents results comparing loan usage between master's and regional universities, and interprets these results by considering prior research and policy relevance. Appendixes A, B, and C provide supporting detail, including variable definitions, regression model summaries, and descriptive statistics. Finally, the Conclusion section summarizes the major findings of this study, acknowledges its limitations, and identifies opportunities for future study.

LITERATURE REVIEW

Graduate student borrowing has been well-studied, with research highlighting variations based on institution types, geographic region, and student background. This review synthesizes key literature on financial aid, institutional resources, and student debt, with a focus on how institutional characteristics influence graduate student borrowing.

Borrowing Patterns and Institutional Resources

The financial resources of an institution have a direct effect on the borrowing behavior of students. The level of debt a graduate student accumulates is closely tied to the financial health of their institution. For many students, their choice of school and its resources shape how much they need to borrow to complete their degree. Institutions with strong financial backing such as large endowments,

significant research funding, and substantial state or federal support are often able to offer scholarships, assistantships, and other forms of financial aid that reduce students' reliance on loans. In contrast, schools with fewer resources, including public and regional institutions, often rely heavily on tuition revenue, leading students to take on more debt to cover rising costs.

Hillman (2015) synthesizes research on how borrowing and repayment outcomes are shaped by institutional context and policy, including institutions' reliance on tuition revenue and state support. Prior research indicates that students attending institutions with lower levels of state appropriations or institutional aid tend to face higher net prices and borrowing levels, while students attending institutions with more financial resources are in a better position to offset costs through grants and assistantships (Craig & Raisanen, 2014; Monks, 2014). These findings underscore meaningful institutional variation in student debt outcomes.

Although Hillman (2015) focuses primarily on undergraduate borrowing and repayment, the relationship between institutional resources, tuition dependence, and student borrowing may also extend to graduate education. Graduate students enroll across institutions that have varying financial capacity, which can influence tuition levels, the availability of assistantships, and access to institutional aid. At public institutions with more-constrained resources, institutions may rely more heavily on tuition revenue to support operations, resulting in higher prices and fewer funding opportunities for graduate students. These conditions may increase students' dependence on loans. In contrast, graduate students at institutions with more financial resources may benefit from research and teaching assistantships, fellowships,

and institutional grant support that reduce borrowing needs.

Miller (2020) echoes these findings, emphasizing how rising tuition costs have contributed to increased student loan dependency. He highlights that students at institutions with limited financial aid options frequently take out larger loans, which might not always be justified by their future earning potential. This growing reliance on loans can create long-term financial challenges, potentially limit their career choices, or delay major life milestones, such as homeownership, starting a family, or saving for retirement.

Analyses of National Postsecondary Student Aid Study data, such as those conducted by Webber and Burns (2020), show substantial variation in graduate borrowing across sectors and program types. Students at well-resourced institutions often benefit from fellowships, research positions, and grants that reduce reliance on loans, whereas students at institutions with less financial support are more likely to depend on borrowing, resulting in higher overall debt burdens after graduation.

Hillman (2015) emphasizes the importance of examining institutional context to better understand disparities in student borrowing. Building on this perspective, Taylor and Cantwell (2019) document how inequalities in institutional wealth and status shape students' opportunities and financial burdens, with resource-limited institutions often relying more heavily on tuition revenue. This reliance can increase students' exposure to borrowing, particularly where institutional grant aid and assistantship support are more limited.

Consistent with this pattern, institutional-level analyses suggest that variations in institutional

resources and funding structures are associated with differences in student debt outcomes (Belasco et al., 2014). Taken together, this body of work highlights how institutional financial conditions and stratification contribute to uneven borrowing patterns across higher education.

Types of Loans and Financial Support Offered

Financial assistance, including aid and loans, is a crucial part of financing postbaccalaureate studies. Federal loans, including the Direct Unsubsidized Loans and the Direct PLUS Loans, are the most commonly used financing options, as noted by graduate students (Baum & Steele, 2018). In Miller's (2020) analysis, the increasing reliance on student loans for postbaccalaureate studies has long-term impacts on students' career paths and financial stability. This issue is particularly significant as tuition costs continue to rise while institutional aid remains limited.

Graduate students typically rely on a mix of loans and other financial aid to cover the cost of their education. However, the types of available financial support vary widely depending on institutional resources, the student's financial need, and their field of study. These financial support options significantly impact how much debt students accumulate and how manageable that debt is after graduation. Understanding these options is key to making informed decisions about financing higher education.

Federal Student Loans

Federal student loans are the most common source of funding for graduate students, offering relatively standardized terms and access compared to private lending options. Two primary federal loan

types are available to graduate students: (1) Direct Unsubsidized Loans, and (2) Direct PLUS Loans.

Direct Unsubsidized Loans are available regardless of financial need, and interest begins accruing at the time of disbursement. Graduate students may borrow up to \$20,500 annually in Direct Unsubsidized Loans, which represents a fixed federal borrowing limit rather than a function of cost of attendance or enrollment intensity (Hegji, 2023). Although these loans generally carry lower interest rates than private alternatives, interest accrual during enrollment can substantially increase total repayment amounts over time.

Graduate PLUS Loans, a type of Direct PLUS Loan, are available to graduate and professional students who require funding beyond the Direct Unsubsidized Loan limit. Borrowers may obtain financing up to the full cost of attendance, minus other financial aid received, including tuition, fees, and living expenses. Unlike Direct Unsubsidized Loans, Graduate PLUS Loans require a credit check and carry higher interest rates. Interest begins accruing upon disbursement, and federal guidance indicates that Graduate PLUS loan interest rates are set annually and consistently exceed rates for Direct Unsubsidized Loans (U.S. Department of Education, 2025b, 2025d). While these loans provide important access to funding, their higher borrowing limits and interest rates may contribute to increased cumulative debt among graduate students.

The federal government offers several income-driven repayment plans, including Income-Based Repayment and Pay As You Earn, which cap monthly payments as a percentage of discretionary income. These plans are designed to make repayment more manageable, particularly for borrowers with

high debts relative to income. Depending on the specific plan and borrower eligibility, remaining loan balances may be forgiven after 20 to 25 years of qualifying payments (U.S. Department of Education, 2025c). However, extending the repayment period might increase the total amount repaid over time due to continued interest accrual.

Institutional Financial Support

Some institutions provide financial support to graduate students to reduce reliance on loans, including scholarships, fellowships, and research or teaching assistantships. Scholarships represent one form of aid that does not require repayment; they are typically awarded based on academic merit, financial need, or a combination of both. While more common at the undergraduate level, and although funding is often limited, scholarships are also used in certain graduate programs, particularly in fields such as business, law, and the humanities to recruit competitive applicants.

Fellowships, which can be funded by institutions, government agencies, or private foundations, provide more-comprehensive support and are common across Science, Technology, Engineering, and Math (STEM), social science, and humanities fields. In addition, assistantships (e.g., research or teaching roles) offer stipends and tuition support in exchange for academic or instructional work. Together, these forms of institutional and external aid can reduce students' dependence on borrowing, although the availability of this aid varies considerably by field and institutional resources (Dynarski, 2014; Ehrenberg et al., 2010).

Additionally, some graduate students work as teaching assistants or research assistants, assisting a professor in exchange for a stipend and sometimes

tuition remission. These positions provide not only financial support, but also professional development, networking opportunities, and academic experience (Feizi & Elgar, 2023). Assistantships are prevalent in research-intensive fields, serving as both a financial resource and a pathway to career advancement.

Private Loans

Some graduate students turn to private loans to cover financial gaps. Unlike federal student loans, private education loans are generally credit-based and often depend on the borrower's credit history or that of a cosigner, which can affect both eligibility and pricing (Consumer Financial Protection Bureau, 2022). Private loans also lack federal protections such as income-driven repayment plans and loan forgiveness, making them a riskier source of financing and, in most cases, a last resort only after federal aid and institutional funding have been exhausted (Consumer Financial Protection Bureau, 2022; Deller & Parr, 2021).

State-Specific Programs

Many states operate financial aid and loan repayment programs that reduce the financial burden of graduate education. For example, several states provide Loan Repayment Assistance Programs for graduates who enter public interest or qualifying public service careers (American Bar Association, 2022; Equal Justice Works, 2022). Other states administer loan repayment initiatives for health-care professionals who commit to serving in medically underserved areas (Health Resources and Services Administration, 2026; Michigan Department of Health and Human Services, 2026; National Health Services Corps, 2026). Still others offer loan forgiveness and repayment incentives for specific

high-need professions, including teaching, nursing, and agriculture (New York State Higher Education Services Corporation, n.d.). Collectively, these state initiatives can reduce students' reliance on loans, particularly for those pursuing public service or other qualifying careers in states with strong loan repayment or financial aid programs.

Employer-Based Assistance

In addition to state financial aid, some graduate students benefit from employer-sponsored tuition assistance that reduces out-of-pocket expenses and borrowing. Employers in fields such as business, engineering, health care, information technology, and other technical or professional sectors may offer tuition reimbursement or education assistance as part of their benefits packages (Bureau of Labor Statistics, 2025; National Center for Education Statistics, 2025). Society for Human Resource Management (2024) surveys indicate that roughly half of all U.S. employers provide some form of tuition assistance, although coverage levels and eligibility requirements vary and benefits rarely cover the full cost of graduate tuition. Some organizations also offer flexible work arrangements, reduced hours, or leave policies that support employees pursuing advanced degrees (Bureau of Labor Statistics, 2025). However, access to employer benefits is uneven across industries and occupations. Students who are not employed or who work in sectors where tuition assistance is less commonly offered may be less able to rely on employer assistance and instead depend on federal, institutional, or private loans.

Together, these employer-sponsored programs function as an additional mechanism through which individuals can finance graduate education; disparities in access, however, mean that not all

students can rely on employment benefits, which reinforces the continued need for institutional aid, federal support, or student loans.

Differences Across Regions and Institutions in Student Debt

The relationship between an institution's location and the amount of student debt accumulated is a critical aspect of the broader financial aid discussion. Research on geographic disparities finds that debt burdens vary by students' geographic backgrounds (rural, suburban, and urban), with some evidence that young adults from rural areas are more likely to accumulate higher levels of student debt than their suburban and urban counterparts, reflecting geographic disparities in institutional resources and state funding contexts (Board of Governors of the Federal Reserve System, 2024). Studies by Webber and Burns (2020), Burns and Webber (2019), and Belasco et al. (2014) describe the degree to which institutional reliance on tuition revenue and other financial structures contributes to student debt accumulation, particularly across different sectors and institutional types. Universities that are heavily dependent on tuition tend to shift more financial burden onto students, increasing their borrowing levels. This result aligns with institutional research showing that factors such as research activity and state grant aid policies are associated with student debt outcomes, with research-intensive institutions and those in states with more-robust grant aid often experiencing different debt patterns than less-resourced institutions (Eaton et al., 2019).

Debt Load and Consequences After Graduation

Student debt load extends beyond financial and economic concerns to influence personal choices

and career opportunities. Nuckols et al. (2020) find that many graduates viewed their student loans as worthwhile investments in their education; however, they also report that a substantial proportion of graduates experienced significant stress related to repayment obligations. Similarly, Kuhl et al. (2014) investigate students in a genetic counseling program and find that, while many were satisfied with their education, a considerable number felt financially burdened by their student loans. Gulish et al. (2024) highlight the financial risks associated with graduate education, emphasizing that, while these degrees lead to higher earnings, they also create substantial financial strain for students already bearing significant debt.

The amount of debt accumulated by graduate students has risen over the past few decades. Miller (2020) attributes this increase to the rising costs of graduate education as well as the limited availability of institutional aid; together, these changes have led to students' greater reliance on loans. Many students turn to federal Direct PLUS Loans and private loans to bridge the gap between the tuition costs and available financial aid. Using National Postsecondary Student Aid Study data from 2000 and 2016, Webber and Burns (2020) show that graduate and professional student debt increased substantially over time, and that borrowing patterns shifted across fields and student groups. While students in these programs often expect future earnings to justify their loans, the growing debt burden has created a so-called debt trap, leaving many in financial distress after graduation.

Hillman (2015) emphasizes the importance of examining institutional context in understanding borrowing patterns. Building on this perspective, prior institutional-level research suggests that

differences in institutional funding and financial aid availability are associated with variation in student debt outcomes (Craig & Raisanen, 2014; Monks, 2014). Taylor and Cantwell (2019) further demonstrate the ways in which institutional wealth and status inequalities shape students' financial burdens and show that resource-limited institutions rely more heavily on tuition and, in turn, expose students to higher borrowing, a pattern also reflected in institutional analyses of graduate debt (Belasco et al., 2014).

The long-term effects of student debt have serious implications for graduates' financial well-being. Miller (2020) argues that, while early postgraduation years can seem promising, the weight of loan repayment eventually affects graduates' ability to save, invest in homeownership, or pursue certain career paths that align with their interests. High debt loads often push graduates toward high-paying jobs rather than toward roles in public services or lower-paying sectors like education and social work, where loan repayment might be more challenging.

Beyond financial constraints, student debt also affects mental health. Nuckols et al. (2020) find that many graduates experience stress and anxiety related to loan repayment, particularly as they manage ongoing monthly payment obligations. Many struggle to balance loan repayment with other financial obligations, leading to delayed milestones such as homeownership, starting a family, or saving for retirement. Kuhl et al. (2014) reported similar findings in their study of genetic counseling students, finding that even students who were satisfied with their careers expressed concerns about how student debt could affect their long-term financial independence and ability to build wealth.

Repayment Struggles and Default Rates

The difficulties of repaying student loans extend beyond financial stress and often lead to serious financial consequences. Federal evidence indicates that graduate borrowers frequently experience extended repayment periods, with loan obligations persisting well after workforce entry and constraining financial stability (Board of Governors of the Federal Reserve System, 2024; U.S. Department of Education, 2025c). With additional financial pressures, such as housing costs, health care, and family responsibilities, many graduates find themselves in precarious financial situations.

Miller (2020) discusses the role of federal income-driven repayment plans in alleviating some of this burden by tying monthly payments to income levels. However, these plans often extend the repayment period, resulting in higher interest cost over time (U.S. Department of Education, 2025c). In many cases, even regular payments do little to reduce the overall debt balance, and students in lower-paying fields may find it difficult to keep up, increasing the risk of delinquency or default. Federal student loan portfolio data show that a meaningful share of borrowers experience delinquency or default, which can damage credit and create additional financial obstacles (U.S. Department of Education, 2025b).

Effect on Career Choices and Economic Mobility

Graduate student debt also influences career choices, often pushing individuals toward higher-paying careers rather than those that align with their academic interests or passions. Hillman (2015) discusses how institutional context can shape students' postgraduation financial decisions, including the pressure to prioritize higher-paying

employment in order to manage loan repayment obligations. For example, graduates of law or business programs might choose to enter corporate roles despite initial aspirations to work in public service or nonprofit sectors.

Field of study further shapes these debt-induced career patterns. Burns and Webber (2019) find that non-STEM students accumulate higher levels of debt than STEM students, in part because STEM programs provide greater access to assistantships and institutional funding. These funding disparities can intensify the pressure on graduates from non-STEM fields, including graduates from social work, education, and the arts, to seek high-paying employment even when it does not align with their original career goals.

This debt-driven career choice phenomenon limits economic mobility and has broad implications for workforce distribution. Webber and Burns (2020) emphasize that, as student debt levels rise, more graduates abandon preferred career paths in favor of jobs that allow them to repay loans quickly. This dynamic discourages talented professionals from entering critical but lower-paying public sector and nonprofit roles, ultimately reshaping labor market dynamics and the distribution of talent across industries.

Long-Term Financial Consequences

The financial impact of student debt extends far beyond the initial years after graduation. Drawing from graduate perceptions, Nuckols et al. (2020) reported that loan repayment obligations constrained financial flexibility and delayed wealth-building activities, such as homeownership or saving for retirement. The Board of Governors of

the Federal Reserve System (2024) reports that the growing student debt burden has widened the wealth gap, particularly among younger generations, since student loans can account for a large portion of their financial liabilities.

Overall, the mounting debt associated with graduate education continues to shape graduates' financial stability, career paths, and overall well-being. As Miller (2020) and Hillman (2015) highlight, while graduate degrees can increase earning potential, the debt burden often outweighs these benefits, especially when students feel pressured to pursue higher-paying jobs solely to manage their loan repayment obligations.

Policy Implications and Reforms

A growing body of research highlights the need for government policies to alleviate student debt burdens. The increasing reliance on student loans to finance graduate education raises critical policy concerns, particularly regarding the long-term financial well-being of graduates and the sustainability of higher education institutions. According to Brooks and Levitin (2020), the student loan crisis stems not only from the overall volume of debt, but also from structural inefficiencies in the federal student aid system. They argue that current policies fail to provide equitable, income-sensitive repayment options, and often place undue hardship on borrowers. Without systemic reform, the student loan system risks exacerbating socioeconomic inequality and undermining public confidence in the value of higher education.

Brooks and Levitin (2020) argue that reforming repayment structures, such as expanding progressive income-driven repayment plans and debt cancellation programs, could make higher

education more affordable without placing excessive financial strain on borrowers. Webber and Burns (2020) similarly recommend revising government funding policies to better support financially constrained institutions, thereby reducing students' reliance on loans. Hillman (2015) highlights the importance of institutional context in shaping borrowing patterns and calls for greater attention to how institutional and policy environments influence student debt. Consistent with this perspective, prior research finds that institutional funding levels and financial aid availability are associated with variation in student debt outcomes (Craig & Raisanen, 2014; Monks, 2014). Together, these findings suggest that more-equitable funding structures, particularly for lower-resourced institutions, could help mitigate student loan burdens.

Miller (2020) underscores the rising costs of graduate education and the corresponding increase in student loan reliance. He argues that policy interventions, such as tuition price caps and debt-to-earnings assessments, could curb excessive borrowing and make graduate programs more affordable. These recommendations align with prior research showing that institutional finance, state policy, and aid availability shape student borrowing outcomes.

Students attending institutions with fewer financial resources might be more likely to take on substantial debt, thus influencing their career decisions after graduation. As the cost of graduate education continues to rise, it is critical to examine how institutional funding affects student debt in order to shape policies that enhance financial accessibility in higher education.

THEORETICAL FRAMEWORK

This study is grounded in human capital theory and rational choice theory, both of which provide valuable insights into the factors influencing educational decision-making, including graduate borrowing behavior. Human capital theory posits that education is a form of capital investment that enhances an individual's productivity and earning potential, thereby justifying the costs associated with acquiring higher education (Becker, 1993; Schultz, 1961). Within this framework, graduate students use various forms of financial aid including federal, state, institutional, and private loans as a means of investing in their future earning capacity.

While education entails financial costs, Mincer (1984) highlights that the accumulation of human capital plays a critical role not only in personal income growth, but also in broader economic development. Within this framework, advanced skills and knowledge have value beyond the individual because they contribute to workforce capacity, productivity, and knowledge creation. Similarly, Becker (1993) argues that individuals seek to improve their overall well-being through the accumulation of human capital, a concept particularly relevant for graduate students who contribute to the creation and advancement of knowledge. Human capital theory also suggests that borrowing patterns vary by field of study, with those students pursuing degrees that offer higher financial returns being more likely to take on greater amounts of debt (Thomas, 2000).

Desjardins and Toutkoushian (2005) expand on this perspective by asserting that rational decision-making in education is not solely based on maximizing financial returns. Individuals might make educational choices that appear suboptimal from a

financial standpoint but that align with their personal values, goals, and risk tolerance. This suggests that factors such as access to financial information, perceived career benefits, and willingness to take on debt influence how individuals assess the value of higher education (Becker, 1993; Desjardins & Toutkoushian, 2005). Even when educational choices lead to financial strain, they can still be understood within the framework of human capital theory (Belasco et al., 2014).

Beyond individual decision-making, external factors play a significant role in shaping graduate student borrowing (Belasco et al., 2014). The financial resources of graduate programs and institutions influence the availability of fellowships, assistantships, and grants, with well-funded institutions benefiting from diversified revenue streams, such as research funding and philanthropic support (Belasco et al., 2014; Slaughter & Rhoades, 2004). In contrast, students at institutions that are less financially stable, or who are pursuing careers in professional fields with limited institutional funding such as business, law, and education, are more likely to rely on loans to finance their graduate education (Belasco et al., 2014; Monks, 2014; Webber & Burns, 2020).

Furthermore, institutional resources influence students' access to different types of loans: federal and state loan programs generally offer lower interest rates and more-favorable repayment terms, making graduate education more accessible. In contrast, private loans often have higher interest rates and less-flexible repayment options, potentially placing a greater financial burden on students, particularly those attending institutions with limited financial resources. These perspectives motivate our analytic focus on institutional prices, revenue structures, and geographic context as predictors of graduate borrowing at the institutional level.

Building on prior research that links institutional finance and student borrowing (Hillman, 2015; Taylor & Cantwell, 2019; Webber & Burns, 2020), this study extends the analysis to the graduate level using institutional-level borrowing measures from the 2024 NACIQI Institutional Accreditation Dataset. The following section, Methodology, describes the federal data sources, variables, and analytic models used to examine how institutional resources and geographic context influence graduate student borrowing. Furthermore, variables identified and used within the analysis are presented in Appendix A, Table A1. That table includes the variable name and source, variable label, and the values associated with the variable.

METHODOLOGY

This study uses cross-sectional multiple regression models to evaluate how institutional financial resources relate to graduate student loan accumulation. The analytic framework incorporates controls for institutional characteristics and geographic context.

The analysis integrates data from three federal sources. The first is the NACIQI institutional accreditation dataset, which provides institution-level measures of graduate student borrowing, including the weighted median federal loan amount for master's and doctoral program completers. The weighted median represents an institution-level summary measure that accounts for the distribution of borrowing among degree completers, rather than a simple unweighted median across programs. These data are reported by institutions and published as part of accreditation-related reporting to the U.S. Department of Education for academic years 2019 and 2020 (NACIQI, 2024; U.S. Department of Education, 2025b).

The second data source is IPEDS, which provides institutional financial, enrollment, pricing, and revenue metrics, including graduate tuition and fee levels, degree production, and revenue composition. The third data source is the College Scorecard, which provides student outcome indicators, including loan repayment outcomes and sector and geographical attributes. While College Scorecard reports median federal student debt for completers, it does not provide program-weighted median values for graduate credentials at the institutional level (U.S. Department of Education, 2025a).

By merging these datasets, this study compares loan reliance among public institutions that offer master's and doctoral degrees, and evaluates how tuition pricing, revenue structures, and geographic context shape graduate borrowing outcomes. The findings contribute to policy discussions regarding affordability, the role of state funding, and institutional strategies to support graduate students.

Methodology and Descriptive Statistics

To examine how institutional characteristics relate to graduate students' median debt at graduation, we assembled an institution-level dataset using the three data sources described above. The methodology is organized into three sections: Sample, Variables, and Analytical Strategy.

SAMPLE

Our study's sample consisted of 540 public institutions of higher education in the United States that had at least one degree- or certificate-seeking graduate student during the 2019–2020 academic year. For institutions that have multiple branch campuses, we excluded their branch campuses and treated an institution's main campus as a single

entity. Many multi-site institutions report financial data through a single reporting unit rather than separately for each branch campus. Because the datasets used in this study did not consistently contain branch-campus-level financial data, we removed branch campuses to ensure our dataset included only one observation per institution. We also omitted institutions that are not located in a U.S. state (e.g., institutions in Washington, DC, or a U.S. territory) and U.S. military service academies.

VARIABLES

Our models tested two measures of graduate students' federal loans as dependent variables: (a) the weighted median completer borrowing debt for an institution's master's graduates, and (b) the weighted median completer borrowing debt for an institution's doctoral graduates. These variables came from NACIQI's 2024 collection and are based on students who graduated with either of these credentials during the 2019 and 2020 calendar years. This means that an institution's median borrowing amount for each credential includes degree recipients from three academic years (i.e., the 2018–2019 academic year's Spring term, the entirety of the 2019–2020 academic year, and the 2020–2021 academic year's Fall term). Table C1 in Appendix C contains descriptive statistics for our study's variables and indicates that, for institutions in our sample, the median cumulative borrowing amount for their doctoral students is about \$30,000 more than the median cumulative borrowing amount for their students who earned a master's degree.

We conceptualized our study's independent variables as relating to institutional attributes or institutional revenues per full-time equivalent (FTE) student. Starting with institutional characteristics,

we leveraged IPEDS data to include variables that represented institutions' number of graduate students, number of master's and doctoral degrees awarded, and institutions' published tuition and fees prices for in-state and out-of-state students. We used an institution's 12-month unduplicated headcount of graduate students during the 2019–2020 academic year to quantify an institution's graduate student population. With our study's outcome variables spanning 3 academic years, we based our institutional characteristics variables on the 2019–2020 academic year since that academic year best aligned with our outcome variables' timeframe. The institutions in our sample awarded an average of 712 master's degrees and 81 doctoral degrees during the 2019–2020 academic year (see Appendix C, Table C1). We also controlled for institutions' tuition and fee rates and incorporated these costs separately since institutions have different levels of reliance on these student charges. It should be no surprise that the average tuition rate for in-state students is about half of what institutions in our sample charged out-of-state students (\$9,204 vs. \$18,638, respectively), though the average fee rates were similar (\$1,587 vs. \$1,749, respectively).

We brought in data from IPEDS's Finance Survey that pertained to institutional revenues; because these surveys are based on fiscal year, we used data from fiscal year 2020 to align with our other variables. As shown in Appendix C, Table C1, we incorporated seven types of institutional revenues and viewed these revenue streams on a per FTE basis and as a percentage of an institution's total revenue. Starting with institutional revenues per FTE student, on average institutions receive the most revenue per FTE from state appropriations (\$11,302 per FTE) and the least from local appropriations (\$77 per FTE). Government grants and student tuition and fees can also serve as important revenue streams:

these line items provide institutions with an average amount of \$10,003 and \$9,089 per FTE student, respectively. Shifting to institutional revenues as a percentage of total revenues, we see that tuition and fees represent the largest share of our sample's overall revenue, on average, followed closely by state appropriations at 31% and 28%, respectively.

ANALYTICAL STRATEGY

We answered our study's research questions by estimating a series of multiple regression models that adhered to the following equation:

$$Y = \alpha + \beta^1 \text{InstitutionalCharacteristics} + \beta^2 \text{InstitutionalRevenues} + \varepsilon,$$

where Y represents the weighted median borrowing amount for graduate students, with separate models estimated for master's and doctoral program completers. We answered our study's research questions by estimating a series of multiple regression models. First, we estimated institutional characteristics models that included graduate enrollment, master's and doctoral degrees awarded, and in-state and out-of-state tuition and fees as predictors of median graduate borrowing. These models are summarized in Appendix B, Table B1, with detailed master's-level results reported in Appendix C, Table C2. Second, we estimated institutional revenue models using seven revenue measures expressed on a per FTE basis. These models examined whether absolute levels of institutional resources were associated with graduate borrowing. These results are summarized in Appendix B, Table B1, with detailed master's-level results reported in Appendix C, Table C3. Third, we estimated alternative revenue-share models in which institutional revenues were expressed as percentages of total core revenue, with other

revenues serving as the reference category. These models allowed us to assess whether revenue composition, rather than absolute revenue levels, was associated with borrowing. These results are summarized in Appendix B, Table B1, with detailed master's-level results reported in Appendix C, Table C4. Finally, to examine geographic variation, we estimated models that included Census region indicators, with the South as the reference category. Geographic models are summarized in Appendix B, Table B1, with detailed master's-level geographic results reported in Appendix C, Tables C5 and C6. The final combined master's model, which includes institutional characteristics, per FTE revenue measures, and region indicators, is presented in Table 1. Parallel doctoral models are presented in Table 2 and Appendix C, Table C7.

Methodological Note

Although NACIQI and IPEDS datasets span multiple reporting years, this study uses a cross-sectional design rather than a longitudinal or panel analysis. Specifically, institutional financial and borrowing data from fiscal year 2020 were aligned to represent a single point-in-time snapshot. This approach ensures comparability across institutions and maintains consistency with NACIQI's reporting framework, while recognizing that future studies could extend the analysis to multi-year or panel models to examine temporal trends in borrowing.

RESULTS AND DISCUSSION

Handling of Missing Values

To ensure the quality and validity of our regression analyses, we applied a structured approach to

handling missing values. For the dependent variable median borrowing for master's program completers we first removed five institutions that were missing corresponding revenue variables from IPEDS because these variables were essential for our analysis. We also excluded an additional 96 institutions with missing values for median borrowing for master's program completers. The resulting dataset for this model includes 451 institutions.

A similar missing data check found no missing value in the relevant revenue variables for the median borrowing for doctoral program completers model. After excluding records with missing dependent variable values, the final analytic sample for median borrowing for doctoral program completers included 112 institutions.

Assessment of Regression Assumptions

Before estimating our regression models, we examined whether key assumptions for linear regression were reasonably met. We reviewed descriptive statistics for each variable and inspected distributional features (including skewness and kurtosis) to assess for extreme outliers or irregular patterns (Wooldridge, 2016). We also estimated alternative model specifications to assess the stability of results. To address potential multicollinearity, we avoided including overlapping predictors such as raw revenue levels and revenue shares in the same specification (Kutner et al., 2005). After estimating the models, we inspected residual plots and influential observations to check for heteroscedasticity and undue leverage (Fox, 2016). Finally, we reviewed model fit indices (e.g., R^2 and Root Mean Squared Error) to characterize model performance rather than to diagnose assumption violations. Together, these checks suggest that linear regression provides a reasonable analytic approach for our data. We

elected to use ordinary least squares (OLS) rather than multilevel or generalized linear alternatives because the dependent variables are continuous, institution-level measures with no nesting structure in the analytic frame, making OLS an appropriate and efficient estimator for these data (Fox, 2016; Wooldridge, 2016).

Master's Program Completer Borrowing

To examine institutional determinants of master's student borrowing, we estimated a sequence of regression models using institution-level borrowing measures from the 2024 NACIQI Institutional Accreditation Dataset (NACIQI, 2024). Initial models examined institutional traits, institutional revenue measures, and geographic context separately, with full results reported in Appendix C, Tables C2–C5. Across these exploratory specifications, in-state graduate tuition consistently emerged as a positive and statistically significant predictor of median borrowing, while several institutional size and revenue variables exhibited weaker and less-consistent relationships across model forms.

In the institutional traits model (Appendix C, Table C2), higher in-state tuition was associated with higher median borrowing, whereas enrollment size and the number of master's degrees awarded displayed opposing relationships with borrowing, suggesting offsetting structural effects when both variables are included simultaneously. Models focusing on institutional revenues (Appendix C, Tables C3 and C4) indicated that revenue measures expressed in dollar amounts per FTE were more predictive of borrowing than revenue shares expressed as percentages of total institutional revenue, highlighting the importance of absolute resource levels over proportional funding composition. A baseline geographic model (Appendix C, Table C5) further revealed meaningful geographic

variation in borrowing patterns, particularly between institutions in the South and those in the Midwest and Northeast.

Guided by these findings, we estimated a final model incorporating institutional traits, institutional revenues per FTE, and geographic indicators. Table 1 presents the final specification for median borrowing among master's program completers. Results indicate that in-state graduate tuition remains the most robust predictor of borrowing: controlling for

institutional characteristics, revenues, and region, a \$1.00 increase in the in-state tuition is associated with a \$0.91 increase in weighted median borrowing among master's program completers. Geographic differences persist in the final model, with institutions in the Midwest and Northeast exhibiting significantly lower borrowing levels relative to those in the South. Together, these results suggest that institutional pricing decisions and geographic context jointly shape graduate borrowing outcomes, with tuition levels playing a central role across all model specifications.

Final Model With Region Controls for Master's Program Completer Borrowing ($R^2 = .309$)(Model 7)

Table 1. OLS Regression Predicting Median Borrowing for Master's Program Completers with Region Controls

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	0.46	0.42	1.12	.265	-0.35	1.28
Master's degrees awarded	-0.99	1.59	-0.62	.535	-4.12	2.14
Research doctoral degrees awarded	-4.65	5.86	-0.79	.428	-16.16	6.87
In-state graduate tuition (\$)	0.91	0.22	4.15	<.001	0.48	1.35
In-state graduate fees (\$)	0.43	0.62	0.69	0.49	-0.79	1.65
Out-of-state graduate tuition (\$)	-0.21	0.11	-1.96	0.05	-0.43	0.00
Out-of-state graduate fees (\$)	0.21	0.43	0.46	0.64	-0.66	1.06
Tuition and fees revenue per FTE	0.59	0.16	3.69	<.001	0.28	0.91
State appropriations per FTE	0.21	0.62	3.42	<.001	0.09	0.34
Local appropriations per FTE	0.94	0.74	1.28	0.20	-0.50	2.39
Government contracts per FTE	0.01	0.04	0.39	0.69	-0.07	0.10
Private gifts per FTE	0.04	0.04	1.14	0.25	-0.03	0.12
Investment returns per FTE	-0.36	0.25	-1.43	0.15	-0.84	0.13
Other core revenues per FTE	0.13	0.07	1.91	0.05	-0.00	0.27
Midwest (1 = Midwest)	-3,888.30	1,309.12	-2.97	<.001	-6,461.34	-1,315.26
West (1 = West)	-165.52	1,381.98	-0.12	0.91	-2,881.74	2,550.71
Northeast (1 = Northeast)	-7,856.35	1,584.24	-4.96	<.001	-10,970.12	-4,742.57
Constant	23,699.72	1,955.67	12.12	<.001	19,855.93	27,543.51

Note: $N = 451$; $F(17, 433) = 11.41$, $p < .001$; $R^2 = .309$; $adj. R^2 = .2822$; $Root\ MSE = 10,104$. Dependent variable: median borrowing for master's program completers (US\$). South is the omitted reference region.

Alternative Specification Using Revenue Shares (Model 8)

To assess the stability of results across specifications, we estimated an additional model that included region, institutional traits, and institutional revenues expressed as percentages of total revenue (Appendix C, Table C6). Consistent with the final model, in-state graduate tuition remained a statistically significant predictor of median borrowing among master's program completers, with a \$1.08 increase in borrowing associated with a \$1.00 increase in the in-state tuition. In contrast, institutional revenue share variables were not statistically significant in this specification, and standard errors were substantially larger than in the per FTE models. The Northeast region continued to exhibit significantly lower borrowing relative to the South, whereas other geographic contrasts were not statistically significant. Given the weaker explanatory performance of revenue share measures, this model is interpreted as a sensitivity analysis rather than as the primary explanatory specification.

Limitations

This study examines graduate borrowing at public U.S. higher education institutions using an institution-level cross-sectional dataset assembled from NACIQI, IPEDS, and College Scorecard. The analytic frame includes 540 public institutions; multi-campus systems were collapsed to the main campus, and institutions in U.S. territories, the District of Columbia, and military service academies were excluded. Because the sample is limited to public institutions, generalization to the private not-for-profit and for-profit sectors is constrained.

The dependent variables are NACIQI's weighted median federal loan amounts for master's and

doctoral program completers. By construction, these measures capture borrowing among federal loan recipients only (non-borrowers are excluded), and the measures pool graduates across multiple academic periods (Spring 2018–2019, Spring 2019–2020, Fall 2020–2021). As a result, they reflect cumulative federal borrowing near the point of degree completion but cannot be attributed cleanly to borrowing incurred for a single degree program.

All models are estimated at the institutional level, which necessarily masks within-institution heterogeneity by field, program, or student subgroup and limits visibility into the role of assistantships and other program-specific funding. This tradeoff follows directly from the structure of the compiled dataset and the variables available for analysis.

Doctoral estimates warrant caution. In line with AIR's guidance, doctoral findings are interpreted as preliminary, and we avoid making strong causal or generalizable claims. The doctoral analytic sample is substantially smaller (approximately 112 institutions), and the models exhibit lower explanatory power, limiting precision and the weight that should be placed on observed patterns.

Findings are also sensitive to measurement choices. In the master's models, in-state graduate tuition is a consistent positive correlation of borrowing across specifications, whereas out-of-state tuition does not show a reliable association. Relationships for state appropriations are specification-dependent: positive when modeled per FTE, but not statistically significant when modeled as a share of total revenue, suggesting that absolute funding levels and revenue composition capture distinct dimensions of institutional finance.

Geographic context is modeled at the Census-region level. The analysis identifies lower median borrowing

in the Midwest and Northeast relative to the South; however, it does not explicitly model variation in state policy regimes or urbanicity/rurality, both of which may moderate institutional effects on borrowing.

Finally, this study focuses exclusively on federal student loan debt. The borrowing measures reflect total accumulated federal debt at the point of degree completion and could include loans incurred prior to enrollment in the credential of interest. Accordingly, while the analysis provides insight into overall federal debt burdens among master's and doctoral program completers, it cannot isolate borrowing attributable solely to a specific graduate program.

Doctoral Borrowing Models

To examine borrowing patterns among doctoral program completers, we ran parallel models using the median borrowing for doctoral program

completers variable. The analytic sample included 112 institutions, which was substantially smaller than the master's sample, reflecting both data availability and the narrower distribution of research doctorates nationally.

Across all models, we found limited explanatory power (*adj. R*² = 0.005 to 0.20) and relatively few statistically significant predictors. The most consistent pattern emerged in the revenue-per-FTE specification, where local appropriations per FTE were positively associated with borrowing and investment returns per FTE were negatively associated with borrowing. However, given the smaller analytic sample and modest model fit, these findings should be interpreted cautiously. Because this specification produced the clearest doctoral borrowing patterns, Table 2 reports the OLS regression results for doctoral program completers using institutional revenue measures per FTE.

Table 2. OLS Regression Predicting Median Borrowing for Doctoral Program Completers

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Tuition and fees revenue per FTE	-0.04	0.50	-0.07	.944	-1.03	0.96
State appropriations per FTE	0.44	0.44	1.01	.313	-0.42	1.31
Local appropriations per FTE	8.51	3.62	2.35	.021	1.32	15.70
Government contracts revenue FTE	0.31	0.24	1.26	0.21	-0.17	0.78
Private gifts revenue per FTE	-0.15	0.42	-0.04	0.97	-0.86	0.83
Investment returns per FTE	-1.20	0.55	-2.19	0.03	-2.29	-0.11
Other core revenues per FTE	-0.04	0.13	-0.28	0.78	-0.30	0.22
Constant	58,272.62	6,412.11	9.09	<.001	45,557.16	70,988.07

Note: *N* = 112; *F*(7, 104) = 2.93, *p* = .0078; *R*² = .1645; *adj. R*² = .1083; *Root MSE* = 20,804. Dependent variable: median borrowing for doctoral program completers (US\$).

A more-comprehensive specification that adds institutional traits and Census region to the revenue per FTE model is reported in Appendix C, Table C7. In that expanded model, coefficients attenuate and do not reach conventional levels of statistical significance, reinforcing that doctoral borrowing patterns could be driven by factors not well captured in institution-level finance measures.

Implications

While the bulk of our findings center on master's-level debt, the doctoral models offer a valuable starting point for future research. The master's-level findings align with prior research, reinforcing that institutional pricing and resource environments shape borrowing behavior (Hillman, 2015; Taylor & Cantwell, 2019; Webber & Burns, 2020). The relationship across models between in-state tuition and borrowing aligns with the literature that suggests higher tuition rates at resource-limited institutions are associated with greater reliance on loans (Hillman, 2015; Taylor & Cantwell, 2019). Likewise, findings regarding the Midwest and Northeast regions are consistent with prior research suggesting that geographic context and institutional resource environments are associated with variation in student borrowing (Hillman, 2015).

The doctoral borrowing models highlight both the promise and the current limitations of emerging federal data. While our findings were not statistically robust, the effort to model median borrowing for doctoral program completers across institutions demonstrates the feasibility of analyzing doctoral debt at scale. If the availability of the NACIQI dataset and borrowing levels at the degree level variable continue, researchers will be able to build longitudinal or pooled cross-sectional studies to better understand how institutional finance and

structure relate to borrowing at the doctoral level. From a policy perspective, results suggest that public institutions could reduce graduate debt by balancing tuition dependency with increased state appropriations and need-based institutional aid. For practitioners, these findings highlight the importance of transparent communication with graduate students regarding borrowing expectations and financial planning. These future inquiries could inform both federal reporting design and institutional policy, particularly around financial aid transparency and program-level loan counseling for doctoral students.

Policy and Practice Implications

Institutional pricing strategies and revenue structures play a measurable role in shaping graduate borrowing outcomes. For public institutions, policies that balance tuition revenue with increased state appropriations or targeted institutional aid could help reduce student reliance on loans. Transparent communication of expected borrowing and clearer financial planning resources for graduate students could also mitigate financial stress and improve informed decision-making. Together, these actions can support greater affordability and equity across institutional types and regions.

Alternative Approaches

Because one of our research interests is to explore geographic differences in graduate student borrowing levels, future research could adopt an alternative approach by stratifying the dataset by region. Within each region, researchers could examine the extent to which student borrowing levels are influenced by institutional characteristics

and revenue structures. This region-specific analysis may offer a more-nuanced understanding of the factors shaping graduate student borrowing, helping to identify both common and geographically distinct influences. Such insights could provide valuable guidance for policymakers and institutional leaders in developing tailored strategies to address graduate student debt across diverse geographic contexts.

Directions for Future Research

Several extensions follow directly from the scope and measures used here.

First, expanding the frame to private not-for-profit and for-profit institutions would enable explicit sector comparisons and test whether different revenue structures (e.g., endowment income, institutional grant aid, tuition dependence) produce borrowing dynamics that diverge from those observed among public institutions of higher education. The public-only sampling in this study provides a clear starting point for that contrast.

Second, linking institutional outcomes to field-of-study and credential subtype is a priority. The doctoral measure aggregates all doctoral program completers without a consistent flag to separate professional doctorates (e.g., JD, MD, PharmD) from research doctorates; disaggregating by Classification of Instructional Programs (CIP) and degree type would reduce compositional noise and clarify discipline-specific borrowing dynamics.

Third, given the heterogeneity in institutional finance—a segmentation strategy, for example—cluster analysis using the study's revenue and structural variables (tuition and fees per FTE, state and local appropriations per FTE, private gifts/investment returns per FTE, and region) could

group institutions with similar profiles and permit estimation within clusters, potentially revealing patterns obscured in pooled regressions. The variable set assembled for this study supports such an approach.

Fourth, future work should test nonlinearities and interactions among price and revenue measures and context (e.g., region, field mix). The sensitivity of results to how appropriations are operationalized (per FTE versus share of revenue) suggests threshold or compositional effects that linear, pooled models might not fully capture.

Fifth, adding policy and place granularity including state grant regimes, tuition-setting policies, and urbanicity/rurality would move beyond geographic contrasts and better identify policy moderators of institutional effects on graduate borrowing. The current region indicators provide an initial scaffold for that extension.

Sixth, to strengthen inference for doctoral outcomes, researchers should pool additional NACIQI years to increase the doctoral sample and precision and, where possible, distinguish professional doctorates from research doctorates. With richer panels, it would also be feasible to model lags between changes in appropriations/pricing and observed borrowing.

Finally, linking institutional median borrowing measures with program-level or student-level information, such as assistantships, tuition remission, fee waivers, and stipends, would help mitigate ecological inference concerns and tie borrowing more directly to students' actual degree pathways. This approach would also address the timing and attribution constraints of the current measures.

CONCLUSION

This study contributes new institution-level evidence to understanding graduate borrowing in U.S. public higher education. By linking NACIQI's weighted median loan data with IPEDS finance measures and College Scorecard institutional characteristics, we provide one of the first large-scale examinations of how tuition levels, institutional revenue environments, and geographic context relate to graduate student debt. Results show that in-state graduate tuition consistently emerges as the strongest predictor of borrowing at the master's level; geographical differences indicate that students attending institutions in the Midwest and Northeast borrow less than those in the South. Together, these findings reaffirm that institutional pricing and

resource environments shape graduate borrowing outcomes.

Although results for doctoral program completers were less robust due to smaller analytic samples and greater heterogeneity in funding structures, the models establish a foundation for future research using expanded NACIQI data. The findings also carry practical implications: institutions and policymakers should consider how tuition dependency, state appropriations, and financial aid transparency collectively affect students' financial burdens. Future research incorporating program-level detail, private institutions, and alternative modeling approaches may further illuminate how institutional finance shapes graduate affordability and equity in advanced education.

APPENDIX A: VARIABLE DETAILS

Table A1: Variable Details

Variable Name and Source	Variable Label	Values
Median Borrowing by Degree Level Source: NACIQI Accreditor Dashboard Information	Weighted median federal loan debt of master's program completers at an institution	Positive real numbers
	Weighted median federal loan debt of doctoral program completers at an institution	Positive real numbers
Institutional Attributes (Enrollment and Degrees Awarded / Tuition and Fees) Source: IPEDS Institutional Characteristics Survey	Number of graduate students seeking degrees and certificates	Positive real numbers
	Number of master's degrees awarded	Zero or positive real numbers
	Number of doctoral degrees awarded	Zero or positive real numbers
	Average in-state tuition for full-time graduate students	Positive real numbers
	In-state required fees for full-time graduates	Positive real numbers
	Average out-of-state tuition for full-time graduates	Positive real numbers
	Out-of-state required fees for full-time graduates	Positive real numbers
Institutional Revenues per FTE Student Source: IPEDS Finance Survey	Revenues from tuition and fees per FTE student, according to Governmental Accounting Standards Board (GASB)	Positive real numbers
	Revenues from state appropriations per FTE (GASB)	Positive real numbers
	Revenues from local appropriations per FTE (GASB)	Positive real numbers
	Revenues from government grants and contracts per FTE (GASB)	Positive real numbers
	Revenues from private gifts, grants, and contracts per FTE (GASB)	Positive real numbers
	Revenues from investment return per FTE (GASB)	Positive real numbers
	Other core revenues per FTE (GASB)	Positive real numbers
Institutional Revenues as Percentage of Total Revenue Source: IPEDS Finance Survey	Tuition and fees as a percentage of core revenues (GASB)	Percentage
	State appropriations as percentage of core revenues (GASB)	Percentage
	Local appropriations as a percentage of core revenues (GASB)	Percentage
	Government grants and contracts as a percentage of core revenues (GASB)	Percentage
	Private gifts, grants, and contracts as a percentage of core revenues (GASB)	Percentage
	Investment return as a percentage of core revenues (GASB)	Percentage
	Other revenues as a percentage of core revenues (GASB)	Percentage

Variable Name and Source	Variable Label	Values
Region Source: College Scorecard “State” was classified into the four U.S. Census Regions	Institution located in the Midwest region (South is the reference)	1 = Midwest, 0 = otherwise
	Institution located in the West region (South is the reference)	1 = West, 0 = otherwise
	Institution located in the Northeast region (South is the reference)	1 = Northeast, 0 = otherwise

Sources: Data are derived from the National Advisory Committee on Institutional Quality and Integrity (NACIQI) Institutional Accreditation Dataset (U.S. Department of Education, 2024); the Integrated Postsecondary Education Data System (IPEDS) FY 2020 Finance Survey (Institute of Education Sciences, 2025); and the College Scorecard (U.S. Department of Education, 2025a).

APPENDIX B: CROSS-SECTIONAL REGRESSION MODELS

Table B1. Summary of Regression Models Examining Graduate Student Borrowing by Institutional Characteristics, Revenues, and Region

Model	Model Description	Dependent Variable	N	R ²	Key Significant Predictors (p > .05)	Table Reference
Model 1	Base model with institutional traits only	Median borrowing for master's program completers	451	.107	In-state graduate tuition (+)	Table C2
Model 2	Base model with institutional revenues per FTE	Median borrowing for master's program completers	451	.248	State appropriations per FTE (+)	—
Model 3	Base model with institutional revenues as percentage of total revenue	Median borrowing for master's program completers	451	.200	Nonsignificant	—
Model 4	Geographic contrasts (South as reference)	Median borrowing for master's program completers	451	.031	Midwest (–), Northeast (–)	Table C5
Model 5	Expanded revenue model: institutional revenues per FTE	Median borrowing for master's program completers	451	.260	In-state tuition (+), State appropriations (+)	Table C3
Model 6	Expanded Revenue model: institutional revenues as % of total revenues	Median borrowing for master's program completers	451	.247	In-state tuition (+)	Table C4
Model 7	Final model with region controls (per FTE revenues)	Median borrowing for master's program completers	451	.309	In-state tuition (+), Midwest (–), Northeast (–)	Table 1
Model 8	Expanded model with region + percentage revenue controls	Median borrowing for master's program completers	451	.271	In-state tuition (+), Northeast (–)	Table C6
Doctoral Model 1	Institutional revenues per FTE (doctoral sample)	Median borrowing for doctoral program completers	112	.164	Local appropriations (+), Investment returns (–)	Table 2
Doctoral Model 2	Institutional revenues per FTE + region controls	Median borrowing for doctoral program completers	112	.234	None (small N)	Table C7

APPENDIX C: DESCRIPTIVE STATISTICS AND REGRESSION TABLES

Table C1. Descriptive Statistics

	Mean	SD	Min	Max
Median Borrowing by Degree Level				
Master's degree recipients	\$35,505	12,403	\$16,234	\$83,805
Doctoral degree recipients	\$65,161	22,782	\$27,435	\$143,995
Institutional Characteristics				
Number of graduate students	2,987	3,817	24	18,530
Number of master's degrees awarded	712	863	0	4,083
Number of doctoral degrees awarded	81	163	0	806
In-state graduate tuition	\$9,204	4,475	\$2,070	\$24,000
In-state graduate fees	\$1,587	1,366	\$0	\$6,272
Out-of-state graduate tuition	\$18,638	7,742	\$2,250	\$38,820
Out-of-state graduate fees	\$1,749	1,878	\$0	\$11,293
Institutional Revenues per FTE Student				
Student tuition and fees	\$9,089	5,120	\$2,678	\$27,146
State appropriations	\$11,302	36,724	\$0	\$75,332
Local appropriations	\$77	741	\$0	\$1,291
Government grants	\$10,003	26,518	\$1,114	\$150,864
Private gifts	\$4,883	27,967	\$0	\$107,843
Investment returns	\$1,112	5,264	-\$355	\$24,516
Other revenues	\$9,007	57,969	\$73	\$92,613
Institutional Revenues as Percent of Institution's Total Revenue				
Student tuition and fees	.31	.14	.02	.65
State appropriations	.28	.13	.00	.64
Local appropriations	.00	.03	.00	.08
Government grants	.22	.10	.05	.49
Private gifts	.05	.06	.00	.30
Investment returns	.02	.02	-.01	.09
Other revenues	.12	.10	.01	.51

Note: Data are from NACIQI and IPEDS. N = 540.

Table C2. OLS Regression Predicting Median Borrowing for Master's Program Completers With Institutional Characteristics

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	1.10	0.46	2.39	.017	0.19	1.99
Master's degrees awarded	-4.39	1.72	-2.56	.011	-7.76	-1.01
Research doctorates awarded	3.37	6.35	0.53	.596	-9.11	15.84
In-state graduate tuition (\$)	0.69	0.20	3.39	.001	0.29	1.10
In-state graduate fees (\$)	-0.25	0.48	-0.52	.604	-1.21	0.71
Out-of-state graduate tuition (\$)	0.17	0.13	1.33	.184	-0.08	0.42
Out-of-state graduate fees (\$)	0.40	0.34	1.20	.229	-0.25	1.36
Constant	25,963.22	2,000.61	12.98	<.001	22,031.36	29,895.09

Note: $N = 451$; $F(7, 443) = 7.56$, $p < .001$; $R^2 = .107$; adj. $R^2 = .092$; Root MSE = 11,360. Dependent variable: median borrowing for master's program completers (US\$).

Table C3. OLS Regression Predicting Median Borrowing for Master's Program Completers With Institutional Revenue Measures per FTE

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	0.51	0.43	1.20	.232	-0.33	1.36
Master's degrees awarded	-0.95	1.64	-0.58	.562	-4.18	2.27
Research doctorates awarded	-4.11	6.02	-0.68	.495	-15.94	7.72
In-state graduate tuition (\$)	0.44	0.21	2.12	0.04	0.32	0.85
In-state graduate fees (\$)	-0.12	0.63	-0.19	0.85	-1.35	1.11
Out-of-state graduate tuition (\$)	-0.11	0.11	-0.97	0.33	-0.32	0.11
Out-of-state graduate fees (\$)	0.41	0.45	0.91	0.36	-0.47	1.28
Tuition and fees revenue per FTE	0.64	0.16	3.82	0.00	0.31	0.97
State appropriations per FTE	0.16	0.06	2.64	0.01	0.04	0.28
Local appropriations per FTE	0.55	0.75	0.72	0.47	-0.94	2.02
Government contracts revenue FTE	-0.01	0.04	-0.13	0.89	-0.09	0.08
Private gifts revenue per FTE	0.06	0.40	1.63	0.10	-0.13	0.14
Investment returns per FTE	-0.19	0.25	-0.77	0.44	-0.69	0.30
Other core revenues per FTE	0.02	0.07	2.19	0.03	0.16	0.30
Constant	24,005.4	1,910.27	12.57	<.001	20,250.93	27,759.88

Note: $N = 451$; $F(14, 436) = 10.99$; $p < .001$; $R^2 = .26$; adj. $R^2 = .23$; Root MSE = 10,416. Dependent variable: median borrowing for master's program completers (US\$).

Table C4. OLS Regression Predicting Median Borrowing for Master's Program Completers With Revenue Share Measures

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	0.66	0.44	1.51	0.13	-0.20	1.52
Master's degrees awarded	-2.33	1.68	-1.39	0.16	-5.63	0.98
Research doctorates awarded	-7.02	6.11	-1.15	0.25	-19.03	4.99
In-state graduate tuition (\$)	0.76	0.19	3.81	<.001	0.37	1.15
In-state graduate fees (\$)	0.40	0.63	0.64	0.52	-0.84	1.65
Out-of-state graduate tuition (\$)	-0.14	0.11	-0.13	0.89	-0.46	0.20
Out-of-state graduate fees (\$)	0.41	0.45	0.91	0.36	-0.48	1.30
Tuition and fees revenue per FTE	16,078.42	70,585.84	0.23	0.82	-122,362.0	154,809.2
State appropriations per FTE	14,639.77	70,636.16	0.21	0.83	-124,189.5	153,469.5
Local appropriations per FTE	34,269.44	72,180.71	0.47	0.63	-107,596.0	176,134.9
Government grants per FTE	55,351.70	70,655.57	0.78	0.43	-83,516.0	194,219.6
Private gifts per FTE	65,876.56	70,956.33	0.93	0.35	-85,124.0	205,335.5
Investment returns per FTE	63,626.90	73,002.35	0.87	0.38	-73,582.0	207,107.2
Other core revenues per FTE	38,791.87	70,526.08	0.55	0.58	-98,821.0	177,405.2
Constant	-2,322.38	70,485.79	-0.03	0.97	-140,856.5	136,211.8

Note: $N = 451$; $F(14, 436) = 10.23$, $p < .001$; $R^2 = .2473$; $adj. R^2 = .2231$; $Root\ MSE = 10,512$. Dependent variable: median borrowing for master's program completers (US\$).

Table C5. OLS Regression Predicting Median Borrowing for Master's Program Completers by Region (South = Reference)

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Midwest (1 = Midwest)	-3,113.71	1,436.65	-2.17	.031	-5,937.13	-290.29
West (1 = West)	1,386.27	1,562.92	0.89	.376	-1,685.31	4,457.85
Northeast (1 = Northeast)	-4,436.15	1,598.56	-2.78	.006	-7,577.78	-1,294.53
Constant	36,489.66	854.47	42.70	<.001	34,810.39	38,168.93

Note: $N = 451$; $F(3, 447) = 4.79$, $p = .0027$; $R^2 = .0311$; $adj. R^2 = .0246$; $Root\ MSE = 11,778$. Dependent variable: median borrowing for master's program completers (US\$). South is the omitted reference category.

Table C6. OLS Regression Predicting Median Borrowing for Master's Program Completers With Geographic Controls

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	0.67	0.43	1.54	0.12	-0.18	1.51
Master's degrees awarded	-2.48	1.66	-1.49	0.13	-5.74	0.78
Research doctorates awarded	-6.68	6.06	-1.10	0.27	-18.59	5.23
In-state graduate tuition (\$)	1.08	0.22	5.03	<.000	0.66	1.50
In-state graduate fees (\$)	0.76	0.64	1.19	0.23	-0.50	2.01
Out-of-state graduate tuition (\$)	-0.08	0.11	-0.72	0.47	-0.30	0.13
Out-of-state graduate fees (\$)	0.26	0.45	0.57	0.56	-0.62	1.14
Tuition and fees revenue per FTE	21,120.72	69,801.25	0.30	0.76	-116,070.7	1,583
State appropriations per FTE	21,601.63	69,879.87	0.31	0.76	-115,744.3	1,589
Local appropriations per FTE	47,100.12	71,467.36	0.66	0.51	-93,365.95	1,875
Government contracts per FTE	55,992.88	69,930.63	0.80	0.42	-81,452.82	1,934
Private gifts per FTE	67,595.01	70,147.07	0.96	0.33	-70,276.09	2,054
Investment returns per FTE	54,744.77	72,198.42	0.76	0.44	-87,158.17	1,966
Other core revenues per FTE	42,060.69	69,764.18	0.60	0.54	-95,057.85	1,791
South (reference)	853.15	1,419.79	0.60	0.54	-1,937.39	3,643
Midwest	-2,129.18	1,650.71	-1.29	0.19	-5,373.53	1,115.17
Northeast	-4,958.07	1,824.20	-2.72	0.01	-8,543.45	-1,372.70
West	Omitted	—	—	—	—	—
Constant	-7,321.60	69,806.43	-0.10	0.92	-144,523.2	129,880.0

Note: $N = 451$; $F(17, 433) = 9.46$, $p > .001$; $R^2 = .2709$; adj. $R^2 = .2423$; $Root\ MSE = 10,381$. Dependent variable: median borrowing for master's program completers (US\$). West is the omitted reference region.

Table C7. OLS Regression Predicting Median Borrowing for Doctoral Program Completers with Geographic Controls

Predictor	b	SE	t	p	95% CI LL	95% CI UL
Degree-seeking graduate students	0.99	1.19	0.84	0.40	-1.37	3.37
Master's degrees awarded	-4.00	4.97	-0.81	0.42	-13.87	5.86
Research doctorates awarded	-0.09	18.44	-0.01	0.99	-36.70	36.51
In-state graduate tuition (\$)	1.69	0.99	1.71	0.09	-0.28	3.66
In-state graduate fees (\$)	0.00	2.89	0.00	0.99	-5.73	5.74
Out-of-state graduate tuition (\$)	-0.40	4.71	-0.85	0.39	-1.33	0.53
Out-of-state graduate fees (\$)	-0.81	1.36	-0.59	0.55	-3.51	1.89
Tuition and fees revenue per FTE	-0.41	0.68	-0.60	0.55	-1.77	0.95
State appropriations per FTE	0.78	0.50	1.56	0.12	-0.21	1.78
Local appropriations per FTE	7.34	3.75	1.96	.053	-0.11	14.78
Government contracts per FTE	0.17	0.26	0.64	.523	-0.35	0.68
Private gifts per FTE	-0.21	0.47	-0.45	.651	-1.15	0.72
Investment returns per FTE	-1.04	0.61	-1.69	0.09	-2.25	0.18
Other core revenues per FTE	-0.00	0.15	-0.03	0.97	-0.30	0.29
Midwest (1 = Midwest)	-3,288.00	5,929.23	-0.55	0.58	-15,060.56	8,484.69
West (1 = West)	8,075.25	5,896.88	1.37	0.17	-3,633.15	19,783.66
Northeast (1 = Northeast)	-7148.88	9,031.18	-0.79	0.43	-25080.5	10,782.73
Constant	54,146.54	10,116.56	5.35	<.001	34,059.87	74,233.20

Note: $N = 112$; $F(17, 94) = 1.69$, $p = .0583$; $R^2 = .2340$; adj. $R^2 = .0955$; $Root\ MSE = 20,953$. Dependent variable: median borrowing for doctoral program completers (US\$). South is the omitted reference region.

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Higher Education Workforce Artificial Intelligence Skill Development

A Policy Consideration Analysis Through the Applied Lens of Practical Conversational Coding

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Abstract

Higher education (HE) professionals with limited technical or coding experience can now use generative artificial intelligence (AI)-assisted coding tools to create software applications; the recent availability of these coding tools likely impacts the HE workforce that leverages institutional data to meet stakeholder needs and solve organizational problems. In this paper we examine policy considerations culturally, organizationally, and

operationally through the lens of a combined design-based research (DBR) and theoretical analysis applied to a proof-of-concept (POC) survey data collection web application built with conversational language. The step-by-step process arrived at a functional POC and revealed practical possibilities for HE workforce development policy. Specifically, from an organizational perspective, HE professionals with limited coding experience could use AI-assisted tools to create software (e.g., tools, interface driven) that addresses the challenges they face in their work. Operationally and culturally, POC alignment to real-world HE problems and their iterative refinement could help meet stakeholder needs via a practitioner-driven approach that would have been technically inaccessible before the development of generative AI. The tangible POC software of this applied contribution coded entirely with natural language can be experienced at https://sbndco-michael-littrell.shinyapps.io/weather_survey_v2/ with a password of 1234.

Keywords: artificial intelligence, institutional policy, higher education, conversational coding, professional development

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INTRODUCTION

Recently, the rapid growth of artificial intelligence (AI) large language models that are publicly available have spearheaded changes in higher education (HE) administration processes that hold implications for improvement or challenges in different HE areas (Robert, 2024). Possibly AI's biggest impact on HE is not simply as a tool to help with writing, information searches, or teaching; instead, its largest effect is likely expressed as a catalyst that has significantly remolded faculty, staff, and students into computational thinkers and programmers, whether or not that effect is generally recognized yet. In this paper, computational thinking and, by extension, the agentive thinker, is defined closely with Wing (2008) as a mode of systematic mentation directed by the harnessing of technology to answer questions and serve society broadly. This change in training needs is best exhibited in areas where AI is most proficient, such as computer code generation.

AI is very capable when creating computer code from natural language; these proficiencies have empowered nontechnical employees to make meaningful progress in technical tasks that were not possible before (Chen et al., 2021; Crompton & Burke, 2023). The skillsets most notably influenced by this type of growth and technical need relate to data collection, visualization, analysis, and evaluation, particularly in HE areas like recruitment, enrollment, and institutional effectiveness (Gagliardi, 2022; Webber & Zheng, 2023).

In this paper, we investigate AI's potential impact on educational employment and professional development in these specific areas (recruitment, enrollment, and institutional effectiveness), focusing on the changing nature of HE administration processes and related policy implications. We

focus this paper on the following two exploratory questions: (1) In what ways is generative AI democratizing programming and data science skills for HE professionals? (2) How does integrating generative AI into HE professional development shape institutional policy? Specifically, we leverage a combined design-based research (DBR) and theoretical approach to present and analyze how a proof-of-concept (POC) survey application that integrates AI is allowing HE professionals to extend their evaluative capacities within the parameters of available postsecondary resources and changing policy regarding professional development practices. DBR is a method of educational research that investigates the "iterative development of solutions (e.g., educational products, processes, programs or policies)" as pragmatic innovations to real-world applications (McKenney & Reeves, 2013, p. 133). A POC is defined as a software application that is limited in scope to demonstrating the viability and feasibility of an idea (Atlassian, n.d.). Utilizing the POC, we walk through specific steps of the DBR process (e.g., exploration, design, and production) and expand on how this AI-anchored intervention can be beneficial in improving institutional research (IR) professional training (Anderson, 2005; Bannan-Ritland, 2003).

Specifically, an applied and practical step-by-step process is demonstrated with all relevant information for HE professionals who may have limited coding or technical experience so that they could replicate our results and extend them to their own professional goals. To provide context, we offer background on the scholarship in AI in terms of definitions and applications in HE professional development and couch it within recruitment and enrollment data efforts. Since we are educators in an online, doctoral program for HE administrators and professionals, this POC is also an example of

how we incorporate AI into data science courses that are currently being developed, and provides a specific application of how the integration of AI is enhancing training in survey development for administrative purposes.

This paper is particularly timely and relevant because HE institutions are striving to understand generative AI's implications for postsecondary education. While this effort is occurring broadly, scholarship focusing on HE policy through the lens of practical application appears to be less common (Crompton & Burke, 2023). As AI becomes an increasingly common part of professional workflows in HE, the need to understand this technology in ways that translate to institutional policy and pragmatic usage becomes increasingly urgent. This paper is intended to be a contribution to an emerging body of thought. Although literature of this nature could stop at scholarly analysis, this paper provides an analytical example of a functioning POC to help bridge theoretical and pragmatic gaps (Anderson, 2005).

BACKGROUND

What Is AI?

Scholars denote that the current information age took almost a decade and a half to start to make a difference in our lives, but within the past 3 years alone the impact of generative AI on teaching and learning in HE has been unparalleled (Parnell, 2024; Robert, 2024). For example, Bickerstaff (2025) shared data that showed how generative AI reading comprehension took less than a year to match parity with human capabilities. These milestones in generative AI transformations build on past technological advances, including theories of AI (i.e., building machines to think like humans), machine

learning (i.e., the ability for computers to learn from experience vs. engage with programming), and deep learning (i.e., the use of artificial neural networks for machines to complete complex tasks) (Bobula, 2024; Robert, 2024). However, the transformative aspect of generative AI rests on its technological capability to create something new (including texts, images, videos, etc.), impacting more than 86 percent of jobs, displacing more than 92 million jobs, and creating 170 million jobs that can leverage technological skills (Bickerstaff, 2025). Despite these advances, within U.S. higher education institutions (HEI), rigid organizational structures and resource-based challenges may implicate how well institutions can address rapid technological changes, such as the integration of AI into professional development processes (Gaftandzhieva et al., 2023; Grassian, 2020; Robert, 2024).

Impact of AI in HE Administration

Changes in HE funding, pressures from globalization, and the evolving supply and demand for postsecondary education may also impact the type of leadership and transformative strategies adopted regarding AI integration (Daniel, 2019). Most U.S. HEIs follow directives from various authoritative bodies, reflecting the shared governance structures typical of these types of institutions that may hinder grassroots-level innovation efforts concerning technology (Mitchell & King, 2018). In describing the changing debates on AI integration in HE administration, Tsai et al. (2019) illustrated a landscape of competing perspectives, with concerns about ethical inclusion of AI in the learning process contrasted with ideals of leveraging AI for enhanced efficiency purposes.

In this way, the adoption of AI within U.S. HEIs is staggered, with institutional policies on generative

AI adoption providing a more centralized approach to understanding and navigating these changes in classroom dynamics, and providing less guidance on the adoption and use of AI from an administrative point of view (Daniel, 2019; Tsai et al., 2019). Effectively, when HE leadership addresses rapid technological shifts, adoptions, or changes, it can be described as a slow-moving entity, marred by prolonged procedural battles that make it less apt to adjust and adapt to these rapid shifts (Bollaert, 2025; Gaftandzhieva et al., 2023; Mitchell & King, 2018). Any policy shifts to include appropriate generative AI integration in professional development for HE personnel must take into consideration the technical, cultural, and social aspects that usher in significant technological changes to organizational functions in HEIs (Tsai et al., 2019). To this end, Bollaert (2025) noted, “HEIs risk falling behind in a world where technology is central to academic success, operational efficiency, and student satisfaction” (p. 218).

AI Literacy in Professional Development

What Bollaert said is effectively the case regarding generative AI training and professional development for HE personnel. In data shared by Bickerstaff (2025) concerning top sought-after industry skills, employers voted AI literacy as number one, with 62 percent of those surveyed believing that employees should have basic AI literacy skills. AI literacy can be defined as the knowledge, skills, and mindsets that allow individuals to use AI safely, ethically, and effectively (Organisation of Economic Co-operation and Development [OECD], 2025). AI literacy is different from being digitally native (i.e., familiar with technology), a state that scholars contend does not transfer to digital literacy (i.e., skilled in effective use of technology), contributing to the overall digital divide (Bickerstaff, 2025).

This nuance holds implications for how professional development and training curriculum can leverage these tools to foster skills like creativity, critical thinking, and learning agility, all of which contribute to AI literacy. Learning agility is particularly important for HE personnel since it builds the foundation for adaptability in nuanced job expectations, including the incorporation of data analytics, visualization, and programming skills (Gaftandzhieva et al., 2023). Furthermore, for HEIs in general, learning to leverage generative AI as a capacity-building tool through targeted professional development efforts can be pivotal for small offices that depend on human resource skills to fill gaps in technological infrastructure (Agasisti & Bowers, 2017; Bickerstaff, 2025).

Arriving at actionable insight and applying results from data analysis are essential components of a modern data-focused HE workforce; this skillset is greatly needed by many professionals (Mikalef et al., 2018). These data abilities are meaningful in an HE policy context where alignment of data strategies and decision-making processes can meaningfully contribute to meeting a broad range of institutional goals in domains such as effectiveness and sustainability (Chigbu & Makapela, 2025). To realize these outcomes, institutions must capture high-quality data that are both informative and aligned with their strategic objectives. From a workforce development standpoint, AI will impact the data processes across the data-science workflow in many different ways and HE professionals will need to be prepared to engage with AI's influence.

Data-Driven Expertise

Most HEIs rely on data-driven or data-informed decision-making processes to improve the efficiency of metrics and tools used to help support their

enrollment and marketing objectives (Gagliardi, 2022). A nuanced clarification between data-driven and data-informed is that the former indicates that decisions are based on data, wherein the latter indicates that data are one of many metrics informing decision-making capabilities at HEIs (Webber & Zheng, 2023). Both processes have been used in HE leadership to gain insight and monitor progress on a variety of aspects related to postsecondary activities, including but not limited to student performance, enrollment trends, academic productivity, cost management, compliance, value building, and capacity building (Gaftandzhieva et al., 2023).

Through intuitive dashboards, tracking and analyzing trends, and observing key performance indicators, HE leaders can use evidence for informed decision-making that aligns with larger strategic-planning goals with respect to growth toward strategic planning metrics (Flori et al., 2023; Gaftandzhieva et al., 2023). Due to the reliance on data-driven and data-informed decision-making processes, HEIs have become increasingly dependent on the collection, storage, analysis, and processing of large datasets as part of these organizational changes; this dependence implicates the digital literacy skillsets needed for HE professionals (Gaftandzhieva et al., 2023).

For example, in the processes of refining HE leadership initiatives to be more data-driven or data-informed processes, Agasisti and Bowers (2017) underscored the nuanced differences in the types of data helping to inform these larger decisions. They explored how three different data-driven approaches (educational data mining, learning analytics data, and academic analytics) have impacted the creation of education policy and learning innovations at HEIs (Agasisti & Bowers,

2017). Through these approaches, institutions leveraged data loops to marry business intelligence to educational landscapes, attempting to generate value for institutions that are reflected in larger, strategic planning goals (Agasisti & Bowers, 2017). HE capacity, however, in the form of human and technological infrastructure on the nature of data science systems, is limited by financial, organizational, and cultural challenges (Tsai et al., 2019). Tsai et al. (2019) have noted a plateau in skillset efficiency in HEIs, stressing that “adoption has mostly been constrained to basic levels of extraction and reporting of data, instead of prescribing personalized and timely support strategies that can aid teaching quality and improve student learning experiences” (p. 2).

SIGNIFICANCE

To appropriately leverage data-driven analytics in HE, several challenges arise, most notably those centered on human resource capacity and technological infrastructure. Scholars have pointed to the recursive nature of data-informed decision-making processes that require consecutive iterations of cleaning, integrating, analyzing, and representing new data to ensure relevance and accuracy (Agasisti & Bowers, 2017). To this end, the sustainability of data-driven decision-making processes in HE is dependent on personnel that inherently understand this process and the ethics behind using appropriate data (Chigbu & Makapela, 2025). A consequence of engaging in data-driven decision-making processes with data that are not reflective of the current context includes implications for data-driven leadership in HE governance, teaching, and learning strategies that may impact institutional efficacy, aligned curricula, student outcomes, and overall academic performance (Chigbu & Makapela, 2025).

This spiral effect is an inherently human-centered challenge, driven by the level of robust data analytics capabilities used by the administrative staff at various institutions (Webber & Zheng, 2023).

However, addressing the human resource gap is only one side of the challenge that HEIs face. Even if HEIs have the data analytics capacity in the form of human resources, few HEIs, if any, hold the technological infrastructure needed to support and navigate the types of data required to make data-informed decisions (Flori et al., 2023; Gaftandzhieva et al., 2023). Webber and Zheng (2023) describe the complexities of these challenges by underscoring the intersection of competing institutional priorities, increasing operating costs, and financial limitations in terms of state support or tuition increases, all of which contribute to the infrastructure quality at HEIs.

Subsequently, what HEIs are facing is a dual human-technical gap that is aggrandized either by an investment in advanced technology that rests stagnant as professionals build skills to leverage it to its full potential, or by investments in professional development skills for HE personnel that do not have access to the technological infrastructure where these skills would be featured (Bollaert, 2025; Chigbu & Makapela, 2025; Webber & Zheng, 2023). To this end, human and technical resource challenges implicate HE institutions' ability to navigate and integrate AI into its processes and effect positive change.

ANCHORING THE CONTEXT

In-Time Generative AI Professional Development

One of the areas where enhanced data science

and analytics skills are becoming increasingly important is an understanding of enrollment and marketing trends for HEIs. It is no surprise that HEIs, particularly public institutions in the United States, compete for stable financial revenue in the form of enrollment and tuition fees (Gagliardi, 2022; Mitchell & King, 2018). Due to this reliance on the changing nature of enrollment, the interests and engagement trends of new student generations, and the requirement of retooling and reskilling programs to fit workforce demands, the need for data-driven or data-informed processes in enrollment and marketing is pivotal to the efficiency and effectiveness of HE institutions' leadership strategies (Gaftandzhieva et al., 2023; Gagliardi, 2022). The application of advanced data analytics skills by enrollment and marketing HE professionals therefore contributes directly to the actionable items HEIs can make from leveraging data, and thus impacting sustainability measures (Chigbu & Makapela, 2025).

However, one of the biggest challenges in HE is finding professionals with the required set of data skills needed to transform enrollment and marketing data into actionable insight (Mikalef et al., 2018). Not only are these professionals required to hold content knowledge in HE trends and communication strategies, but also, as existing studies have argued, the data science base for these individuals far exceeds that of computer scientists, programmers, and information system specialists (Mikalef et al., 2018; Tsai et al., 2019). Furthermore, once professionals hold these skills, it becomes more difficult to recruit them into HE industries, since business and other corporate entities can offer higher salaries, better benefits, and more opportunities for professional growth (Daniel, 2019; Gagliardi, 2022; Gkrimpizi et al., 2023).

One area where professional development policies can help address this growing gap is to offer in-time data science and analytics support to professionals already in HEIs. For HE professionals already handling large educational datasets, this type of support may help them gain the agility needed to engage in more innovative continual improvement processes related to strategic planning goals (Al-Hemyari & Al Rajhi, 2022; Daniel, 2019). Providing in-time support to HE professionals to become transformational data-driven or data-informed leaders in enrollment and marketing requires agile professional development that encompasses several different data characteristics, including programming, visualization, transformation, and analytical skills (Gkrimpizi et al., 2023). Due to the nature of generative AI and the feasibility by which users can engage and leverage its processes, building these skills through AI's integration into HE processes can become a powerful capacity-building mechanism (Bickerstaff, 2025). In the following section, we outline a POC recruitment survey as an example of one such practical application, demonstrating how AI could change the nature of data ingest to support professional development and policy direction.

The Case of Survey-Based Skills

One of the most practically transformative, but perhaps yet underappreciated, aspects of generative AI's impact in HE is its enabling of professionals with limited technical or computer coding skills to make significant progress toward overcoming software and technical limitations in data collection and analysis. Common survey platforms such as Qualtrics, Survey Monkey, and Microsoft Forms are powerful tools for survey data collection within the existing scope of the application as determined by their respective

company stakeholders such as executives, product managers, and developers. While robust, the one-size-fits-all nature of an off-the-shelf survey platform can hinder HE professionals from being able to explore the creation of context-focused data collection or visualization tools where the primary goal is to better serve HEI stakeholders as part of institutional policy.

Generative AI-assisted development tools to some extent have enabled nontechnical professionals with limited computer programming experience to easily and quickly create POC applications as prototypes for more-innovative and more-focused data capture methods that could be more closely aligned with and informative to HEI policies. These prototypes allow HEIs to test novel data collection ideas and validate their helpfulness before spending resources to have them completely developed by tech professionals. To illustrate this workforce generative AI transformation in practice, we present in this paper a POC survey application developed with natural language as a response to a limitation in a commonly used survey platform. This context-focused presentation is meant to highlight some potential avenues for workforce development as well as to reveal implications of how AI can be used to support HE institutional policy.

METHODOLOGY AND FRAMEWORK

To align this POC to policy implications in HE professional development, this study is guided by two exploratory questions: (1) In what ways is generative AI democratizing programming and data science skills for HE professionals? (2) How does integrating generative AI into HE professional development shape institutional policy? To answer

the first question, we leverage the first phases of the DBR approach anchored in exploration, design, and production. A type of applied research, DBR is a methodology that seeks to guide, inform, and improve research and practice in educational contexts (Anderson & Shattuck, 2012) through a dual purpose of “putting knowledge to use, and through that process, generating new knowledge” (McKenney & Reeves, 2013, p. 139). DBR requires researchers to bridge theory and pedagogy to practice through the focus on a design and testing of an intervention that is situated in a real educational context and that has undergone several iterations (Anderson, 2005; Anderson & Shattuck, 2012). Bannan-Ritland (2003) proposed four stages of DBR that helped guide the development of our POC as an educational production for IR professionals. The four stages are (1) informed exploration of the context, including literature review, theoretical extrapolation, and connections to the educational context; (2) constructing the intervention and documenting the design and production of the educational innovation; (3) evaluating the application of the intervention in an appropriate educational context, typically using a mixed-methods approach; and (4) understanding and refining the broader impacts of the intervention for larger generalizations (Anderson, 2005; Bannan-Ritland, 2003).

Through a paired DBR-theoretical approach, our purpose in this study is to feature the first two stages of the initial pedagogical design and integration of AI as a learning mechanism, defining the existing issue as part of the Significance and Anchoring the Context sections, and then analyzing how each skill developed aligns with a policy implication for democratizing programming skills in HE administrators. Traditionally used to better understand technological interventions in education, DBR can contribute usable knowledge to

online programs, for example (Hoadley & Campos, 2022). Specifically, Hoadley and Campos argue, “The complexities of online learning reveal the pitfalls of lack of mutuality between research and design.” Lack of mutuality can be clarified through DBR studies that help to understand if learning stems from technological interventions or human interactions, as well as the psychology behind these dynamics (Hoadley & Campos, 2022, p. 208). This clarification is particularly relevant in this study since we center the design on a POC learning intervention conceptualized as a survey application with weather data for HE recruitment events, or other transferable applications in IR. Because weather has been recently linked to student enrollment and recruitment decisions (Alonso, 2026), using this type of data for this POC demonstration provides for relevance and alignment to current HE professional applications. In this POC we demonstrate an advanced design of an AI-supported learning intervention for graduate students in an online HE program.

To help us answer the second research question, we adopt a theoretical analysis guided by Gkrimpizi et al.’s (2023) conceptualization of digital transformation; this conceptualization is defined by three types of change: cultural, organizational, and operational. Since HEIs are considered complex organizations, Gkrimpizi et al. (2023) argued that transformations, particularly digital transformations such as the current trends related to generative AI, can implicate multiple shifts within organizational structure. Cultural change is often denoted in the shared values, behaviors, professional norms, or perspectives adopted by the people within HE institutions that may facilitate digital innovation. Structural changes that impact governance, processes, or policies that support infrastructure related to digital transformation are reflective

of organizational change. Operational related changes occur when the integration of technological transformations impact business processes, day-to-day workflows, or institutional dynamics (Gkrimpizi et al., 2023). In using these denominations, we analyze each step of the POC survey application, couched within the context of this program, as a data point for aligning potential data-relevant policy implications to either cultural, organizational, or operational changes founded in generative AI professional development.

LIMITATIONS

Methodological and applications-based limitations relate to this study. Concerning methodology, as noted, this study is centered on the first two stages of the DBR process (Anderson, 2005; Bannan-Ritland, 2003) and provides a deeper, yet focused, exploration on the development of a POC as an educational intervention in the form of an AI-anchored training for HE professionals. Due to the nature of this research, the focus therefore remains on the theoretical and pragmatic stages of the DBR process, rather than on the evaluative stages (Anderson, 2005; Bannan-Ritland, 2003). This focus allowed us to pair these parts of the DBR process with a theoretical analysis of policy development related to a potential POC application in HE. However, this approach also inherently denotes the limitations within the study. For example, evaluative data in the form of mixed-methods research to help understand the implications of the POC on different HE educational trainers was not collected at this time, which implies there was no requirement for Institutional Review Board approval since no human subjects participated in these initial stages. This potential data collection is set to be part of the next step of this DBR process

but limits the generalizability of the findings of the study. Additionally, because we pair this study with a theoretical analysis, we are presenting our design and development stages of the POC and the theoretical connections as findings, which differ from the more traditional quantitative and qualitative analyses of a DBR work. In the section below we share these paired DBR-theoretical analyses findings, focusing on the exploration, design and production stages of this process.

Regarding applications-based limitations, several can be noted. For example, we caution readers with respect to the accuracy of the survey generated and how its generation from AI-anchored enhancements may impact the way it can be interpreted by HE professionals. Furthermore, this POC was meant to serve as an example for training and is still in the design and production stage. To this end, we underscore that the use of the data shared as factual needs to be mediated and verified before any institutional use. Also, we acknowledge that the theoretical implications of this piece hold weight for policy introductions in the area of AI training. However, we cannot anticipate how the democratization of these skills through uneven organizational contributions may impact the frequency and accuracy of the data collected by HE institutions overall.

DBR APPLICATION

Exploration: Educational Context

The POC for this study was developed as part of a data science course design process for an HE online graduate-level program for HE professionals. However, the exploration stage of this process began with a deep investigation of the current

literature on HE professional training, as evidenced with the above discussions, as well as connections to the context in which this POC can be applied. After investigating the initial gaps in training for HE professionals with respect to AI integration and data science, we turned our attention to the design and development of this POC for our courses as a way to explore its integration to a practical context. Since the population we serve in this program is mostly HE personnel, several of the skills developed in the content and data science courses are directly applicable to HE professional roles. In the iterative versions of this POC, we aimed to intentionally integrate generative AI in skillset development processes that could be transferable to professional development trainings at various HEIs. The purpose of the POC was to help HE personnel with limited technical or computer science knowledge (e.g., current students in our courses) to engage in generative AI integration to develop a survey application responsive to evolving recruitment needs at HEIs, enhancing basic survey designs with weather-based data to understand how this may impact engagement and university perceptions at different events. As a note, during our initial exploration, recent findings have indicated that weather-related experiences may influence students' enrollment or recruitment actions, making this POC development particularly relevant for HE professional trainings (Alonso, 2026).

Design: POC Survey Example

The current version of the POC recruitment event feedback survey application presented here was made entirely by communicating with the Claude large language models in normal conversational language. Specifically, the app automatically collects and transforms historical weather data to give context to recruitment event satisfaction scores

obtained from Likert survey responses. At the time of this writing, the common survey platform assessed lacked the ability to retrieve and make use of historical weather data during survey submission while applying conditional logic (e.g., transforming meteorological codes based on precipitation amounts) to ensure data were interpretable and presented on an in-application dashboard for analysis.

The platform for which this POC is offered in response does offer some limited features to retrieve data from external web-based sources and dashboard presentations. These functions require paid subscriptions, have overly simple off-the-shelf visualizations with limited functionality, and ingest data in a way that would require export for intuitive interpretation and calculations of the weather data. This type of impromptu infrastructure building that is heavily based on human resource allocations in the way of programming and software knowledge further exacerbates the technological limitations of smaller institutions with limited funds that cannot afford to hire external teams for these grassroots-type functions (Gagliardi, 2022). The custom POC application presented in the paper demonstrates how AI-assisted development would allow nontechnical stakeholders to explore context-specific data collection that might not be obtainable in existing survey platforms when striving to support HE institutional policy.

Overview of Setup for HE Professional Development

The prerequisites for HEI professionals to develop POC survey applications to test custom data collection approaches can be minimal. A subscription at the free or pro tier (~\$17 per month) to Anthropic's product Claude AI and the

freely available R and Posit's RStudio would suffice for many projects. Beyond this basic setup, an installation of Microsoft's freely available Visual Studio Code (VS Code) and the free extension in VS Code called Claude Code for VS Code (Figure 1) will make the iterative conversational development of the POC require less copying and pasting since Claude will be able to work directly in the folder with the user. Additionally, having a free subscription to Posit's shinyapps.io hosting platform will make

deployments of apps possible for stakeholders to engage with them online. Used in the DBR study is the mentioned VS Code with Claude Code extension seen in Figure 1. The resulting product was deployed to shinyapps.io to share as an example approach to that could be exhibited to stakeholders. Although helpful, a basic understanding of R and Shiny is not strictly necessary. Table 1 summarizes the setup factors to consider succinctly.

Figure 1. VS Code with the Claude Code Extension

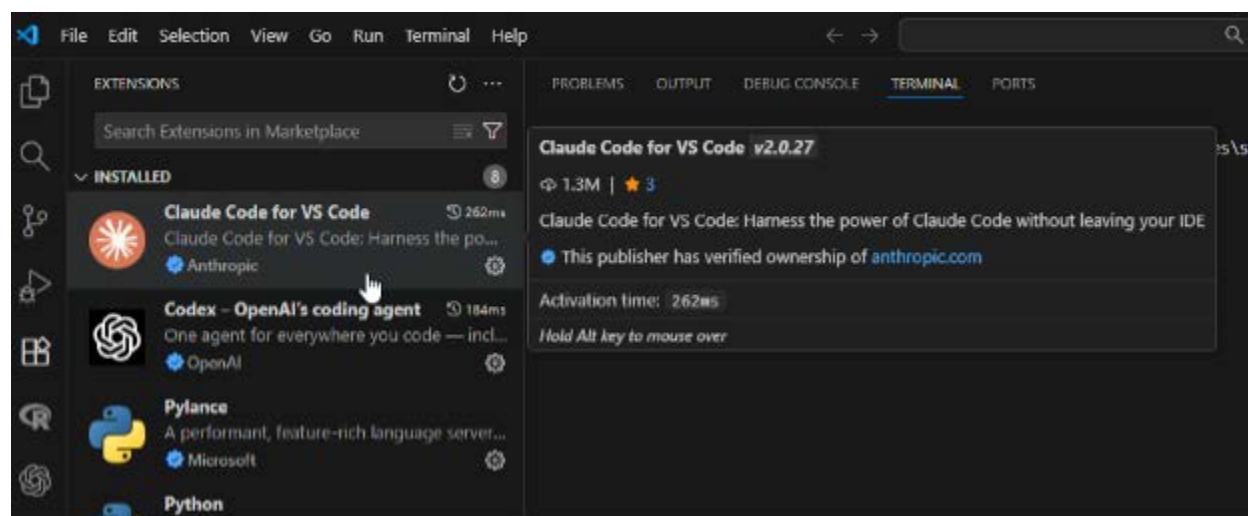


Table 1. Example Setup for Creating POC Applications with Natural Language

Setup Component	Purpose	Workforce Training Possibilities
Generative AI Access (e.g., Claude)	Used to interpret natural language input to code	- Natural language to code - Various AI model strengths and limitations
Coding language interpreter and development environment (e.g., R and R Studio)	Provides the programming language and respective tools for AI-assisted code	- Basic understanding of AI coding - Basic workflow for prototyping
Integrated AI assistant (e.g., Claude Code extension in VS Code)	Enables iterative conversational coding directly in project folder	- AI-assisted software creation workflow basics - Code creation to refinement
Infrastructure: local or remote (e.g., Shinyapp.io)	Determines who will be able to interact with the POC and how	Basics of infrastructure for simple web apps

The setup components mentioned are not difficult to implement but can be more easily accomplished and improved with experience. This example setup further exposes professional development opportunities for HE professionals who do not hold expansive technical knowledge but could benefit from some basic conceptual understandings to aid in rapid prototyping of POC applications. This type of training would not only assist HE professionals to better work with generative AI, but could also potentially make progress in overcoming the barriers to digital transformation at HEIs (Gkrimpizi et al., 2023).

Production: POC Iterations

The first iteration produced from this POC natural language coding process varied. In the initial stage, factors such as previous conversations held in memory by the large language models chatbot from other communications or stored user profiles played a role in what the AI tool produced. Initially, the result was quite close to what was requested, but it needed improvement. The first hurdle was to maintain persistent data after the application was closed in the browser for testing and to exhibit the POC for stakeholders in order to use this as a professional development tool. In subsequent iterations, the data displayed on the administrator panel (hereafter as admin panel) dashboard also had issues. Through testing and manual verification, days that were not rainy were showing up as rainy and it was not easy to interpret the raw weather data in the table. We addressed this challenge by adding logic to calculate precipitation conditions to represent actual weather conditions. In this same iteration, testing was also slower when we had entered data manually; a template was created to rapidly enter data into the system for the POC

testing and demonstration to stakeholders. The issues discussed in the paragraph were resolved when we created the final iteration.

POC Result

The completed iteration of the POC application developed completely with natural language prompts was deployed to https://sbndco-michael-littrell.shinyapps.io/weather_survey_v2/ with a password of 1234. This prototype is an interactive means to understand and demonstrate how a completely developed and robust application could meet the needs of HE stakeholders who collect data to support institutional policy. The core workflow of this app starts with data ingested as a result of student surveys responses. When the submission occurs, the POC reaches out to the Open-Meteo application programming interface (API) for historical weather data. Each survey record is collated in a table in the admin panel where statistics and data visualizations are seen to aide analysis. Comma-separated values files can be downloaded and uploaded for external analysis and testing of the POC. Figure 2 shows an image capture of part of the dashboard. Seen here are the buttons for managing data, scorecards with calculated variables, and data visualizations showing satisfaction in relation to temperature and time of occurrence. The survey user interface (UI) where students would enter their responses is shown in Figure 3. The application R Shiny code can be found at https://github.com/mlittrell-ttu/hred_weather. Finally, Figure 4 shows an interaction with generative AI where conversational language prompts are entered to work with files in a shared folder where the POC application is constructed. Together, these three figures show the complete conversational input process with resulting output from the implementation of the POC.

Figure 2. Admin Dashboard Developed with AI Tools

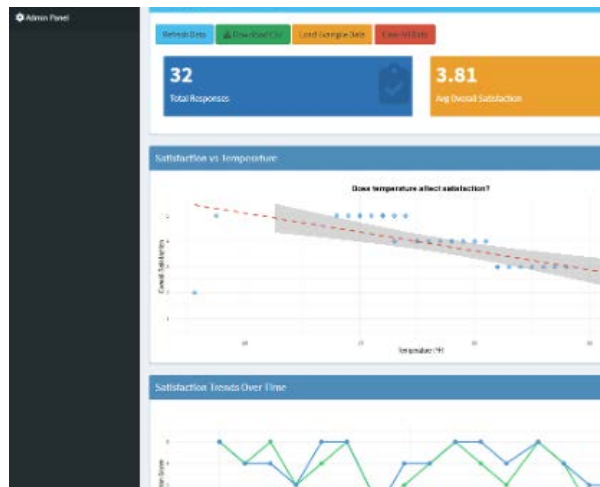
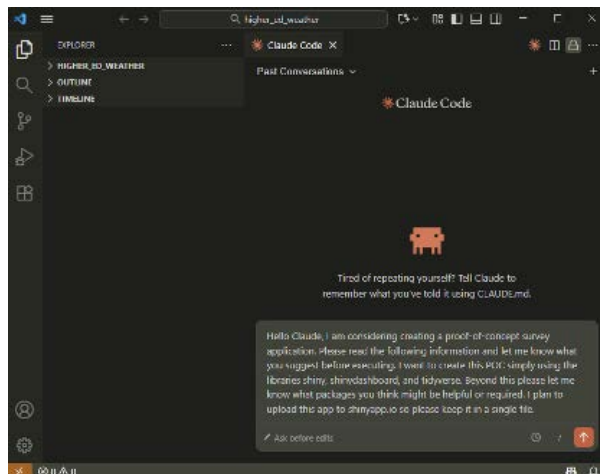


Figure 3. Survey UI Developed with AI Tools

The Event Feedback Survey form is titled 'Event Feedback Survey' and includes a thank-you message: 'Thank you for attending our event! Please share your feedback.' The form contains several input fields: 'Student ID:' with a placeholder 'Enter your student ID', 'Date of the Event:' with a date picker set to '2024-12-08', and 'Event Location (City):' with a placeholder 'Chattanooga, TN'. Below these are two rating sections. The first is 'Please rate your experience:' with a title 'How satisfied were you with the overall event?' and five radio button options: 'Very Dissatisfied', 'Dissatisfied', 'Neutral', 'Satisfied', and 'Very Satisfied'. The second is 'How satisfied were you with the organization and logistics of the event?' with the same five radio button options. A 'Go back to Survey' button is at the bottom.

Figure 4. Claude AI in VS Code Receiving Prompts to Create Code



POC Lessons Learned

The example POC application for this study was built with simple conversational language prompts and the editing of code was avoided to be accessible for HE professionals who might not have coding experience. This process is presented here through the DBR analysis in a templated way that can be fed directly to Claude to create a data collection survey application. This was intended to be an illustrative example of AI implications for modern data workers in HE. Possibilities for workforce policy implications emerge through the natural language coding theoretical analysis.

THEORETICAL ANALYSIS

Example of a Natural Language Coding Workflow

As part of this theoretical analysis, workforce-related and policy-related connections to Gkrimpizi et al.'s (2023) digital transformation theory (i.e., cultural, organizational, or operational changes) were utilized to understand implications of the POC for professional development in HEIs. Table 2 illustrates a complete breakdown of the POC workflow as detailed in the DBR Application section of this paper with connections to potential policy implications for HEIs and relevant explanations to the impact of generative AI in these areas. This process is further broken down into the sections that follow, detailing the different parts to consider when constructing the application where the conversational language prompts are seen first. Each section will include the explanation of the step, starting with the command or script needed to begin the step, followed by the purpose and connections to policy implications.

Table 2. Natural Language Workflow for POC Creation

Step	Purpose	Policy Connection
0 Scoping Greeting	Defines project scope and specific packages	Cultural: AI enables nontechnical professionals to initiate basic infrastructure and project scope for creating POC apps that support HEI policy.
1 Articulation of the Problem	Couches the POC as a means to solve a problem	Organizational: AI underscores the need for HE professionals to understand basics of software creation as a response to a problem.
2 Ideal Solution	Focuses the AI on the POC outcome	Operational: AI connects solution design and to institutional policy and goals through POC creation.
3 Specifics (UI, Admin, Logic)	Details key app components for the user, admin, and backend logic	Organizational: AI frames basic applied software literacy as HE workforce development priority where nontechnical professionals can make meaningful technical contributions to support HEI goals.
4 Iteration and Refinement	Tests and refines iteratively through multiple interactions	Cultural: In these iterations AI is illustrated as an effective tool for refining POC apps, further underscoring the importance of workforce training of nontechnical HE professionals.

Step 0: Scoping Greeting

STARTING SCRIPT TO ENGAGE WITH AI.

Hello Claude. I am considering creating a POC survey application. Please read the following information and let me know what you suggest before executing. I want this POC to be created simply with the libraries shiny, shinydashboard, and tidyverse. I plan to upload this POC to shinyapp.io so make sure it is a single file. Beyond this, let me know any other packages or approaches you think would be helpful.

EXPLANATION

Here the scope of the project is specified for Claude since Claude tends to overbuild and overcomplicate. For context, if the reader has no previous R or Shiny experience, these packages can build many applications. The instructions are calling for the Shiny web application framework to build the app with a dashboard specific package (shinydashboard) to keep the UI simple. The tidyverse package performs calculations and creates data visualizations. This step establishes the foundation for a well-understood workflow with the AI tool. Its purpose is to ensure clarity and to restrict any unnecessary complexity while the code is being generated.

POLICY CONNECTION ANALYSIS: CULTURAL

Reaching toward generative AI coding tools to overcome current survey platform limitations for data collection represents a shift of professional culture where innovative technical approaches are now available to nontechnical employees through democratized AI-assisted computer coding. Stakeholders can use conversational language to initiate infrastructure and project scope. This

more-general access to previously exclusive areas of professional work in pursuit of institutional policy goals by nontechnical workers underscores the need for AI-focused workforce training. For example, HEIs could implement training by creating programs to teach professionals the basics of POC app infrastructure to ensure their projects have a greater chance of success.

Step 1: Articulate the Problem

WHAT PROBLEM DO I WANT TO ADDRESS?

I collect surveys with an existing survey platform after campus recruitment events across Tennessee. Later, I pull all responses into a spreadsheet and then I look up weather data for each event date and city because I think bad weather could impact our event satisfaction scores. Looking up historical weather data and transforming it into interpretable info takes a long time for each event. The current platform doesn't let me collect and look up weather data in a useful way.

EXPLANATION

Including the information in this step can be helpful to Claude to understand what the intended outcome is and as input to refer back to when working to iteratively improve the POC app. The real-world problem is communicated at this step to increase the chances that AI will produce something helpful. Breaking the problem down into clear parts provides space for the professional to engage with computational thinking to understand how to most efficiently resolve the issue with the POC solution. Represented here too is a process that can be honed and practiced as the HE professional gains experience prototyping with AI in pursuit of meeting HE policy goals.

POLICY CONNECTION ANALYSIS: ORGANIZATIONAL

Describing a problem conversationally where the possibility of progress on a POC app solution despite little or no computer programming experience is a skill that is likely unique and new in many professional organizations. It is one facet of the implications of the impact of AI that will be important to train HE professionals so they can be productive members of a modern workforce. A possible emerging workflow where POCs are created with conversational language could invite the reconsideration of cross-departmental work. Instead of work being divided cleanly into technical and nontechnical parts, POC development by nontechnical stakeholders could serve as the initial step that guides the creation of robust and complete applications.

Step 2: Ideal Solution

IDEALLY, HOW WOULD I ADDRESS THIS ISSUE?

I would like to create an app that collects data from students after university recruitment events that automatically retrieves weather data for a given city. The data collected needs to be easy to interpret and visible on a dashboard that will be helpful to recruitment planning professionals.

EXPLANATION

This step is for the HE professional to describe outcomes in plain language before the code is generated. At this point in the POC process, the HE professional generally defines the solution and can communicate about the broad pieces of the app structure. This step can be helpful to the AI chatbot for distinguishing what is essential and what might be out of scope. Directly clarifying goals can increase the odds that the resulting POC will meet

expectations with less refinement. Like all the other steps in the process, this step also provides an input to refer back to when iteratively improving the app.

POLICY CONNECTION ANALYSIS: OPERATIONAL

Defining the ideal solution can be a meaningful part in the process where the HE professional connects the POC possible outcome to policy goals. Essentially it can serve as the point at which HE expertise and the understanding of the problem are manifested into alignment with institutional policy goals to support stakeholder evidence-based decisions. This step reinforces the notion that software creation can be an effective way to overcome professional obstacles. POC solutions could be beneficial across a wide range of policy objectives and departments. As such, workforce development that teaches HE nontechnical professionals to work with AI-assisted coding tools to create prototypes to solve problems could be fruitful.

Step 3: Specifics

SURVEY UI

I need to capture data entered by students in the user facing part of the application that includes an anonymous student ID created by students at the event, the date of the event, and their location in Tennessee (i.e., Nashville, Knoxville, Murfreesboro, Cookeville, Memphis). Also ask two survey questions of the students (How satisfied were you with the overall event? How satisfied were you with the organization and logistics of the event?) and present Likert response options (Very Dissatisfied, Dissatisfied, Neutral, Satisfied, Very Satisfied). Students should be able to submit their survey and the application should capture weather data for the city specified automatically.

ADMIN UI

I need an administrative dashboard to capture and analyze the results of all survey responses and the respective weather data collected. Create scorecards to highlight total responses, overall satisfaction, average temperature, and rainy events. Create graphs that show satisfaction by temperature, satisfaction by weather condition as a box plot, and satisfaction trends over time for both overall and organization satisfaction. Also create a table that shows the variables captured for each survey submission including timestamp, student id, event date and location, overall satisfaction rating, organization satisfaction rating, temperature in Fahrenheit, the weather condition category, precipitation amount (inches), relative humidity percentage, and maximum wind speed (miles per hour).

SERVER LOGIC

Use the Open-Meteo Historical Weather API to automatically retrieve weather data for each survey submission based on the event date and location. Store latitude and longitude coordinates for each Tennessee city mentioned. Collection timestamps in my local time zone. I want to know: the average temperature in Fahrenheit, how much it rained (inches), the humidity percentage, wind speed (miles per hour), and what the overall weather condition was (e.g., sunny, rainy, cloudy). Store all of this information in a comma-separated values file and set a simple password (1234) for the admin panel.

EXPLANATION

Specified in this step are the three key components of the POC. The survey interface is communicated to the AI tool in terms of what data to collect and what

questions to answer. When this part of the app is specified, the mechanisms by which the end user will interface with and experience the app are forefront. The data collected here could be aligned with HEI goals and policies. Specific terminology can be found at the official shiny component documentation (<https://shiny.posit.co/r/components/>) and serves as a helpful visual guide. For the admin dashboard, visualizations such as scorecards, box plots, and trends over time can be requested. Essentially, almost any common data visualization can be used on the dashboard and customized to a high degree with ggplot2. Its documentation is here: <https://ggplot2.tidyverse.org/reference/>.

For the logic of the POC app, generative AI is solid at explaining the small behind-the-scenes (i.e., backend) considerations needed to be hosted on shinyapp.io or locally on the creator's own computer. Generally, these considerations are typically about where the data come from, where data will be stored (CSV files work well), and how the data should be processed and transformed before being displayed to the user. AI can also help you locate good free educational resources if more understanding is essential. Querying the AI tool for these types of information is not represented in the present paper but could be a part of the workflow. If any necessary details are not included for any aspect of the app, the AI tool will typically try to implement an essential feature that can serve as a starting point for iteration.

POLICY CONNECTION ANALYSIS: ORGANIZATIONAL

Knowledge essential to this step is not a software developer's deeply technical knowledge. It is more like a skillset that is part applied data science and part conceptual knowledge of the basic workings

of computer applications all couched within HE domain expertise. These parts all work in concert to iteratively create the POC to support institutional policy goals. Developing this combination of blended skills could be a policy priority for the future of workforce development where HE professionals are taught to engage with AI in this way.

As AI becomes a common part of expected workflows at HEIs, professional training programs could consider offering more than the teaching of traditional data skills. Instead, this training could benefit from being refocused to include technology and AI considerations. It might be beneficial to develop a new cross-functional approach that incorporates aspects of data science, tech systems, and iterative software design to overcome problems. This proposed training methodology could be well aligned with emerging HE policy issues faced today since institutions strive to redefine their policy goals in an increasingly uncertain educational environment.

Step 4: Iterate

PERSISTENT DATA

I notice that the app is not saving the data entered when the browser is closed. I would like to have this data persist for demonstrating the POC. What are the options that would work online at shinyapp.io and the other options that would work offline on my computer?

API DOCUMENTATION CHECK

I want to check that the variables being used line up with what I'm seeing in the app. Provide a list of the variables used from the Open-Meteo API and explain how they are being used in the app.

WEATHER CODE CONVERSION

I notice that the weather condition displayed on the table is not matching reality and is not easy to interpret. This is an essential part of the app. I looked up the codes in the Open-Meteo documentation. Please map them like this:

- Code 0 = Clear Sky
- Codes 1–3 = Partly Cloudy
- Codes 45, 48 = Foggy
- Codes 51, 53, 55 = Drizzle
- Codes 61, 63, 65 = Rain
- Codes 71, 73, 75 = Snow
- Codes 80, 81, 82 = Rain Showers
- Codes 95, 96, 99 = Thunderstorm

For the codes about rain, transform them with this logic for interpretation on the dashboard:

- If the weather code says “drizzle” (codes 51–55) but precipitation is less than .01 inches, call it “Clear sky” instead.
- If the weather code says “rain” (codes 61–65) but precipitation is less than .05 inches, call it “Partly cloudy” instead.
- If the weather code says “rain showers” (codes 80–82) but precipitation is less than .05 inches, call it “Partly cloudy” instead.

TEMPLATE WITH DUMMY DATA

I need to be able to show this POC to stakeholders and entering data from the survey UI takes time. Can you create an admin dashboard button to download a CSV template populated with 100 mock observations that could highlight a couple of trends in the dashboard visuals?

EXPLANATION

AI worked from the first version of the requested POC app built with conversational language prompts and addressed several issues iteratively with the AI tool to ensure the POC worked in the intended way and was demonstratable. Collected survey and weather data needed to persist after the browser was closed. The AI tool presented various possibilities, including local comma-separated values files and cloud-based databases. A free solution that used Google Sheets was implemented where data were stored in a single spreadsheet in a free account. This minimal setup was handled mostly by AI; where human intervention was needed, AI clearly spelled out instructions.

Reviewing the Open-Meteo API documentation helped ensure accuracy and clarity of the data being collected by the POC. AI checked variables in the documentation against the dashboard results for alignment. Weather code conversion addressed inconsistencies in the data collected and real-world conditions. Numerical codes were mapped to human-readable categories (e.g., Clear sky). Additional logic was added to calculate the conditions with precipitation thresholds to more accurately represent weather conditions. Template functionality was also included to rapidly populate the dashboard with mock observations for demonstrations to stakeholders and for testing.

POLICY CONNECTION ANALYSIS: CULTURAL

The iterative step emphasizes a potential workforce development policy opportunity to train modern HE workers on workflows for iterative design to overcome professional obstacles with prototyping. The opportunity could be indicative of a new set of AI-centric skills needed to meaningfully contribute

to and refine a functional POC in support of institutional policy goals. Potentially, connections could be made more broadly to concepts related to prototype iterations such as Design Thinking and Human Centered Design. This AI literacy could be an important foundational part of working to prototype applications and other AI-assisted workflows that have yet to be conceived.

IMPLICATIONS

The Democratization of AI Skills for HE Professionals

The DBR analysis for this study offers a path to creating a data collection survey POC that can be replicated with minimal technical expertise and that can be improved with practice. It demonstrates how an HE professional with limited coding experience could meaningfully contribute to the creation of software tools to surpass the features of off-the-shelf survey platform solutions to support institutional policy goals. The resulting prototype could be a means to validate and iteratively improve while verifying its usefulness. This POC could then be extended to a fully developed application by technical experts. The workflow presented to arrive at this POC iteration highlights opportunities for workforce development and the ways in which this technology can be leveraged to democratize AI skills for HE professionals. The POC process as displayed in this paper was just one example. However, the process is very flexible and can be suited to a wide variety of use cases since R is a free and open-source statistical computing language with a deep pragmatic history. In this sense, the language and the Shiny web framework can largely be applied to most any data and context relevant to the HE practitioner seeking to create a POC. Again,

the intention with using a weather-based example stems from recent studies that indicate weather-related experiences impact students' enrollment or recruitment decisions (Alonso, 2026). To this end, we also acknowledge that this specific POC focuses on training that may be more relevant to specific HE positions, including those in enrollment, admissions, or students' affairs units. However, these skills and applications are transferable and can be applicable to IR specialists in different institutions. For example, IR professionals who create enrollment reports, or who work with student affairs specialists to better understand student-related data and help to create interactive and practical dashboards, could leverage the skills highlighted in this paper for broader IR applications in HE (Gagliardi, 2022).

The Transformation of Institutional Policy

The theoretical analysis for this study highlighted areas where AI can transform policy. Potential cultural implications for HE workforce training are revealed through the theoretical analysis presented in this paper. The digital transformation is both important and ongoing (Chigbu & Makapela, 2025). The need for generative AI workforce training is likely related to the overall digital transformation and could make it even more critical, especially in data-rich areas leveraging institutional data. The capabilities of generative AI are likely more understood when working with coding tasks (Chen et al., 2021) compared to nontechnical tasks. Teaching the value of these generative AI capabilities and their value in the service of institutional policy goals and stakeholders for nontechnical employees will be important for workforce development.

Organizational opportunities for workforce development could also be understood from the POC presented here. HEIs may need to consider how generative AI workloads would be carried out across departments. If POC development and greater technical ability by nontechnical workers becomes the new standard operational dynamic, then partnerships between technical departments and more-traditional departments could be beneficial. Cross-functional teams comprised of a blend of domain and tech experts could work in tandem to create software tools that support institutional policy objectives. IT and technology infrastructure work also need to be planned to best support workflows for prototype development and deployment for stakeholder review and testing by nontechnical workers.

The implications for HE workforce training and their implementation could look different depending on the HEI. As an example, provosts and academic affairs offices could create formal AI-assisted training and prototyping policies to provide formal pathways for the initial creation and further review of POCs by IT departments for consideration to be more robustly developed. Professional development committees could adopt conversational coding competencies as an explicit part of staff training that could complement existing data and technology skill training requirements. At the state systems level, governing boards could prioritize the funding and piloting of programs that teach coding with natural language to address the technical gap that resource-constrained institutions face when attempting to build data-informed decision-making capacity. The policies that could govern this type of training could be created in tandem with faculty senates and administrative councils to ensure their broad adoption and support.

Perils

Potential perils of AI-assisted code generation exist. As Igoe (2025) indicated, “Much like a healthy lifestyle preempts future health problems, proactively addressing one’s digital health is essential” (para. 11). To this end, since nontechnical workers are newly empowered to create and alter software, they must be cognizant of and have a basic understanding of issues such as data governance, security, and access; their understanding will need to be continuously updated and checked for quality assurance purposes. Security issues and vulnerabilities will also need to be considered by tech professionals to ensure that prototype software created is not harmful to existing environments (Taeb et al., 2024). While there is risk, it is likely that AI and its capabilities will become an integral part of many HE institutional workflows. At the same time, for institutions that would like to anticipate addressing these issues, having a data governance program and implementing Identity and Access Management (i.e., system access and permissions) rigorously may provide a proactive posture. Overcoming these potential pitfalls while having in place training programs that ensure HE professionals are both aware and understand the implications of extensive AI use in this content will be part of that adoption process. It is the involvement of expert technology stakeholders (e.g., cyber security vendors, information technology departments) that is essential to mitigating perils of these efforts.

CONCLUSION

Historically, HE workers with no application development experience who wanted to overcome professional data collection limitations by making

progress toward the creation of a digital tool tailored to their specific context, would likely have had to work with technology professionals or study application development in depth to become proficient with a programming language. Even if the HE professional worked closely with a development team, some degree of agency and fidelity is lost in the process where the needs of the user and domain context are best understood by the expert seeking the creation of the application. Although not perfectly refined, as seen through the POC survey application illustrated in this paper, AI tools have altered this dynamic of software creation by enhancing and supporting nontechnical workers to make progress in this way with natural conversational language of desired functionality to generate new capacity building support for HEIs.

Through this DBR study, we not only show how the POC survey applications use generative AI to build capacity, but we also use Gkrimpizi et al.’s (2023) conceptualization of digital transformations to demonstrate how each step in this process holds a professional development policy implication. Through the five steps in the POC survey application process, we see there are two cultural, two organizational, and one operational policy implication that holds weight to how effective such integrations can be at digital transformations that leverage institutional data. Specifically, in steps 0 and 4 generative AI serves as a tool for capacity building, asking HE professionals to not be experts in digital literacy, but rather to hold AI literacy to be able to enact transformative change (Bickerstaff, 2025). In steps 2 and 4, the organizational changes, as demonstrated by articulating the program and detailing key app components, tasks HE professionals with leveraging AI literacy to affect the efficiency of nuanced institutional processes or procedures. In step 2, the ideal solution, operational

change is evident, wherein HE professionals connect solution design to impact daily operations through larger institutional policies or goals.

Effectively, through the integration of generative AI in the development of POCs, such as the one illustrated here, or others, it becomes more relevant for professional development to focus on AI literacy and competency to become capacity builders rather than experts in specific areas such as data analytics or programming (Bickerstaff, 2025; Gaftandzhieva et al., 2023). This example provides an illustration for HE professionals that also holds implications to how AI is potentially reshaping existing workflows with respect to how professionals and administrators can leverage institutional data to affect institutional growth. In using similar POCs in other HE areas, like admissions, student engagement, or teaching and learning, this technological integration holds the potential to support HEI in ushering in the current digital transformation through intentional professional development in this area.

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