INTELLIGENT TECHNOLOGIES IN EDUCATION

Potentially Divergent Paths in the AI Era? A Mixed-Method Policy Analysis of Artificial Intelligence Integration Frameworks Across Texas Hispanic-Serving Institutions

Dr Chunling Niu[a], Soheila Sadeghi[a], Dr. Jin Rui[b], Dr. Stephanie Grote-Garcia[a], Dr. Ashley Love[c], Brian Waltman[a], Dr. Theresa Garfield[d], and Dr Arthur Hernandez[a]
[a] University of the Incarnate Word, USA; [b] Shenzhen University, P.R.C; [c]Southern New Hampshire University; [d] Texas A&M University-San Antonio, USA

Abstract

As artificial intelligence (AI) transforms higher education, institutions face critical challenges in developing appropriate governance frameworks, particularly in U.S. Hispanic-Serving Institutions (HSIs) where technological integration intersects with educational equity concerns. Drawing on institutional isomorphism theory and the framework of policy diffusion, this study conducts a systematic comparative analysis of AI integration policies across nineteen U.S. HSIs in Texas to understand how different types of institutions approach AI governance. This study employs mixed methods combining qualitative content analysis, policy network analysis, and quantitative scoring of institutional documents. The analysis reveals seven distinct AI policy approaches among U.S. HSIs, ranging from Holistic Integrators to Emerging Adopters. Policy network analysis demonstrates strong diffusion patterns among institutions within the same university systems, while quantitative scoring indicates significant disparities between research-intensive universities and other institutions. The findings suggest that institutional characteristics significantly influence AI policy development, revealing a concerning policy development gap between research-intensive universities and teaching-focused institutions or community colleges. These findings provide crucial insights for policymakers and institutional leaders working to develop equitable higher-ed AI integration frameworks.

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Introduction

Higher education institutions are facing an unprecedented challenge as artificial intelligence (AI) technologies rapidly evolve and permeate various aspects of academic life. Unlike traditional educational AI that follows predetermined rules (automated grading, adaptive learning), generative AI tools like ChatGPT create original content and human-like responses, fundamentally challenging academic authorship, assessment, and integrity policies (Dwivedi et al., 2023). Rather than seamless integration, many institutions find themselves grappling with uncertainty, scepticism, and complex questions about AI's role in education. Recent surveys indicate widespread apprehension among faculty about AI's impact on academic integrity, teaching methodologies, and institutional values (Eaton, 2023). This hesitation is particularly evident in policy development, where institutions must balance innovation with ethical considerations and educational equity.

Current State and Emerging Challenges

The current landscape of AI in higher education is marked by significant disparities in institutional readiness, understanding, and approach. While some institutions rush to embrace AI technologies, others maintain cautious scepticism, leading to a fragmented response across the sector. In terms of AI policy development, higher education institutions around the world have adopted varied approaches, offering important lessons and revealing persistent gaps. The European Union's universities have emphasized ethical AI frameworks, with institutions like the University of Amsterdam and ETH Zurich developing comprehensive guidelines that prioritize transparency and accountability (Molina-Carmona & García-Peñalvo, 2024). Australian universities have focused on academic integrity, with multiple institutions collaborating to create unified assessment guidelines (Gulumbe, Audu, & Hashim, 2025). Asian institutions, particularly in Singapore and South Korea, have integrated AI literacy into core curricula (Wong, Aristidou, & Scheuermann, 2025). However, these initiatives predominantly emerge from well-resourced institutions, leaving critical gaps: (1) limited frameworks for resource-constrained institutions, (2) insufficient attention to culturally responsive AI integration for diverse student populations, and (3) absence of models that balance innovation with equity considerations specific to minority-serving institutions. As Hu (2023) notes, the lack of coordinated policy responses to AI integration risks exacerbating existing technological and educational disparities, particularly affecting minority-serving institutions and their stakeholders. These gaps underscore the need for context-specific research on how minority-serving institutions, particularly Hispanic-Serving Institutions (HSIs) in the United States, navigate AI policy development within their unique institutional constraints and missions.

Hispanic-Serving Institutions (HSIs) represent a critical yet understudied context for AI policy development for higher education in the United States. HSIs are U.S. federal designations for accredited institutions enrolling at least 25% Hispanic students, comprising 19% of all U.S. colleges but serving 67% of Hispanic undergraduates - Texas has one of the largest concentrations of HSIs nationally, with the 19 institutions in our study ranging from R1 research universities to community colleges, primarily serving first-generation, low-income students with instruction predominantly in English though some offer bilingual support services (Excelencia in Education, 2023). HSIs face unique challenges in technology integration: they typically operate with fewer resources than their non-HSI counterparts - receiving an average of $3,000 less per student in federal funding (Garcia et al., 2019) - while serving a student population with distinct needs, including higher percentages of first-generation college students, part-time enrolees, and students from low-income backgrounds (Nuñez & Bowers, 2011). The intersection of rapid AI advancement with these institutional characteristics creates a particularly complex policy landscape that demands focused investigation. While research has examined AI policy development in elite institutions (Wu, Zhang, & Carroll, 2024) and international contexts (UNESCO, 2023), the specific challenges and approaches of HSIs remain largely unexplored, despite their crucial role in advancing educational equity for the fastest-growing demographic in U.S. higher education.

To address this critical need to understand the current state of AI policy development across HSIs, this study aims to: (1) systematically analyze and categorize current AI policy approaches across nineteen Hispanic-Serving Institutions in Texas, USA; (2) identify patterns of policy diffusion and institutional factors that influence AI governance framework development; and (3) evaluate the alignment between AI policies and HSI missions of educational equity. Through this comprehensive analysis, we seek to answer three research questions:

RQ1: What distinct approaches to AI policy development have emerged across Texas HSIs, and how do these approaches vary by institutional characteristics?

RQ2: What patterns of policy diffusion exist among Texas HSIs, and how do institutional networks influence AI policy adoption?

RQ3: To what extent do current AI policies address equity considerations central to HSI missions?

By addressing these questions through mixed-methods analysis combining qualitative content analysis, policy network analysis, and quantitative scoring, this study provides evidence-based insights for policymakers and institutional leaders working to develop equitable AI integration frameworks that advance rather than hinder the educational missions of minority-serving institutions.

Literature

The emergence of artificial intelligence in higher education presents unprecedented challenges to institutional policy frameworks and governance structures. This review examines how higher education institutions, particularly Hispanic-Serving Institutions (HSIs), navigate policy development in response to rapid technological change, revealing critical gaps in our understanding of AI policy formation in minority-serving institutions as they balance innovation with their distinct educational missions.

Challenges in Institutional Policy Adaptation to Rapid Technological Change

Higher education institutions face mounting pressure to develop and adapt policies in response to accelerating technological change. Recent research highlights the significant challenges institutions encounter when attempting to formulate timely and effective responses to technological innovations. A comprehensive study by George and Wooden (2023) found that over 70% of U.S. higher education institutions lack structured frameworks for evaluating and responding to emerging technologies, leading to reactive rather than proactive policy development.

The rapid emergence of generative AI technologies has particularly exposed institutional vulnerabilities in policy adaptation. Niraula (2024) documents how U.S. institutions struggled to respond to ChatGPT's release, with many hastily implementing restrictive policies that proved difficult to enforce and potentially counterproductive to educational goals. This reactive approach often stems from what Klimenko (2024) identifies as a technological policy lag - the growing gap between the pace of technological advancement and institutional policy development capabilities. This lag is particularly evident in higher education, where traditional governance structures and deliberate decision-making processes struggle to keep pace with rapidly evolving technologies (Bastedo, 2012). Studies across multiple institutional contexts confirm this pattern, with policy development cycles averaging 18-24 months while major AI capabilities advance in 3–6-month intervals (Marcucci & Verhulst, 2025).

For Hispanic-Serving Institutions, these challenges are often compounded by resource constraints and unique institutional missions. Research by Bell, Aubele, and Perruso (2022) reveals that U.S. HSIs face additional complexities in technology policy development, as they must balance innovation with their commitment to serving historically underrepresented student populations. This balancing act becomes particularly critical as evidence suggests that poorly planned technological integration can exacerbate existing educational inequities (Safidon, 2024).

Factors Influencing Institutional Policy Formation & Development

The development of institutional policies in higher education is shaped by a complex interplay of internal and external factors that significantly influence both the process and outcomes of policy formation. Understanding these factors becomes particularly crucial as institutions grapple with emerging technologies that challenge traditional policy frameworks. Research has identified several key determinants that shape institutional policy development, especially in the context of technological integration.

Institutional characteristics, including size, research classification, and resource availability, play a fundamental role in policy development capabilities. Hewitt-Dundas (2012) demonstrates that UK research-intensive universities typically possess more robust policy development infrastructures, allowing for more comprehensive and proactive policy creation. However, this advantage often creates a so-called "policy development divide" between well-resourced institutions and those with more limited means (Ortagus et al., 2023).

External pressures, including accreditation requirements, federal regulations, and market competition, significantly influence institutional policy trajectories. Yorke and Vidovich (2016) reveal how these external forces in Australian universities often create tension between institutional autonomy and the need for standardization in policy approaches. This tension becomes particularly evident in minority-serving institutions, where unique institutional missions must be balanced against external policy pressures.

Organizational culture and governance structures emerge as critical factors in successful policy development. Recent research by Elken (2024) highlights how institutions with more collaborative governance models tend to develop more effective and sustainable policies, particularly when addressing technological innovation. However, the same study notes that establishing such collaborative structures remains challenging for many institutions, particularly those with limited resources or traditional hierarchical structures.

Current Landscape of AI Integration in U.S. Higher Education

While global perspectives inform our understanding, this section focuses primarily on the U.S. higher education context, where HSIs operate within unique federal, state, and accreditation frameworks. The landscape of AI integration in U.S. higher education is characterized by significant variability in institutional readiness, approach, and implementation. The rapid emergence of sophisticated AI tools, particularly generative AI platforms, has created an "institutional policy vacuum" where many colleges and universities find themselves struggling to develop appropriate governance frameworks (Fowler et al., 2023). This situation is particularly evident in the wake of ChatGPT's release, which prompted widespread but often uncoordinated institutional responses.

Recent surveys indicate substantial disparities in institutional approaches to AI integration. Based on the 2024 Survey of U.S. College and University Presidents, only 18% of institutions whose presidents responded have published or adopted policies governing the use of AI on campus. This means that 82% or more of institutions have not yet established formal AI policies. This lack of formal AI policies is particularly noteworthy given the growing impact of AI in higher education. The survey also reveals that about 50% of college presidents feel optimistic about AI's impact on higher education, with only 6% expressing significant concern. Despite this optimism, the low rate of policy adoption suggests a gap between recognizing AI's potential and implementing formal governance structures (Inside Higher Ed, 2024). These findings align with Song's (2024) observation that many institutions are caught in a reactive stance, attempting to address AI-related challenges through existing academic integrity policies rather than developing comprehensive AI integration frameworks.

For minority-serving institutions, particularly Hispanic-Serving Institutions, the challenges of AI integration intersect with broader questions of educational equity and institutional mission. Research by Taylor, Ortega, and Hernández (2024) demonstrate that HSIs often face additional barriers in developing and implementing AI policies, including resource constraints and the need to ensure that AI integration supports rather than undermines their mission of serving historically underrepresented student populations. This concern is particularly salient given emerging evidence that disparities in institutional AI readiness may exacerbate existing educational equity gaps.

Furthermore, the current landscape reveals significant variations in institutional capacity for AI policy development. A comprehensive analysis by Jin et al. (2024) identifies a growing divide between institutions with robust technological infrastructure and those without, suggesting that the ability to develop and implement effective AI policies may become a new marker of institutional stratification in higher education.

Theoretical Frameworks

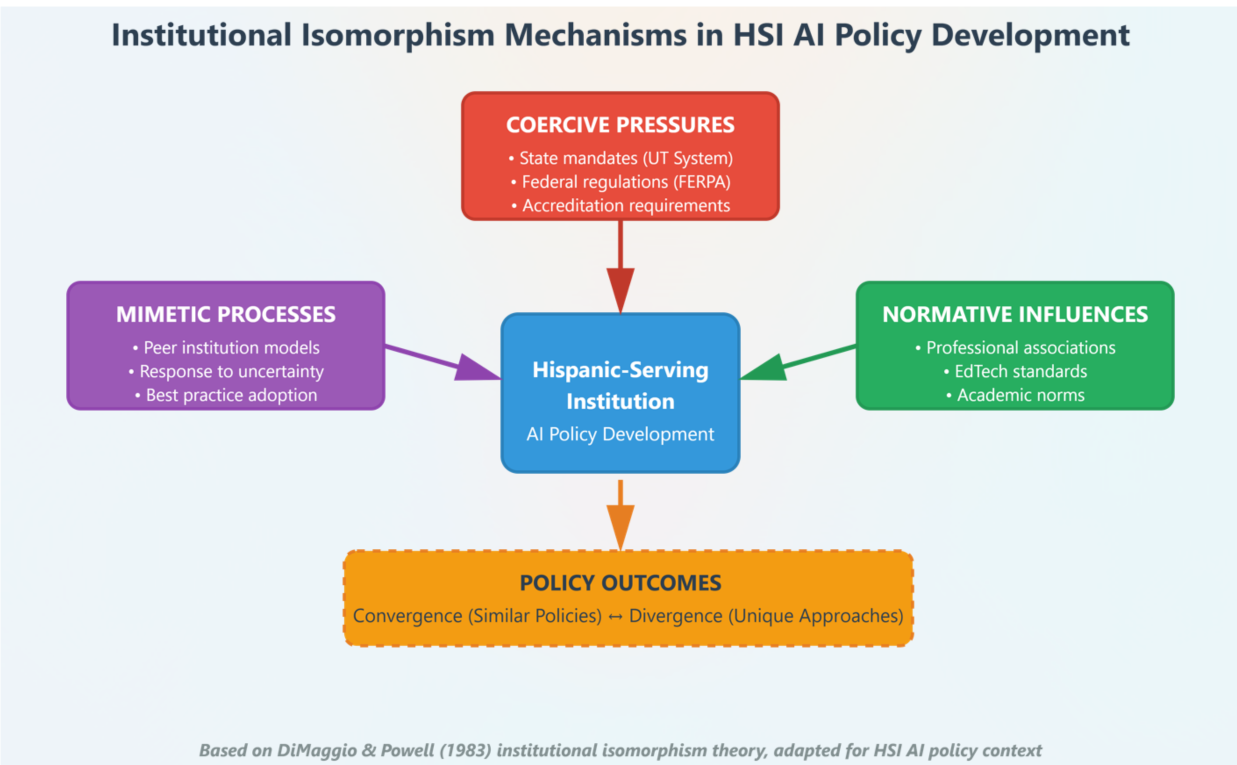
This study integrates institutional isomorphism theory and policy diffusion framework to analyze AI policy development across Hispanic-Serving Institutions in Texas. These complementary frameworks illuminate both the mechanisms driving institutional policy choices and the patterns of policy adoption across different types of institutions, providing a theoretical foundation for understanding the emergence of potentially divergent approaches to AI governance.

Institutional Isomorphism Theory

Institutional isomorphism theory, first articulated by DiMaggio and Powell (1983), provides a crucial framework for understanding how organizations within the same field tend to adopt similar structures and practices over time. This theoretical perspective suggests that institutions face three primary mechanisms of isomorphic pressure (Figure 1): coercive (stemming from political influence and legitimacy problems), mimetic (resulting from standard responses to uncertainty), and normative (associated with professionalization). In the context of AI policy development, these mechanisms offer valuable insights into why institutions might adopt similar approaches or, conversely, why they might resist isomorphic pressures.

Figure 1

Institutional Isomorphism Mechanisms in HSI AI Policy Development



Note. This framework illustrates how coercive pressures (state mandates, regulations), mimetic processes (peer modelling in response to uncertainty), and normative influences (professional standards) shape AI policy development in Hispanic-Serving Institutions, leading to either policy convergence or divergence. Based on DiMaggio & Powell (1983).

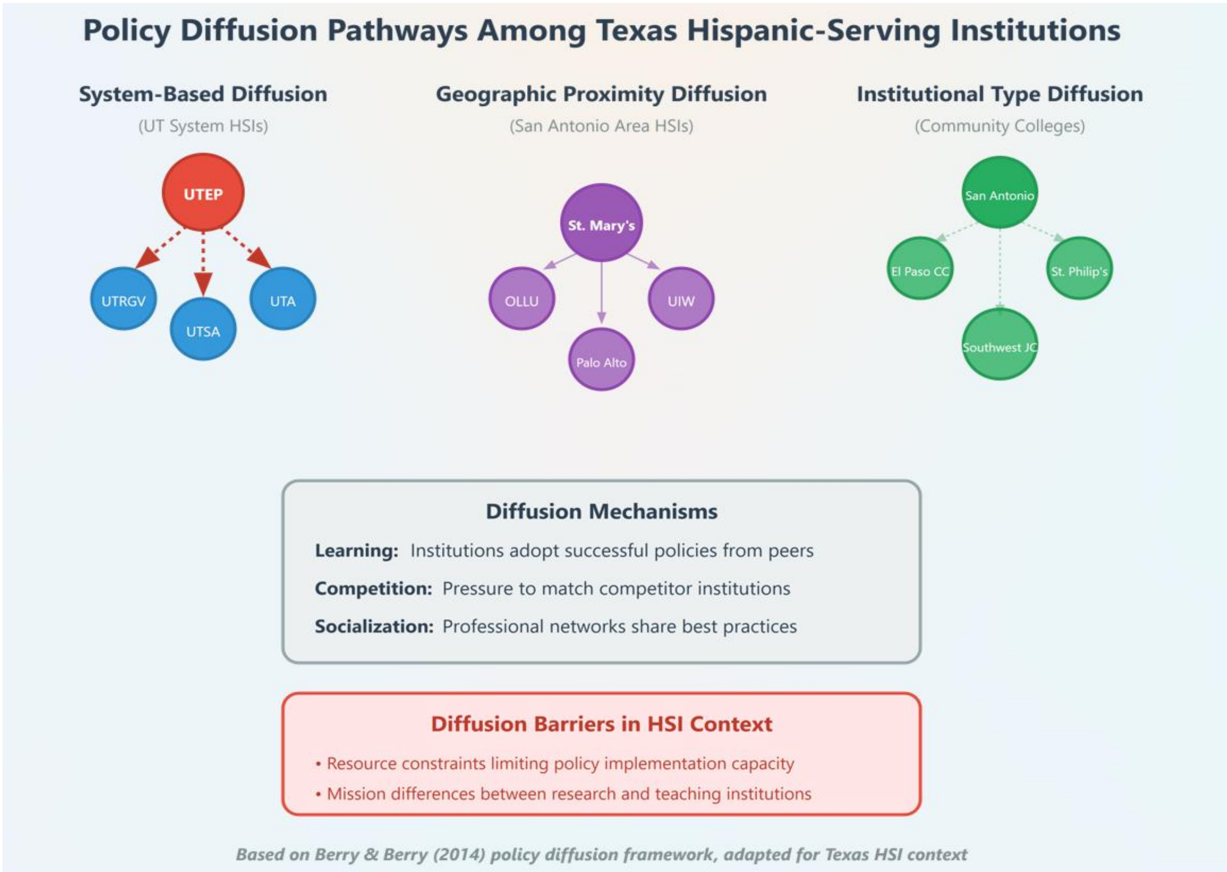
Institutional isomorphism theory provides a validated framework for analyzing policy convergence and divergence in higher education (Beckert, 2010), with particular relevance to minority-serving institutions navigating competing pressures (Cardona Mejía, Pardo del Val, & Dasí Coscollar, 2020). As illustrated in Figure 1, this framework captures how Texas HSIs may experience three distinct pressures shaping AI policy: coercive forces from UT System mandates and federal regulations, mimetic processes as institutions copy successful peers' approaches amid AI uncertainty, and normative influences from educational technology associations establishing professional standards. This theoretical lens has proven effective in explaining technology policy adoption across diverse institutional contexts (Lu & Wang, 2023), making it ideal for understanding why some HSIs develop similar AI policies while others pursue unique approaches despite serving comparable student populations. However, resource constraints and unique institutional missions, especially prevalent among HSIs, may create resistance to such isomorphic pressures, leading to potentially divergent policy paths.

Policy Diffusion Framework

The policy diffusion framework, established through seminal work by Berry and Berry (2014), examines how policies spread across institutions and jurisdictions over time. This theoretical perspective emphasizes that policy adoption is not merely a product of internal determinants but is significantly influenced by how organizations learn from and respond to the policy choices of others. In the context of higher education, policy diffusion occurs through various mechanisms including learning, competition, and socialization processes between institutions.

Figure 2

Policy Diffusion Pathways Among Texas Hispanic-Serving Institutions



*Note***.** The diagram shows three primary diffusion patterns observed in our analysis: system-based diffusion (strongest within University of Texas - UT System), geographic proximity diffusion (weaker among co-located institutions), and institutional type diffusion (limited among community colleges). Diffusion mechanisms and HSI-specific barriers are highlighted. Based on Berry & Berry (2014).

When applied to AI policy development in Hispanic-Serving Institutions, the policy diffusion framework illuminates how geographic proximity, institutional networks, and system affiliations influence policy adoption patterns. Berry and Berry's (2014) framework suggests that institutions are more likely to adopt policies similar to those of geographically proximate peers or institutions within the same organizational system. This spatial diffusion pattern becomes particularly relevant when examining how AI policies spread across Texas HSIs, where institutional relationships and regional networks may significantly influence policy development approaches.

Integration of Theoretical Perspectives

The integration of institutional isomorphism theory and policy diffusion framework creates a comprehensive analytical lens for examining AI policy development across Texas HSIs. While institutional isomorphism explains the forces driving policy similarities or differences, policy diffusion illuminates how these policies spread through institutional networks. This combined framework reveals how institutional characteristics, resource availability, and regional networks collectively shape AI policy development patterns, explaining why some institutions emerge as policy leaders while others adopt more reactive stances.

Significance of Current Study

The above reviewed literature reveals significant gaps in our understanding of AI policy development in higher education, particularly within Hispanic-Serving Institutions. While existing research documents the challenges institutions face in responding to technological change and the factors influencing policy development, there remains limited empirical evidence and systematic analysis of how different types of institutions approach AI governance. This gap is especially pronounced in the context of HSIs, where the intersection of technological integration and educational equity creates unique policy challenges.

Our study addresses these gaps by providing the first systematic comparative analysis of AI policy development across Texas HSIs. Through the integrated lens of institutional isomorphism and policy diffusion theories, this research offers crucial insights into how institutional characteristics, resource availability, and regional networks influence AI policy formation. Understanding these patterns and their implications is vital for informing evidence-based policy development that supports both technological innovation and educational equity in minority-serving institutions.

Method

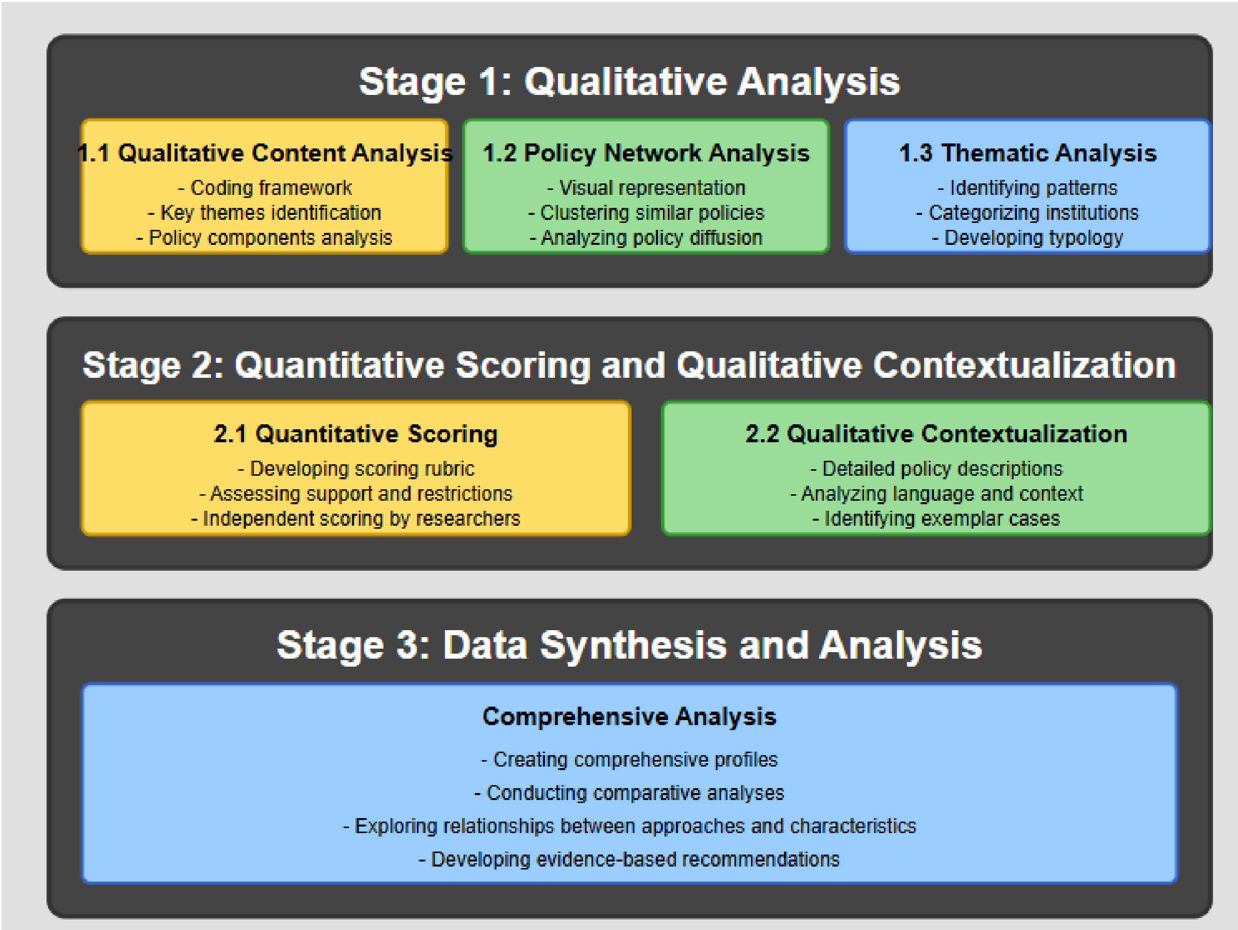
This section details the methodological approach used to analyze AI policies across Texas HSIs. We describe the research design, sample selection and data collection procedures, followed by our three-stage analytical process encompassing qualitative analysis, policy network analysis, quantitative scoring with contextual analysis, and data synthesis.

Research Design

We employed a mixed-methods policy analysis approach to examine AI policies across 19 Hispanic-Serving Institutions (HSIs) in Texas. This design was selected to address the complex nature of institutional AI policy development while capturing both explicit policy statements and implicit institutional approaches. The combination of qualitative content analysis with quantitative scoring methods enabled us to develop a comprehensive understanding of how different institutions approach AI integration within their unique contexts.

Figure 3

Research Design Overview Map



As illustrated in Figure 3, our analytical framework consisted of three interconnected stages. Stage 1 focused on qualitative analysis through content analysis, policy network analysis, and thematic analysis to identify patterns and relationships within institutional policies. Stage 2 combined quantitative scoring with qualitative contextualization to assess policy comprehensiveness and implementation readiness. Stage 3 synthesized findings to develop institutional profiles and evidence-based recommendations.

Our three-stage methodological approach also directly operationalizes both theoretical frameworks illustrated earlier. For institutional isomorphism (Figure 1), Stage 1's content analysis identifies coercive pressures by documenting system mandates and regulatory requirements in policy texts, mimetic processes through similarity scoring between peer institutions, and normative influences via professional standards referenced. For policy diffusion (Figure 2), Stage 2's network analysis maps the three pathways we hypothesized: system-based diffusion through UT System similarity clusters, geographic diffusion through co-location patterns, and institutional-type diffusion among community colleges. Stage 3 synthesizes how these mechanisms interact - testing whether system membership creates stronger isomorphic pressures than geographic proximity, and whether resource-constrained institutions resist convergence pressures, producing the divergent approaches our title references. This design enables replication by providing clear operational definitions: policy similarity (cosine similarity ≥0.75), diffusion evidence (temporal adoption sequences), and isomorphic pressure strength (frequency of mandate references).

The selection of this comprehensive approach was driven by two key factors. First, the diverse nature of HSIs in Texas, ranging from research-intensive universities to community colleges, required an analytical framework that could account for varying institutional contexts and resources. Second, the rapidly evolving landscape of AI in higher education demanded a multi-faceted analysis that could examine both policy content and implementation considerations. This structured progression enabled us to identify both common patterns across institutions and unique characteristics influencing AI policy development among Texas HSIs, while providing actionable insights for institutions at various stages of AI policy development.

Sample Selection and Data Collection

Our sample comprised 19 Hispanic-Serving Institutions in Texas, representing diverse institutional types including research universities, teaching-focused institutions, and community colleges. These institutions were selected based on their official HSI designation by the U.S. Department of Education, which requires at least 25% Hispanic student enrollment. The sample included both public and private institutions, providing a comprehensive representation of the state's higher education landscape (See Table 1 below).

Table 1

Summary Institutional Characteristics of the Nineteen HSIs in Texas

ID	Institution	Private/Public	Research Classification	Size	% Hispanic Students	Year Recognized as HSI	UT System
1	The University of Texas at El Paso	Public	R1	Large	83.8%	1994	Yes
2	The University of Texas Rio Grande Valley	Public	R2	Large	89.8%	1994	Yes
3	Texas A&M International University	Public	R2	Medium	94.5%	1995	No
4	The University of Texas at San Antonio	Public	R1	Large	57.5%	1994	Yes
5	Texas A&M University-Corpus Christi	Public	R2	Large	52.3%	1998	No

ID	Institution	Private/Public	Research Classification	Size	% Hispanic Students	Year Recognized as HSI	UT System
6	The University of Texas at Arlington	Public	R1	Large	31.2%	2014	Yes
7	University of Houston	Public	R1	Large	35.8%	2012	No
8	Texas State University	Public	R2	Large	39.4%	2012	No
9	University of North Texas	Public	R1	Large	28.5%	2020	No
10	University of Houston-Downtown	Public	Teaching	Medium	54.2%	2005	No
11	Texas A&M University-Kingsville	Public	R2	Medium	71.8%	1995	No
12	St. Mary's University	Private	Teaching	Small	72.6%	2001	No
13	Our Lady of the Lake University	Private	Teaching	Small	77.3%	1995	No
14	University of the Incarnate Word	Private	Teaching	Medium	57.4%	1999	No
15	Palo Alto College	Public	Community	Medium	67.9%	1996	No
16	San Antonio College	Public	Community	Large	60.8%	1996	No
17	St. Philip's College	Public	Community	Medium	56.3%	1996	No
18	Southwest Texas Junior College	Public	Community	Medium	88.4%	1995	No
19	El Paso Community College	Public	Community	Large	85.2%	1996	No

Note. [1]Research Classification follows the Carnegie Classification of Institutions of Higher Education (Carnegie Commission on Higher Education, 2021): R1 = Very High Research Activity (doctoral universities with very high research activity as measured by research expenditures, doctoral degrees awarded, and research staff); R2 = High Research Activity (doctoral universities with high research activity); Teaching = institutions primarily focused on undergraduate education with limited graduate programs; Community = two-year institutions offering associate degrees and certificates.
[2]UT System = University of Texas System, a state university system comprising 13 institutions (8 academic and 5 health institutions) governed by a Board of Regents appointed by the Governor of Texas. UT System membership indicates shared governance structures, coordinated policy frameworks, and system-wide initiatives that may influence institutional AI policy development.
[3]Institution size categories based on total enrollment: Small (<5,000), Medium (5,000-15,000), Large (>15,000).

For data collection, we conducted a systematic review of AI-related policy documents available on each institution's official website between May and August 2024. All data collected were exclusively from publicly available internet resources posted on the institutions' official websites, requiring no further institutional permission for analysis or use. The collected documents included formal/informal AI policies, academic integrity guidelines, teaching and learning resources, research protocols, and strategic planning documents that addressed AI integration.

Specifically, online documents were included if they: (1) contained explicit AI-related terms ("artificial intelligence," "AI," "ChatGPT," "generative AI"); (2) addressed institutional policy or guidelines for AI use; (3) were officially published by the institution (not individual faculty pages); and (4) were posted/updated after November 2022 (ChatGPT's release). We systematically searched institutional policy repositories, academic affairs sites, teaching centers, and research offices using both Google site-specific searches (site:institution.edu “artificial intelligence” policy) and manual navigation. We excluded unofficial blogs, news articles without policy content, and technical AI research papers lacking institutional policy implications.

We observed significant variation in policy presence across institutions, as we gathered between 0 to 14 documents per institution. Notably, several HSIs had no AI-related policy documents published on their websites during our data collection period, explaining the lower bound of zero documents for some institutions. When policies did exist, document length varied considerably. Some sources contained single AI-related paragraphs or policy statements, while others comprised comprehensive AI resources, policies, or guidelines spanning dozens of pages.

Our search encompassed both standalone AI policies and AI-related content integrated within broader institutional policies. We focused on publicly available information to ensure transparency and replicability of our analysis, while also acknowledging that this approach might not capture internal policies or those in development.

The collected documents were organized into a systematic database, with careful documentation of their source, date of access, and institutional context. This organizational structure facilitated subsequent analysis while maintaining the ability to trace findings back to their original sources.

Stage 1: Qualitative Analysis & Policy Network Analysis

The first stage of our analysis employed three complementary qualitative approaches: content analysis, policy network analysis, and thematic analysis, as outlined in Figure 3. These methods were selected to provide a comprehensive understanding of both individual institutional policies and the broader patterns of AI policy development across the 19 Texas HSIs.

We began by developing a comprehensive coding framework through an iterative process that combined both inductive and deductive approaches. Initially, we conducted preliminary scans of the collected documents to identify emergent "grand" themes. This empirical approach was complemented by a theoretical foundation drawing from established frameworks in higher education policy analysis, AI governance literature, and research on Hispanic-Serving Institutions.

Specifically, we anchored our analysis in Weimer and Vining's (2017) policy analysis framework, which emphasizes the need to examine policies across core institutional functions in higher education - teaching, learning, and research. Their approach suggests that comprehensive policy analysis should address how innovations (such as AI) impact these three fundamental domains of academic work. Additionally, we incorporated concepts from Fjeld et al.'s (2020) comprehensive mapping of AI ethics principles, which identifies key ethical themes across global AI governance documents, including transparency, justice and fairness, non-maleficence, responsibility, and privacy. This theoretical underpinning ensured our coding framework was both empirically grounded in the data and conceptually aligned with scholarly discourse on AI in higher education contexts.

Through this process, we initially identified four main categories: (1) AI Integration in Teaching and Learning, (2) Ethical Considerations, (3) Academic Integrity, and (4) Research and Innovation. Through multiple rounds of analysis, we refined these categories by combining some areas and expanding others, resulting in a more streamlined framework with three primary categories (as shown in Table 2).

Two researchers then independently coded the documents using this framework, which later was checked for interrater reliability. Inter-rater reliability was assessed using Cohen's Kappa, with k > 0.70 indicating substantial agreement (Hallgren, 2012). Statistical analyses included cosine similarity calculations for policy document comparisons, hierarchical clustering using Ward's method for institutional groupings (Figures 4-5), and network analysis with similarity thresholds ≥0.75 for identifying policy relationships (Figure 6).

Table 2

Comparison of Initial and Refined Coding Frameworks

Initial Framework	Refined Framework	Key Changes
1. AI Integration in Teaching and Learning 1.1 Guidelines for AI use in coursework 1.2 AI literacy and education 1.3 AI-enhanced curriculum	1. AI Integration in Teaching and Learning 1.1 Guidelines for AI use in coursework 1.2 AI literacy and education 1.3 AI-enhanced curriculum and pedagogical innovation	- Added emphasis on pedagogical innovation in 1.3

Initial Framework	Refined Framework	Key Changes
2. Ethical Considerations 2.1 Responsible AI use 2.2 Fairness and bias mitigation 2.3 Transparency and explainability 3. Academic Integrity 3.1 Plagiarism and AI-generated content 3.2 Citation and attribution of AI use 3.3 Assessment strategies	2. Ethical Considerations and Academic Integrity 2.1 Responsible AI use and ethical guidelines 2.2 Plagiarism prevention and AI-generated content 2.3 Citation and attribution of AI use 2.4 AI-aware assessment strategies	- Combined Ethical Considerations and Academic Integrity - Integrated fairness, bias mitigation, transparency into overall ethical guidelines - Emphasized plagiarism prevention - Specified AI-aware assessment strategies
4. Research and Innovation 4.1 AI in research methodologies 4.2 AI-driven research initiatives 4.3 Collaboration and partnerships	3. Research, Innovation, and Partnerships 3.1 AI-driven research initiatives 3.2 Collaboration and industry partnerships 3.3 AI in research methodologies	- Elevated partnerships to category title - Reordered subcategories to emphasize initiatives and partnerships

Following the content analysis, we conducted a policy network analysis using Python in Google Colab, leveraging its free GPUs for enhanced computational efficiency. We calculated policy similarities among the 19 Hispanic-Serving Institutions (HSIs) in Texas using cosine similarity on binary feature matrices derived from AI policy documents, accounting for the presence of shared key terms and entities (e.g., nouns, proper nouns, and policy-related entities) extracted via spaCy, while assigning low similarity (0.1) to institutions without any AI policy documents at the point of data collection. The visualization pipeline employed several Python libraries: Seaborn and Matplotlib for generating the similarity heatmap and policy network graph, NetworkX for constructing the directed policy network based on similarity thresholds, and PyTorch Geometric for potential graph neural network (GNN) analysis to identify clusters or diffusion patterns. These visualizations collectively revealed patterns of policy similarity and potential diffusion pathways among institutions.

The final component of Stage 1 involved thematic analysis to identify recurring patterns and develop a typology of institutional approaches to AI policy. This analysis revealed distinct categories of institutions based on their primary policy focus, such as research integration, teaching emphasis, or ethical considerations. The resulting typology provided a framework for understanding how different types of HSIs approach AI policy development based on their institutional missions and resources.

Stage 2: Quantitative Scoring & Qualitative Contextualization

The second stage of our analysis combined quantitative assessment with qualitative contextualization to evaluate the comprehensiveness and implementation readiness of institutional AI policies. For the quantitative component, we developed a structured scoring rubric with six key dimensions: Clarity in Policy Guidance, Relative Support in AI Use, Relative Restrictions in AI Use, AI Literacy Initiatives, Research Integration, and Ethical Considerations. Each dimension was scored on a scale from 0 to 4, with detailed criteria for each scoring level. A score of 0 indicated no evidence of policy development in that dimension, while a score of 4 represented comprehensive, well-developed policies (See Table 3).

Our six-dimension scoring rubric adapts Bauer and Knill's (2014) framework for comparative policy analysis, which emphasizes measuring policy presence, density, and intensity across multiple dimensions. We identified six critical dimensions through preliminary document analysis and existing AI governance literature (Fjeld et al., 2020): policy clarity (presence), support mechanisms (density), restrictions (intensity), AI literacy initiatives (capacity building), research integration (scope), and ethical frameworks (comprehensiveness).

Table 3

AI Policy Scoring Rubric with Detailed Criteria for Each Dimension

Dimension	*0 - Absent*	*1 - Minimal*	*2 - Developing*	*3 - Established*	*4 - Comprehensive*
Clarity in Policy Guidance	No AI policy or guidelines exist	Vague mentions of AI without specific guidance	Basic guidelines exist but lack detail or examples	Clear guidelines covering most use scenarios	Detailed, specific guidance with examples, procedures, and decision trees
Relative Support in AI Use	No support for AI use mentioned	Generally, discourages or prohibits AI use	Limited support with many caveats and restrictions	Encourages appropriate use with some resources	Actively promotes AI integration with training, tools, and resources
Relative Restrictions in AI Use	No restrictions or boundaries stated	Blanket prohibition or near-total ban	Heavy restrictions significantly limiting use	Balanced restrictions focused on academic integrity	Nuanced, context-specific restrictions with clear rationale
AI Literacy Initiatives	No AI literacy efforts identified	AI mentioned in isolated contexts only	Basic training or resources mentioned but not implemented	Regular workshops and resources available	Comprehensive literacy program integrated into curriculum
Research Integration	No mention of AI in research	AI use in research discouraged or prohibited	Limited guidance for research applications	Research protocols and guidelines established	Advanced integration with ethics review and methodology frameworks
Ethical Considerations	No ethical guidelines present	Ethics mentioned briefly without specifics	Basic ethical principles stated generally	Detailed ethical framework with multiple dimensions	Comprehensive ethics addressing equity, bias, privacy, and transparency

Table 3 above presents our scoring rubric with detailed criteria for each dimension. Two independent coders (Authors 1 and 2) with expertise in educational technology policy applied this rubric to all institutional documents. To minimize bias, we implemented a three-phase calibration process: (1) joint coding of three institutions to establish shared understanding, (2) independent coding of remaining institutions with regular calibration sessions to resolve discrepancies, and (3) calculation of inter-rater reliability (Cohen's Kappa = 0.73, indicating substantial agreement per Hallgren, 2012). Disagreements were resolved through discussion with a third coder (Author 3) serving as arbiter when consensus could not be reached. This quantitative scoring system allowed us to identify areas of institutional strengths and opportunities for development on a comparable scale.

The qualitative contextualization phase focused on developing a typology of AI policy approaches among Texas HSIs. Through careful analysis of policy language, implementation strategies, and institutional contexts, we identified seven distinct approaches: Holistic Integration, Research and Innovation Driven, Teaching and Learning Focused, Ethically Anchored, Community and Workforce Oriented, Cautious Adoption, and Emerging Framework. This typology revealed how institutions with different missions, resources, and student populations approached AI policy development (see Table 1 and Table 1 Note for detailed institutional characteristics).

Stage 3: Data Synthesis and Analysis

The final stage of our analysis focused on integrating and synthesizing findings from the previous stages. We combined the qualitative content analysis patterns and network relationships from Stage 1 with the quantitative scores and typological classifications from Stage 2 to develop comprehensive institutional profiles. Stage 3 synthesized findings from the qualitative and quantitative analyses to identify evidence-based patterns that inform recommendations. These recommendations, derived from successful policy elements in high-scoring institutions (scores ≥3), implementation patterns across typologies, and identified gaps in current approaches, are detailed in the Discussion section with their supporting evidence.

Results

Following our three-stage analytical framework, we present our findings on AI policy development across 19 Texas HSIs. Stage 1 results reveal patterns from qualitative content and network analyses, highlighting institutional relationships and policy similarities. Stage 2 findings present quantitative scoring outcomes across six dimensions and a typology of institutional approaches. Stage 3 synthesizes these analyses to identify key factors influencing AI policy development and implementation readiness across different institutional contexts.

Stage 1 Findings

Qualitative Analysis Results

The content analysis of AI policies across 19 Texas HSIs revealed seven primary themes with varying levels of institutional emphasis. As detailed in the preceding Methods section, two researchers independently coded the policy documents using our refined framework, achieving a Cohen's Kappa of 0.73, indicating good inter-rater reliability (Hallgren, 2012).

As shown in Table 4 below, AI Integration in Teaching and Learning emerged as a prominent theme, with six institutions (UTEP, UTRGV, UTSA, UTA, UH, and Texas State) demonstrating strong implementation guidelines for coursework and AI literacy development. Ethical Considerations and Academic Integrity showed significant overlap in institutional focus, with nine institutions, primarily research-intensive universities, establishing comprehensive guidelines for responsible AI use and academic honesty. These institutions particularly emphasized plagiarism prevention and proper attribution of AI-generated content.

Table 4

Initial Coding Results: Key Themes in HSI AI Policies

Theme	Key Findings	HSIs with Strong Focus
AI Integration in Teaching and Learning	- Many institutions provide guidelines for AI use in coursework - Focus on enhancing AI literacy among students and faculty - Some institutions are developing AI-enhanced curricula	UTEP, UTRGV, UTSA, UTA, UH, Texas State
Ethical Considerations	- Emphasis on responsible and ethical use of AI - Some policies address fairness and bias mitigation - Transparency in AI use is a common theme	UTEP, UTRGV, TAMIU, UTSA, UTA, UH
Academic Integrity	- Strong focus on maintaining academic integrity with AI use - Guidelines for citing and attributing AI-generated content - Development of AI-aware assessment strategies	UTEP, UTRGV, TAMIU, UTSA, UTA, UH, Texas State, UNT, St. Mary's
Research and Innovation	- Several institutions have AI-driven research initiatives - Some are forming partnerships for AI research and development - Integration of AI in research methodologies is emerging	UTEP, UTRGV, TAMIU, TAMU-CC, UTA, UH
Administrative Use of AI	- Limited explicit policies on AI in institutional operations - Some focus on data governance and privacy in AI context - Emerging interest in AI-enhanced student services	UTA, UH, Texas State
Policy Implementation	- Many institutions offer faculty training and support for AI integration - Student guidance on AI use is common - Monitoring and enforcement mechanisms are being developed	UTEP, UTRGV, UTSA, UTA, UH, Texas State, UNT, St. Mary's
Institutional AI Strategy	- Some institutions have clear visions and goals for AI adoption - Resource allocation for AI initiatives varies	UTRGV, UTSA, UTA, UH, Texas State

Theme	Key Findings	HSIs with Strong Focus
	- Alignment with institutional mission, especially regarding Hispanic -serving status, is not always explicit in AI policies	

Research and Innovation initiatives were concentrated among six institutions (UTEP, UTRGV, TAMIU, TAMU-CC, UTA, and UH), reflecting their research-intensive missions. Administrative Use of AI showed limited development across institutions, with only three (UTA, UH, and Texas State) having explicit policies regarding institutional operations and data governance.

Further analysis revealed distinct institutional approaches to AI policy development, resulting in seven categories based on policy focus and implementation strategy (Table 5). Comprehensive Adopters, comprising five large research universities (UTEP, UTRGV, UTSA, UTA, and UH), demonstrated well-developed policies across multiple themes. Research Focused and Teaching Centric institutions showed more specialized approaches aligned with their institutional missions. Community colleges and smaller institutions typically fell into the Emerging Adopters category, indicating early stages of policy development.

Table 5

Categorization of HSIs Based on Primary AI Policy Focuses and Approach

Category	Description	Institutions
Comprehensive Adopters	Institutions with broad, well-developed AI policies covering multiple themes	UTEP, UTRGV, UTSA, UTA, UH
Research Focused	Institutions emphasizing AI integration in research methodologies and projects	TAMIU, Texas State, UNT
Teaching Centric	Institutions prioritizing AI in curriculum enhancement and teaching methodologies	UH-Downtown, TAMU-CC, St. Mary's
Ethical Emphasis	Institutions with a strong focus on ethical considerations and academic integrity	TAMU-Kingsville, OLLU, UIW
Emerging Adopters	Institutions in early stages of AI policy development, often community colleges	Palo Alto College, San Antonio College, St. Philip's College
Industry Aligned	Institutions emphasizing partnerships with AI industries and practical applications	Texas State, UNT
Community Oriented	Institutions extending AI initiatives to serve broader community needs	El Paso CC, Southwest Texas JC

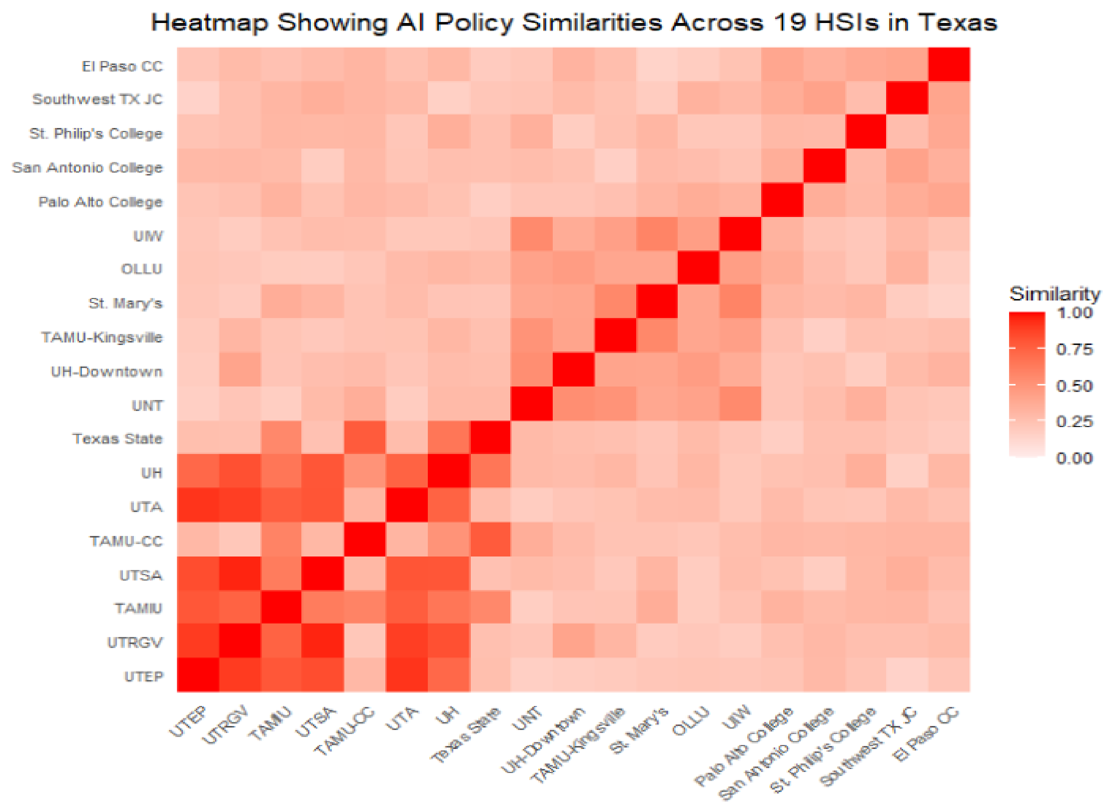
Policy Implementation and Institutional AI Strategy showed notable variation, with larger institutions generally demonstrating more developed faculty support systems and clearer strategic visions. However, explicit alignment between AI policies and HSI mission was limited across institutions, suggesting an opportunity for more intentional integration of these elements.

Policy Network Analysis Results

The policy network analysis revealed distinctive patterns in AI policy similarities across Texas HSIs through complementary analytical approaches. The heatmap (Figure 4) illustrates a clear bifurcation in policy similarity, with a pronounced cluster of high similarity (dark red) among research-intensive universities, particularly UTEP through UH. This cluster shows similarity coefficients ranging from 0.75 to 1.0, indicating strong policy alignment. The remainder of the matrix displays notably lighter shades, suggesting limited policy similarity among teaching-focused institutions and community colleges.

Figure 4

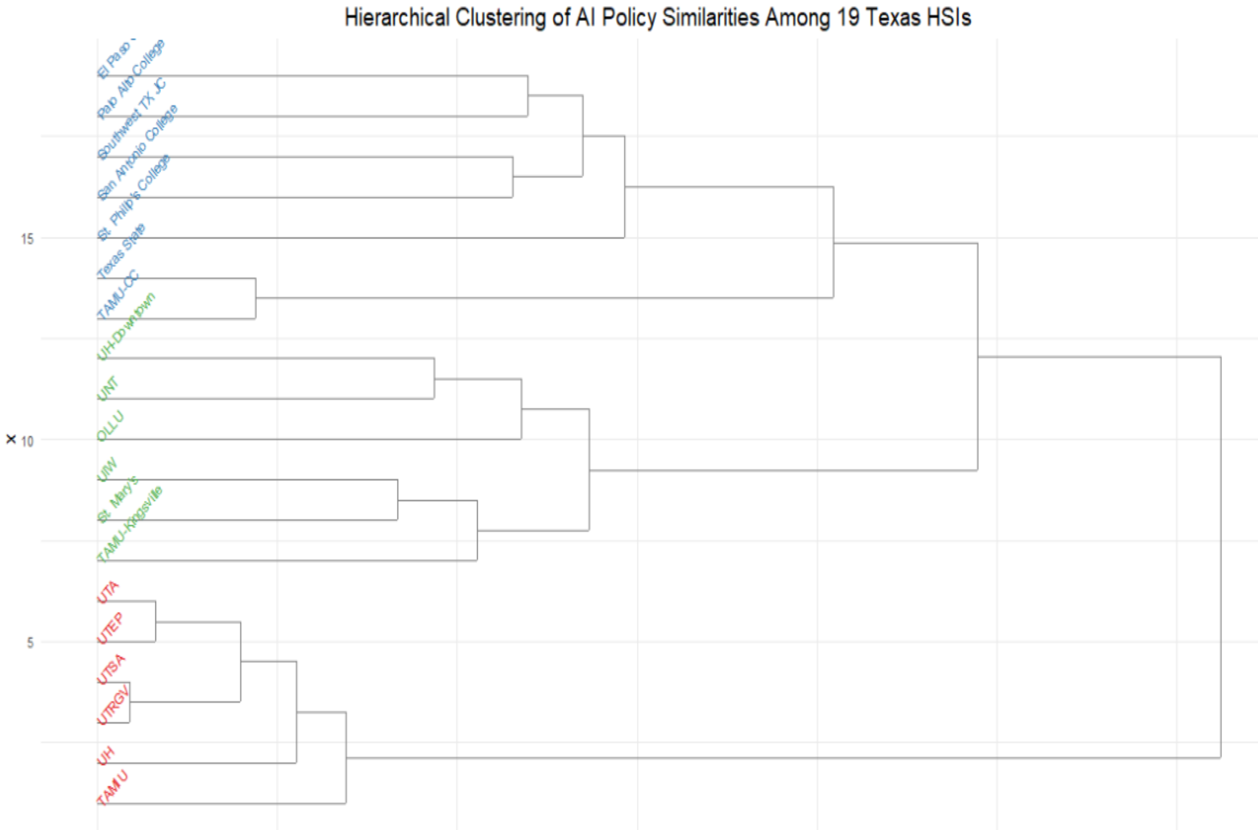
Heatmap Showing AI Policy Similarities Across 19 HSIs in Texas



The hierarchical clustering dendrogram (Figure 5) provides additional granularity in understanding these relationships. The visualization reveals three distinct tiers: a tightly clustered group of research universities at the bottom (including UTEP, UTRGV, and TAMIU), a middle cluster comprising private and public teaching institutions (including UIW and TAMU-Kingsville), and a top cluster predominantly consisting of community colleges. Notably, the height of the connecting branches indicates substantial distance between these clusters, suggesting distinct approaches to AI policy development across institutional types.

Figure 5

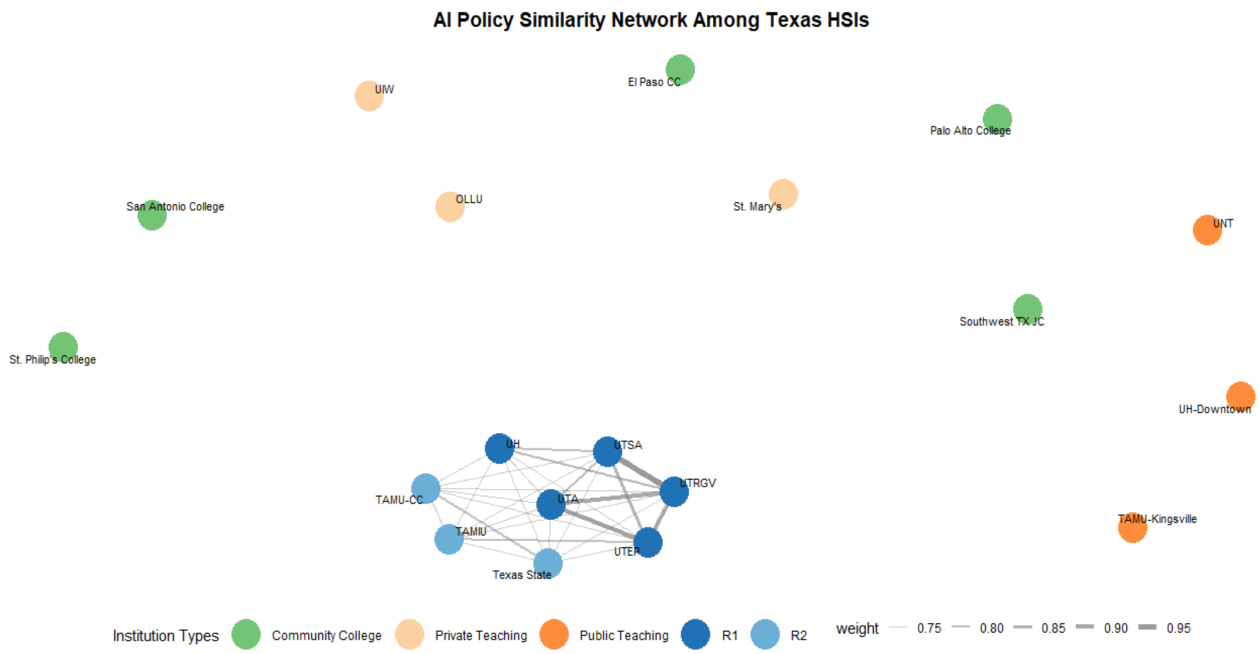
Hierarchical Clustering of AI Policy Similarities Among 19 Texas HSIs



The network diagram (Figure 6) reinforces these findings while emphasizing the structural relationships between institutions. The visualization reveals a densely interconnected cluster of research institutions, with particularly strong connections among UT System members, while other institutions appear as disconnected nodes in the network periphery. The weighted edges (0.75-0.95) within the research cluster indicate varying degrees of policy alignment, with the strongest connections observed between UT System institutions.

Figure 6

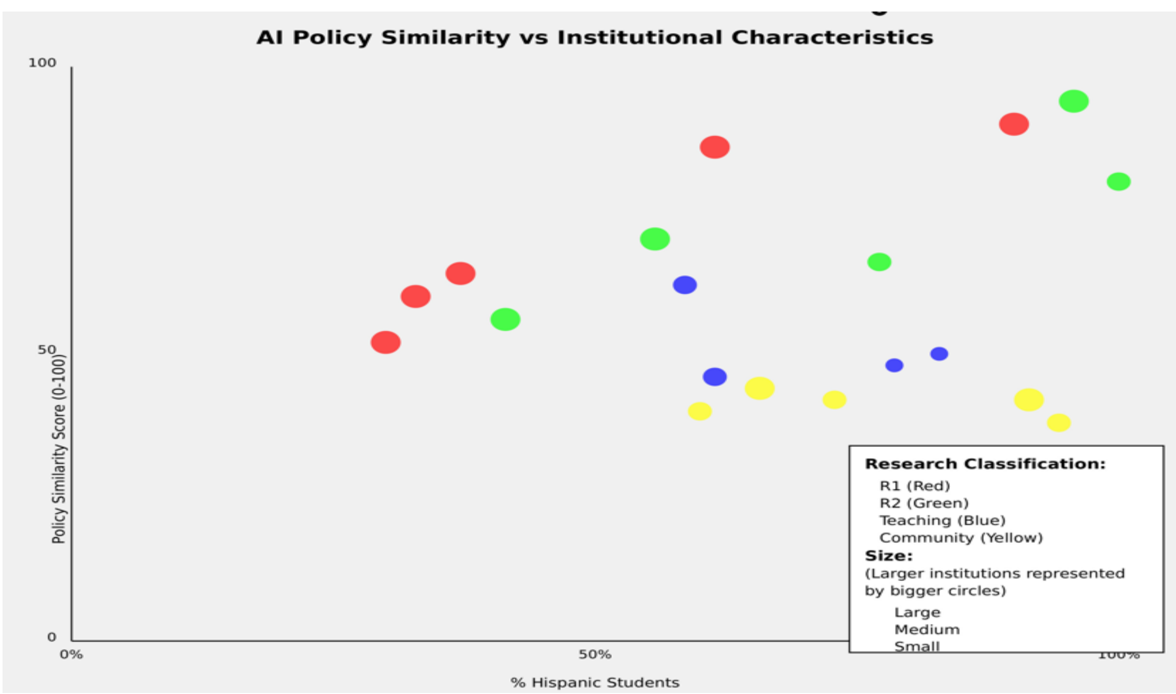
AI Policy Similarity Network Among 19 Texas HSIs



The scatter plot (Figure 7) adds an institutional characteristics dimension, demonstrating that research classification correlates more strongly with policy similarity than Hispanic student enrollment percentage. This finding suggests that institutional mission and research intensity, rather than HSI status alone, primarily drive AI policy development approaches among Texas HSIs.

Figure 7

Scatter Plot of AI Policy Similarity with Institutional Characteristics



Thematic Analysis Results

The thematic analysis of AI policies across the 19 Texas HSIs revealed distinct patterns in policy focus and development (Table 6). Two themes emerged as consistently high-priority areas: Ethical AI Use and Academic Integrity. Institutions demonstrated strong emphasis on establishing guidelines for responsible AI implementation and maintaining academic standards, particularly regarding AI-generated content and assessment strategies.

Four themes showed moderate prevalence across institutions: AI Literacy, Research Integration, Curriculum Enhancement, and Data Governance. These themes reflect growing institutional attention to building AI competencies among faculty and students, incorporating AI into research methodologies, integrating AI-related content into curricula, and establishing frameworks for data management and privacy.

However, several important themes appeared less frequently in institutional policies. Equity and Accessibility considerations, despite their particular relevance to HSIs' missions, received limited explicit attention in AI policies. Similarly, Industry Partnerships, Administrative AI Implementation, and Community Outreach emerged as less common themes, suggesting potential areas for future policy development.

Table 6

Recurring Themes and Patterns in AI Policies Across 19 Texas HSIs

Theme	Description	Frequency
Ethical AI Use	Guidelines for responsible and ethical use of AI technologies	High
Academic Integrity	Policies on AI use in coursework, assessments, and research	High
AI Literacy	Programs to educate students and faculty about AI capabilities and limitations	Medium
Research Integration	Initiatives to incorporate AI in research methodologies and projects	Medium
Curriculum Enhancement	Efforts to integrate AI-related content into existing courses or create new AI-focused courses	Medium
Data Governance	Policies on data privacy, security, and management in AI contexts	Medium
Equity and Accessibility	Measures to ensure AI technologies are accessible and do not perpetuate biases	Low
Industry Partnerships	Collaborations with AI companies or industry for research or educational purposes	Low
AI in Administration	Use of AI in institutional operations and decision-making processes	Low
Community Outreach	Programs to extend AI education and resources to the broader community	Low

Note. Frequency categories based on the number of institutions demonstrating substantial engagement with each theme: High = 13-19 institutions (≥68%), Medium = 7-12 institutions (37-67%), Low = 0-6 institutions (≤36%).
"Substantial engagement" defined as explicit policy content addressing the theme beyond brief mentions.

This thematic distribution suggests that most Texas HSIs are prioritizing immediate academic concerns and ethical considerations in their AI policies while still developing approaches to broader institutional and community applications. The relative underemphasis on equity considerations and community engagement may represent a significant opportunity for policy enhancement, particularly given these institutions' role in serving Hispanic and underrepresented communities.

Stage 2 Findings

Quantitative Scoring and Qualitative Contextualization Results

The quantitative scoring and qualitative contextualization analysis revealed distinct tiers of AI policy development among the 19 Texas HSIs (Table 7). Leading institutions, primarily research-intensive universities within the UT System (UTEP, UTRGV, UTSA, UTA) and the University of Houston, demonstrated comprehensive policy development with consistently high scores (3-4) across all dimensions. These institutions exhibited particular strength in policy guidance clarity, AI support, and ethical considerations, indicating a well-balanced approach to AI integration.

Table 7

Quantitative Scoring of AI Policies Focus Areas Across 19 HSIs in Texas (0-4)

Institution	Clarity in Policy Guidance	Relative Support in AI Use	Relative Restrictions in AI Use	AI Literacy Initiatives	Research Integration	Ethical Considerations
UTEP	4	4	3	4	3	4
UTRGV	4	4	3	4	4	4
TAMIU	3	3	3	2	3	4
UTSA	4	4	3	3	3	4
TAMU-CC	3	3	2	3	3	2
UTA	4	4	3	3	4	4
UH	4	4	3	3	4	4
Texas State	3	3	2	3	3	3
UNT	3	3	3	3	3	4
UH-Downtown	3	3	2	4	2	3
TAMU-Kingsville	2	2	2	2	1	2

Institution	Clarity in Policy Guidance	Relative Support in AI Use	Relative Restrictions in AI Use	AI Literacy Initiatives	Research Integration	Ethical Considerations
St. Mary’s	2	2	3	2	0	3
OLLU	0	0	0	0	0	0
UIW	1	1	2	1	0	2
Palo Alto College	0	0	0	0	0	0
San Antonio College	1	0	1	0	0	1
St. Philip’s College	0	0	0	0	0	0
Southwest Texas JC	1	0	3	0	0	1
El Paso CC	0	0	0	0	0	0

A second tier of institutions, including TAMIU, TAMU-CC, Texas State, UNT, and UH-Downtown, showed moderate development with scores ranging from 2 to 3 across most dimensions. While these institutions demonstrated solid foundations in policy guidance and AI literacy initiatives, they typically scored lower in research integration and relative support for AI use, suggesting a more cautious approach to AI adoption.

A notable pattern emerged in the relative balance between support and restrictions in AI use. Even high-scoring institutions maintained moderate levels of restrictions (scoring 2-3) while showing strong support (scoring 3-4), indicating a thoughtful approach to balancing innovation with academic integrity. This pattern was particularly evident in research-intensive institutions, which demonstrated the highest scores in both supportive and restrictive policy measures.

The analysis revealed significant disparities between larger research universities and smaller institutions. Private universities and community colleges generally scored between 0 and 2 across dimensions, with some institutions showing no formal AI policies. However, exceptions emerged in specific areas - for instance, St. Mary's University scored relatively high (3) in ethical considerations despite lower scores in other dimensions, suggesting targeted policy development based on institutional priorities.

These findings underscore a clear relationship between institutional resources (i.e., capacity indicators) and comprehensive AI policy development, while also highlighting opportunities for targeted support and policy framework sharing across different types of HSIs. Resource availability was inferred through three proxies: Carnegie classification (R1/R2 institutions receive substantially higher research funding), institutional size (larger enrollments correlate with bigger operating budgets per IPEDS data), and system membership (UT System institutions benefit from shared resources and coordinated support). Institutions with all three indicators (e.g., UTEP, UTA) consistently scored 3-4 across dimensions, while those with none (e.g., OLLU, Palo Alto College) scored 0-2, suggesting resource constraints significantly impact policy development capacity.

Stage 3 Findings

Data Synthesis and Profiling Analysis Results

The synthesis of our Stage 1 and Stage 2 findings revealed seven distinct typologies/profiles of AI policy approaches among Texas HSIs, reflecting diverse institutional contexts and strategic priorities (Table 8). Institutions demonstrating Holistic Integration, exemplified by UTEP, UTRGV, and UTA, have developed comprehensive policies that address multiple dimensions of AI implementation, from ethical considerations to administrative applications. These institutions typically represent well-resourced universities with established research infrastructures, enabling them to take a leadership role in AI policy development.

Research and Innovation Driven institutions, such as TAMIU and UNT, have focused their policies primarily on leveraging AI for research advancement, while Teaching and Learning Focused institutions like UH-Downtown and St. Mary's have prioritized classroom applications and pedagogical innovation. This differentiation in approach appears closely aligned with institutional missions and available resources, suggesting that institutions are strategically adapting AI policies to their specific contexts and strengths.

The emergence of Ethically Anchored approaches, represented by TAMU-Kingsville and OLLU, highlights a growing emphasis on responsible AI adoption and equity considerations. Similarly, the Community and Workforce Oriented category, exemplified by Texas State and El Paso CC, demonstrates how some institutions are prioritizing practical applications and community impact, particularly in regions with strong industry connections.

The identification of Cautious Adoption and Emerging Framework categories, including institutions like UIW and Palo Alto College, suggests a developmental continuum in AI policy maturation. These institutions' approaches indicate that policy development is an iterative process, with some institutions taking a measured approach while others are in early stages of policy formulation, often drawing from peer institutions' experiences.

Table 8

Typology/Profiles of AI Policy Approaches Across 19 Texas HSIs

Type	Characteristics	Examples
Holistic Integration	Comprehensive policies covering ethical use, academic applications, research, and administration	UTEP, UTRGV, UTA
Research and Innovation Driven	Policies centered on leveraging AI for research advancement and innovation	TAMIU, UNT
Teaching and Learning Focused	Emphasis on AI literacy, curriculum integration, and innovative pedagogies	UH-Downtown, St. Mary’s
Ethically Anchored	Strong emphasis on responsible AI use, equity, and maintaining academic integrity	TAMU-Kingsville, OLLU

Type	Characteristics	Examples
Community and Workforce Oriented	Focus on practical AI skills, industry partnerships, and community impact	Texas State, El Paso CC
Cautious Adoption	Measured approach to AI integration, with emphasis on risk mitigation	UIW, St. Philip’s College
Emerging Framework	Early-stage policies, often adapting approaches from other institutions	Palo Alto College

This typological analysis provides a framework for understanding the diverse landscape of AI policy development in Texas HSIs, while also highlighting opportunities for inter-institutional collaboration and knowledge sharing across different policy approach types.

Discussion

Our analysis of AI policy development across 19 Texas HSIs reveals distinct patterns in institutional approaches, policy diffusion mechanisms, and equity considerations. This discussion examines these findings through the lens of institutional adaptation to technological change, while addressing implications for policy development and inter-institutional collaboration in advancing AI integration within the unique context of Hispanic-Serving Institutions.

Evolution of AI Policy Development in Texas HSIs

The evolution of AI policy development among Texas HSIs reflects broader patterns of institutional adaptation to rapid technological change noted in recent literature. Our findings align with George and Wooden's (2023) observation regarding institutions' struggles with structured frameworks for emerging technologies, particularly evident in the stark division between research-intensive universities and other institutions. The comprehensive policies developed by UT System institutions demonstrate proactive approaches to AI governance, contrasting with Niraula's (2024) documentation of reactive policy implementation following ChatGPT's emergence.

However, the significant variations in policy comprehensiveness across institutions underscore what Klimenko (2024) terms the "technological policy lag." This lag is particularly pronounced in smaller institutions and community colleges, where resource constraints often impede rapid policy development. Our analysis reveals that while research universities have developed robust frameworks addressing multiple dimensions of AI integration, many smaller HSIs remain in early stages of policy formulation, reflecting broader patterns of technological adoption disparities in higher education (Taylor et al., 2024).

The emergence of distinct policy approaches, from holistic integration to cautious adoption, suggests an evolving landscape where institutions balance innovation imperatives with their specific contexts and constraints. This evolution parallels recent findings by Sinha et al. (2024) on how minority-serving institutions navigate technological integration while maintaining their core educational missions. The strong emphasis on ethical considerations across institutions that have developed AI policies indicates growing recognition of AI's broader implications, supporting Bell et al.'s (2022) observations about HSIs' unique responsibilities in technological integration.

Institutional Characteristics and AI Policy Approaches

The relationship between institutional characteristics and AI policy approaches observed in our study aligns with institutional isomorphism theory (DiMaggio & Powell, 1983). Research-intensive universities, particularly within the UT System, demonstrate what Mpuangnan and Roboji (2024) term "policy leadership capacity," developing comprehensive frameworks that address multiple dimensions of AI integration. This pattern supports Hewitt-Dundas's (2012) findings regarding the relationship between research intensity and policy development capabilities.

Our analysis reveals that institutional resource availability significantly influences not only the comprehensiveness of AI policies but also their strategic orientation. While well-resourced institutions pursue holistic integration approaches, others adopt more focused strategies aligned with their primary missions and available resources. This differentiation echoes recent findings by Zou (2023) on resource-based determinants of technological policy development in education.

The emergence of distinct policy typologies among Texas HSIs suggests that despite isomorphic pressures, institutions maintain significant autonomy in policy approach. This finding extends Elken's (2024) work on organizational governance by demonstrating how institutions adapt policy frameworks to their specific contexts while responding to broader sectoral trends. However, the considerable gap between research universities and other institutions in policy development raises concerns about what Ortagus et al. (2023) identified as the "policy development divide," suggesting that institutional characteristics may become increasingly crucial determinants of AI readiness and integration capacity.

Policy Diffusion Patterns and Regional Dynamics

Policy diffusion patterns among the 19 Texas HSIs demonstrate complex regional and system-based dynamics that extend beyond traditional geographic proximity effects described in Berry and Berry's (2014) framework. Our analysis reveals that system affiliation, particularly within the UT System, serves as a stronger determinant of policy similarity than geographic location. This finding aligns with Dusdal et al's (2021) observation that modern institutional networks transcend physical boundaries in policy development processes.

The emergence of the UT System institutions as policy leaders suggests what Taylor and Nowell (2024) term "network-based policy diffusion," where institutional relationships and system-wide coordination drive policy development more significantly than regional proximity. This pattern is particularly evident in the high similarity scores among UT System institutions, despite their geographic dispersion across Texas. However, the limited policy diffusion to non-system institutions, even those in close proximity, indicates potential barriers in cross-institutional knowledge sharing that warrant further investigation.

These findings build upon recent work by Jin et al (2024) on policy transfer mechanisms in higher education, suggesting that formal institutional networks may become increasingly crucial for effective AI policy development and dissemination. The observed patterns also raise important questions about equitable access to policy development resources and expertise, particularly for institutions outside major university systems. As Moisio (2018) notes, such network-based diffusion patterns may inadvertently reinforce existing institutional hierarchies in technological readiness and adaptation.

Equity Considerations and HSI Mission Alignment

The intersection of AI policy development and HSI mission alignment reveals critical equity considerations that extend beyond technological integration. Our findings highlight concerning disparities in policy development capabilities that could exacerbate existing educational inequities, supporting Taylor et al.'s (2024) observations about unique barriers faced by HSIs. The significant variation in policy comprehensiveness between well-resourced research universities and other HSIs suggests what Bada et al (2024) note as an equity-innovation paradox, where institutions most focused on serving underrepresented students often have the least developed AI governance frameworks.

Critically, only 3 of the 19 HSIs (16%) explicitly mention racial or socioeconomic equity in their AI policies - UTEP and UTRGV include some bias mitigation training, while St. Mary's references digital divide concerns. None, however, provide comprehensive frameworks for ensuring equitable AI access across income levels or addressing algorithmic bias against Hispanic students and non-native English speakers. This absence is particularly troubling given that these institutions average 77% Hispanic enrollment with majority first-generation, low-income students. While ethical considerations emerge as a consistent theme across institutions with developed policies, this explicit equity gap reveals a notable misalignment between HSI missions and their AI governance approaches.

Our analysis aligns with Safidon's (2024) concerns that inadequate technological policy frameworks may disproportionately impact historically marginalized students. The observed pattern suggests that without targeted intervention, AI integration might reinforce rather than reduce existing educational disparities. Even institutions with “Ethically Anchored” approaches often lack frameworks for ensuring equitable AI access and implementation. As Mangal and Pardos (2024) argue, this gap between ethical awareness and equity-focused implementation represents a critical challenge for HSIs. The findings underscore Jin et al.'s (2024) warning about technological readiness becoming a new dimension of institutional stratification, with particular implications for HSIs' core mission of advancing educational equity.

Theoretical Contributions

Our dual-framework analytical approach reveals dynamics invisible through single-theory analyses. Institutional isomorphism alone would suggest uniform policy convergence, yet we observe systematic divergence - community colleges resist mimetic pressures despite exposure to R1 university models, indicating resource constraints override isomorphic forces to certain extents. Policy diffusion theory alone would predict geographic clustering, yet system membership (UT) proves stronger than proximity, demonstrating how formal governance structures channel policy spread more effectively than informal regional networks. This integrated analysis addresses critical gaps: (1) explaining why similar institutions (all HSIs) develop somewhat divergent approaches, (2) identifying when isomorphic pressures fail (resource thresholds), and (3) revealing how diffusion pathways differ in resource-constrained contexts. These insights extend theory by showing that in technological policy development, institutional capacity moderates both isomorphic pressures and diffusion mechanisms - a finding particularly relevant for understanding innovation adoption in minority-serving institutions.

Implications

Our findings point to several critical implications for AI policy development in higher education, particularly within the HSI context. The clear stratification in policy development capabilities across institutions suggests an urgent need for what Zhao and Yang (2024) describe as "collaborative policy ecosystems," where resources and expertise can be shared across institutional boundaries. This approach could help address the significant disparities identified in our analysis while preserving institutional autonomy in policy implementation.

The emergence of distinct policy typologies provides a framework for targeted support and development initiatives. Rather than pursuing a one-size-fits-all approach, future policy development efforts should acknowledge and build upon institutions' existing strengths and strategic orientations. This aligns with recent recommendations from D.S. e evaluation to create flexible and adaptive policies that align with institutional goals Teguh et al. (2024) on adaptive policy development frameworks for minority-serving institutions. Furthermore, our analysis suggests that system-level coordination, particularly successful within the UT System, could serve as a model for broader regional or state-wide initiatives supporting AI policy development.

Practically, these findings can translate into immediate, actionable strategies for HSIs. First, resource-constrained institutions should prioritize joining formal collaborative networks - our data show institutions within the UT System demonstrate consistently higher policy scores (averaging 3.75) compared to non-system institutions (averaging 1.8). Second, HSIs can leverage our seven-typology framework as a developmental roadmap: institutions identify their current type, then adopt targeted improvements (e.g., community colleges currently scoring 0-1 could begin with basic policy development following St. Mary's model, which achieved moderate success despite limited resources). Third, the strong system-based diffusion patterns suggest creating HSI-specific consortiums for AI policy development. For instance, institutions scoring 0 across dimensions (OLLU, Palo Alto College, St. Philip's, El Paso CC) could benefit from shared templates and training resources from higher-scoring peers. Even modest improvements - moving from 0 to 2 in key dimensions - would significantly enhance their AI governance capacity. This collaborative approach addresses resource constraints while maintaining institutional autonomy - critical for HSIs balancing innovation with mission.

Looking ahead, the challenges identified in our study call for a coordinated response at multiple levels. State-level initiatives could help establish baseline frameworks while providing resources for institutional policy development. As Nani et al. (2024) suggest, such frameworks must balance standardization with flexibility to accommodate institutional diversity. Additionally, the formation of policy development networks across institutional types could facilitate knowledge sharing and resource optimization, particularly benefiting institutions currently lacking comprehensive AI policies.

The path forward requires careful attention to both innovation and equity considerations. As AI technologies continue to evolve, institutions must develop dynamic policy frameworks that can adapt to changing technological landscapes while advancing educational equity. This development, as Viberg et al. (2024) argue, requires sustained investment in institutional capacity building, particularly among HSIs serving historically underrepresented student populations.

Limitations and Future Research

Three limitations of this study may warrant consideration: (1) analyzing only public-facing policies may underrepresent institutions with robust internal AI governance, (2) Texas-specific focus limits generalizability beyond similar state contexts, and (3) cross-sectional design captures a snapshot rather than policy evolution. Future research should pursue longitudinal policy tracking, multi-state HSI comparisons, interviews with policymakers to understand divergence drivers, and critically, impact studies examining whether comprehensive policies improve outcomes for Hispanic and first-generation students. Investigating the gap between policy sophistication and implementation effectiveness remains essential for advancing equitable AI integration in minority-serving institutions.

Conclusion

This study presents the first empirically rigorous investigation of AI policy development across 19 representative Texas HSIs, employing a sophisticated methodological triangulation approach that combined quantitative scoring, qualitative content analysis, and policy network analysis. The systematic analysis reveals seven distinct governance approaches through mixed-methods analysis. The stark divide - UT System institutions averaging 3.75/4.0 versus others at 1.8/4.0, with 47% lacking any AI policies - raises critical equity concerns for institutions serving predominantly Hispanic and first-generation students.

Our dual-theoretical-framework analysis exposes how system membership trumps geographic proximity in policy diffusion and identifies resource thresholds where institutions resist isomorphic pressures. The seven typologies provide both diagnostic and developmental tools, from Holistic Integrators to Emerging Adopters, offering clear policy-level advancement pathways.

This study makes three specific contributions to higher education policy research. Theoretically, we demonstrate that resource constraints could fundamentally alter isomorphism and diffusion dynamics. Methodologically, our replicable mixed-methods framework combines network, content, and quantitative analyses. Practically, we provide evidence that system-based collaboration doubles policy development effectiveness compared to isolated efforts. As AI transforms higher education, these findings offer minority-serving institutions both theoretical insights and actionable strategies - from consortium formation to tiered implementation - ensuring technological integration advances rather than undermines educational equity.

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