Bridging Policy and Practice: The CLASS AlignED Framework for Responsible AI Integration in Higher Education

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ABSTRACT

The rapid expansion of artificial intelligence (AI), high-performance computing (HPC), and Science Gateway technologies in higher education has created new opportunities for experiential learning while introducing complexity for faculty seeking structured and policy-compliant integration. This paper presents the CLASS AlignED (Course Learning & Analytics Support System) Framework, a faculty-centered, governance-aware architecture designed to support the incorporation of AI, HPC, and Science Gateway technologies into undergraduate curricula. The framework connects institutional AI policy, structured instructional workflows, scalable computing infrastructure, and measurable learning analytics into a unified alignment model. Using a design-based research approach, we describe the conceptual model, system architecture, and planned prototype implementation. The framework proposes embedding compliance logic and cyberinfrastructure guidance directly within AI-assisted workflows to reduce faculty uncertainty and translate institutional policy into actionable instructional practice. CLASS AlignED offers a scalable model for institutions seeking to expand AI- and HPC-enabled instruction while maintaining governance, reproducibility, and equitable access to advanced cyberinfrastructure resources.

CCS CONCEPTS

• Human-centered computing → Interactive systems and tools • Computing methodologies → Artificial intelligence • Social and professional topics → Computing education • Mathematics of computing → Statistical paradigms • Computer systems organization → Distributed architectures

KEYWORDS

Artificial intelligence in education, High-performance computing (HPC), Science Gateways, Faculty development, Learning analytics, Generative AI integration, AI governance and policy compliance, Cyberinfrastructure in undergraduate education, Curriculum alignment, Minority-serving institutions (MSIs)

1 INTRODUCTION

The rapid expansion of generative artificial intelligence (GenAI) has created both a paradigm shift in educational opportunity and growing uncertainty within the higher education landscape [1]. Emerging research demonstrates that these technologies are already reshaping academic environments by enabling personalized learning experiences and supporting student performance prediction [2]. Institutions have moved quickly to formulate policies, with recent document analyses showing that the majority of research-intensive universities now provide guidance or sample syllabi language [1], [3]. However, a critical "integration gap" remains, as institutional governance often struggles to keep pace with the unprecedented speed of student and faculty adoption [4].

Despite top-down institutional efforts, faculty adoption remains uneven and is shaped by a complex interplay of behavioral, social, and technical factors. Empirical studies indicate that educators' willingness to integrate GenAI depends heavily on perceived usefulness, professional development, and their confidence in controlling the technology within specific teaching contexts (4). While faculty increasingly experiment with AI-assisted syllabus design and assessment, many report uncertainty regarding how to balance academic standards with technological realities without consistent infrastructure or policy clarity (4).

These challenges are particularly acute at Historically Black Colleges and Universities (HBCUs). While near-universal AI engagement has been reported among HBCU students and faculty, significant readiness gaps persist; less than half of HBCU faculty report formal institutional implementation of AI tools, and 80% indicate a need for role-specific training to use AI effectively and ethically (5).

This paper introduces CLASS AlignED (Course Learning & Analytics Support System), a structured framework designed to support HBCU faculty in integrating AI tools while maintaining institutional compliance. Developed within the context of SGX3 Spring Training 2026 and ADMI26 workforce development initiatives, CLASS AlignED addresses the integration gap through a four-layer model connecting (1) Institutional AI Policy, (2) AI-enabled workflow tools applied to course design and assessment, (3) High-Performance Computing (HPC) and cyberinfrastructure resources integrated into instructional activities, and (4) measurable learning analytics. Central to this work is the investigation of how automated syllabus parsing and learning objective mapping can support the alignment of course outcomes with AI tools, HPC resources, and Science Gateway platforms while ensuring adherence to institutional policy. By aligning pedagogical innovation with ethical safeguards and scalable computing infrastructure, this framework provides a proactive strategy for HBCUs to lead in the responsible implementation of AI, HPC, and Science Gateway technologies in higher education.

1.1 Contributions

This paper makes four main contributions to the study of artificial intelligence (AI) integration in higher education. First, it introduces a governance-aware instructional framework that connects university AI policies, teaching workflows, computing infrastructure, and measurable learning outcomes. Instead of focusing only on AI tools, the CLASS AlignED Framework treats AI integration as a system-wide alignment challenge that requires policy guidance, structured teaching processes, and technical support working together. Second, the paper presents a structured alignment model that links course syllabi and learning objectives to AI, high-performance computing (HPC), and Science Gateway resources. By embedding policy principles directly into instructional workflows, the framework helps translate university-level AI guidance into practical classroom decisions. Third, the study grounds the framework in a real institutional context by aligning it with the governance structure of the University of North Carolina (UNC) System and Elizabeth City State University (ECSU). This grounding shows how responsible AI integration can be designed within existing university policies rather than outside of them. Fourth, the paper outlines a scalable system architecture and future prototype plan that demonstrates how the framework can be implemented as a working tool. This roadmap shows that the framework is not only theoretical but also technically feasible and ready for future development and evaluation. Together, these contributions offer a structured and practical approach for integrating AI, HPC, and Science Gateway technologies into undergraduate education in a responsible and scalable way.

2 BACKGROUND AND RELATED WORK

Research on AI in education highlights pedagogical innovation, while institutional AI governance research focuses on ethics, data privacy, and oversight. Separately, literature on High Performance Computing (HPC) and Science Gateways emphasizes scalable research infrastructure. Few studies integrate policy, AI workflow, and infrastructure into a unified classroom framework.

2.1 The Complexity of AI Governance

The decentralization of decision-making within higher education institutions introduces significant horizontal and vertical alignments. While central administrations may issue broad ethical mandates, individual departments–ranging from STEM to the humanities–often implement localized interpretations based on their specific technical requirements and pedagogical philosophies. This "pathwork" governance, as characterized by Birkstedt (2023), leads to a lack of interoperability between institutional units, where a tool deemed permissible for data analysis in one faculty may be restricted in another due to differing risk tolerances regarding algorithmic bias or data residency [5].

Beyond internal structural divides, the absence of a unified regulatory standard at the national or internal level compels institutions to navigate a volatile legal landscape in isolation. The intersectionality of intellectual property rights and generative outputs remains a primary point of friction; without centralized guidance, universities risk legal exposure or the inadvertent stifling of research innovation. As Taeihagh (2021) suggests, the challenge is not merely the absence of policy, but the existence of overlapping, contradictory frameworks that fail to address the unique sociotechnical complexities of AI deployment in an academic environment [6].

2.2 Faculty Adoption and Institutional Support

The "human element" of AI integration is a critical determinant of successful digital transformation within the academy. Faulty adoption is not merely a matter of individual technical proficiency but is heavily contingent upon the robust support structures provided by the institution. Research by Wang (2021) and Lee (2024) emphasizes that educators are significantly more likely to adopt AI tools when there is institutional clarity and a well-defined strategy [7], [8]. In the absence of clear guidelines regarding the permissible use of generative tools or the standardized handling of AI-assisted student work, a "cautionary paralysis" often takes hold, where instructors remain hesitant to innovate for fear of violating undefined academic integrity protocols.

The hesitation was further compounded by the perceived workload increase associated with pedagogical redesign. As Lee (2024) notes, the transition to AI-integrated curricula requires faculty to move beyond traditional assessment methods toward more process-oriented or "authentic" assessments [8]. This shift demands substantial institutional investment in professional development and technical scaffolding. Institutions that provide dedicated "AI sandboxes", instructional design support, and clear "safe harbor" policies for experimental teaching methods see a higher rate of successful integration compared to those that rely on top-down mandates.

Furthermore, the psychological readiness of faculty is linked to socio-technical trust. When institutions fail to provide transparent evaluations of the AI tools they endorse–specifically regarding data privacy and algorithmic reliability–faculty often perceive these technologies as administrative impositions rather than pedagogical enhancements. Wang (2021) suggests that building this trust requires a collaborative governance model where faculty are treated as co-architects of AI policy rather than mere end-users [7]. This collaborative approach ensures that support structures are tailored to the nuanced needs of different disciplines, effectively bridging the gap between institutional ambition and classroom reality.

2.3 The Policy-Practice Gap

A critical challenge in the current academic landscape is the phenomenon of "policy decoupling", where a significant hiatus exists between high-level institutional mandates and the localized realities of the classroom. As Wang (2024) and Francis (2025) demonstrate, while many universities have successfully ratified broad ethical statements or "value-based" AI frameworks, these documents frequently lack the granular operational instructions required for diverse academic environments [9], [10]. This abstraction creates a vacuum of actionable guidance, leaving instructors to interpret vague institutional stances within the high-stakes context of grading and academic integrity.

The complexity of this gap is most evident when examining the divergent requirements of specific disciplines:

- **Laboratory and Technical Sciences:** In a chemistry lab, the use of AI for predictive modeling or data synthesis triggers specific concerns regarding experimental reproducibility and "hallucinated" chemical properties. Standard ethics statements rarely provide the technical protocols necessary to audit AI-generated empirical data.
- **Creative and Liberal Arts:** Conversely, in creative writing or philosophy, the primary tension lies in the definition of originality and authorship. A universal policy often fails to distinguish between AI as a "brainstorming collaborator" versus AI as a "surrogate author", leading to inconsistent enforcement of plagiarism standards across departments.

Furthermore, Francis (2025) argues that this decoupling is often a defensive administrative strategy creating "top-level" compliance while offloading the ethical and technical risk onto individual faculty members [10]. Without domain-specific addenda to central policies, the transition from theory to practice remains fragmented. (Wang 2024) suggests that closing this gap requires a shift toward "modular policy-mkaing," where a central core of ethical principles is supplemented by department level protocols that address the unique affordances and risks of AI within that specific field of study [9].

2.4 Methodology

This study employs a design-based research (DBR) methodology to guide the development of the CLASS AlignED Framework. Design-based research is particularly appropriate for complex educational innovations that require the simultaneous development of theory and practical solutions within authentic contexts [11], [12]. Unlike traditional experimental designs that isolate variables under controlled conditions, DBR emphasizes iterative design, contextual grounding, and refinement through real-world implementation [13]. The current study represents the initial design and architectural specification phase of a multi-stage DBR cycle.

The first phase of the research involved a structured synthesis of literature across three intersecting domains: AI governance in higher education, faculty adoption of generative AI technologies, and cyberinfrastructure integration in instructional environments. This review identified recurring challenges, including governance fragmentation, policy-practice decoupling, faculty uncertainty, and the absence of structured integration frameworks. These findings informed the development of the four-layer CLASS AlignED conceptual model. Consistent with DBR principles, the framework was constructed to respond directly to empirically documented problems rather than abstract theoretical assumptions.

The second phase consisted of institutional document analysis within the governance context of the University of North Carolina (UNC) System and Elizabeth City State University (ECSU). System-level AI guidance documents, faculty policy resources, academic integrity codes, and institutional compliance materials were examined to identify operational governance principles. This analysis revealed consistent emphasis on accountability, transparency, privacy protection, and pedagogical adaptation. These principles were systematically translated into the Policy Alignment Layer of the framework, grounding the model within authentic institutional structures.

The third phase involved architectural modeling and system design specification. During this stage, the research team translated the conceptual framework into a proposed modular technical architecture, including workflow pipelines, policy validation logic, infrastructure deployment models, and analytics feedback mechanisms. This stage reflects what DBR literature describes as the "design conjecture" phase, where theoretical principles are embodied within proposed system components [14].

While a functional prototype has not yet been deployed, the architectural specification establishes a technically feasible pathway for implementation and future empirical testing.

The subsequent phase of this research will involve prototype development and iterative evaluation within the ECSU instructional context. Planned evaluation metrics include syllabus parsing accuracy, governance compliance alignment, faculty usability feedback, and alignment clarity across disciplines. Consistent with DBR methodology, empirical findings will inform iterative refinement of both the framework and its technical implementation. Through this phased and contextually grounded approach, the CLASS AlignED study contributes both a theoretically informed instructional architecture and a research-informed pathway toward scalable, governance-aware AI integration in higher education.

3 THE CLASS-ALIGNED FRAMEWORK

3.1 Conceptual Model

The CLASS AlignED Framework is built on the idea that artificial intelligence (AI), high-performance computing (HPC), and Science Gateway technologies should be integrated into courses in a structured and responsible way. Instead of treating AI as an independent tool that instructors use informally, the framework treats it as part of a larger system that includes university policies, teaching workflows, computing infrastructure, and measurable learning outcomes.

Many universities now have AI policies, but faculty are often left to interpret these policies on their own when designing courses. This can create confusion and inconsistency. CLASS AlignED approaches this challenge as an alignment problem. Successful AI integration requires more than access to tools—it requires connecting policy rules, instructional design, technical systems, and student learning goals in a coordinated way.

The framework includes four connected layers as seen in Figure 1: Conceptual Model of the AI Integration Framework Layers:

1. **Policy Alignment Layer** – Defines institutional rules and expectations for AI use, including accountability, transparency, privacy protection, and appropriate assessment practices.
2. **AI Workflow Layer** – Provides structured, repeatable processes for using AI in syllabus design, assignment development, and course improvement. Faculty remain in control, and AI serves as a support tool rather than a replacement for instructor judgment.
3. **Infrastructure Integration Layer** – Connects AI-supported workflows to secure computing systems so that AI use operates within approved and scalable technical environments.
4. **Analytics and Outcomes Layer** – Measures the impact of AI integration on student learning, responsible use, and instructional effectiveness.

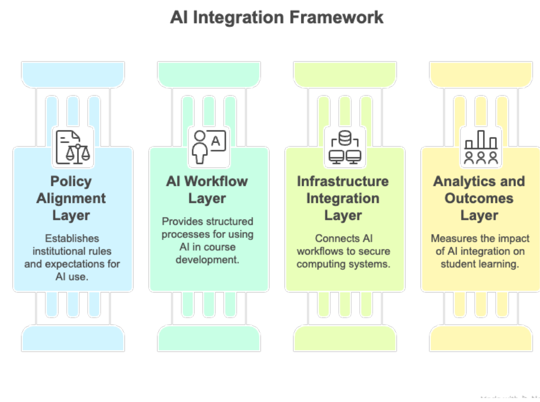

Figure 1: Conceptual Model of the AI Integration Framework Layers

These layers work together in a continuous cycle. Policy guides workflow design, workflows use infrastructure resources, infrastructure generates data, and analytics help improve policy and teaching practices over time.

It is important to distinguish between the CLASS AlignED Framework and the CLASS AlignED Tool. The framework describes the overall design and structure for responsible AI integration. The tool is the software system being developed to put this framework into action through features such as syllabus analysis, learning objective mapping, and compliance checks. By organizing AI integration around these four layers, the CLASS AlignED Framework provides a clear and scalable model for institutions seeking to responsibly incorporate AI, HPC, and Science Gateway technologies into undergraduate education.

3.2 System Architecture

The system architecture of CLASS AlignED explains how the framework is turned into a working technical system. While the conceptual model describes the ideas behind the framework, the architecture describes how the different parts connect and operate together in practice.

At a high level, the CLASS AlignED Tool functions as a structured pipeline. The process begins when a faculty member uploads a course syllabus into the system. The system then performs several steps:

1. **Document Ingestion and Parsing** – The syllabus is read and analyzed. Key sections such as learning objectives, course descriptions, and assessment strategies are identified and extracted.
2. **Learning Objective Mapping** – The extracted learning objectives are analyzed to determine where AI tools, HPC resources, or Science Gateway platforms could support or enhance course goals.
3. **Policy Validation** – The system checks recommendations against institutional AI policies to ensure that suggested uses

align with governance principles such as transparency, privacy, and academic integrity.

4. **Resource Recommendation Generation** – Based on the alignment analysis, the system generates structured guidance for faculty. This may include suggested AI-supported workflows, infrastructure resources, or assessment redesign ideas.

These components are modular, meaning each part operates independently but connects to the larger system. This modular design supports flexibility, maintenance, and scalability.

The architecture also supports multiple deployment environments depending on institutional needs:

- **University IT–Integrated Model** – Uses institutionally approved databases and authentication systems to ensure compatibility with existing campus infrastructure.
- **On-Premises Model** – Keeps all data within local institutional servers for enhanced privacy and compliance.
- **Managed Cloud Model** – Supports scalable, multi-department deployment with high availability and performance.

Across all deployment options, the CLASS AlignED architecture prioritizes security, reliability, scalability, and accountability. Secure authentication and access control ensure that only authorized faculty and institutional users can access the system, typically through campus single sign-on (SSO) systems and role-based permissions. This protects sensitive instructional materials and aligns with institutional data governance policies. The system also relies on containerized and reproducible services, meaning its components are packaged in standardized environments (such as Docker containers) that can be consistently deployed across different servers or campuses. This improves reliability, simplifies updates, and supports long-term sustainability. Scalable vector-based search and retrieval enable the system to efficiently analyze syllabi and match learning objectives to relevant AI, HPC, and Science Gateway resources, even as the number of users and documents grows. Finally, logging and auditability features track system activity, policy checks, and workflow decisions. These records support transparency, institutional oversight, and responsible AI governance by allowing institutions to review how recommendations were generated and applied.

By structuring the system as a clear pipeline with modular components and flexible deployment models, the CLASS AlignED architecture ensures that AI-supported instructional innovation operates within secure, compliant, and sustainable computing environments. This design transforms the conceptual framework into a practical, institution-ready technical system.

3.3 Prototype Implementation (Planned Development)

At the time of writing, the CLASS AlignED Tool has not yet been fully implemented. Instead, this section outlines the planned prototype development that will operationalize the CLASS AlignED Framework. The goal of the future prototype is to translate the four-layer conceptual model into a working faculty-facing system. This planned implementation will allow the research team to evaluate feasibility, alignment accuracy, and governance integration in a controlled instructional environment.

The proposed prototype will begin with automated syllabus ingestion and structured document parsing. Faculty will upload syllabi in common formats such as PDF or DOCX, and the system will extract key components including learning objectives, course descriptions, and assessment structures. These elements will then be processed using embedding models to enable semantic comparison between course goals and available AI, HPC, and Science Gateway resources. This approach is intended to provide an automated yet transparent mechanism for instructional alignment.

Following learning objective extraction, the prototype will include a policy validation module designed to encode institutional governance principles. This module will evaluate whether recommended AI-supported workflows align with institutional standards for transparency, privacy, academic integrity, and faculty oversight. Rather than functioning as a rigid restriction engine, the system will generate compliance-aware recommendations and flag potential conflicts for faculty review. This design ensures that governance remains embedded within the workflow rather than external to it.

Technically, the planned architecture will follow a modular and containerized design. A backend service, potentially built using frameworks such as FastAPI, will manage document processing and workflow logic. A vector database will support semantic search and alignment mapping between syllabus content and curated resource repositories. Containerized deployment will ensure reproducibility, portability, and compatibility with institutional IT environments.

Future validation of the prototype will involve testing with representative syllabi from multiple disciplines. Evaluation metrics will include parsing accuracy, alignment clarity, governance compliance detection, and faculty usability feedback. These pilot studies will provide empirical data to assess the effectiveness of governance-aware syllabus analysis. By outlining this planned implementation pathway, this section demonstrates that the CLASS AlignED Framework is technically feasible and positioned for systematic development and evaluation in future work.

4 DISCUSSION

The adoption of generative artificial intelligence in higher education has accelerated rapidly, prompting institutions to rethink their pedagogical strategies, academic policies, and governance frameworks. A systematic literature review of empirical studies on generative artificial intelligence reveals that these technologies are increasingly viewed as transformative tools capable of fostering enhanced learning, expanding instruction modalities, and supporting future workforce readiness. However, the review also highlights persistent challenges — including concerns about assessment practices, the need for comprehensive institutional strategies, and risks to academic integrity — that require structured institutional responses rather than ad hoc adoption [15].

These broader patterns align closely with the need for governance-oriented frameworks that position AI integration within strategic institutional priorities. For example, the review notes that generative artificial intelligence tools are valued for their versatility and educational enhancement potential, yet scholars emphasize the importance of coherent institutional strategies that address not only technical deployment but also pedagogical alignment, ethical considerations, and workforce preparation [15]. This again underscores that AI adoption cannot remain fragmented or informal; it must be intentional, institutionally accountable, and pedagogically grounded.

Another recent study analyzing university policies surrounding generative AI, particularly ChatGPT, finds that top universities in the U.S. are adopting an "open but cautious" approach, combining acceptance of AI technologies with careful attention to ethical usage, accuracy, and data privacy. In practice, many institutions are issuing resources such as syllabus templates, workshops, and consultations to help faculty navigate this new terrain while aligning AI use with curricular goals and academic integrity standards [9]. These policy efforts reflect a broader recognition that governance must be embedded into instructional planning, not merely appended as an administrative afterthought.

The design of CLASS AlignED, which emphasizes embedded governance in AI workflows, syllabus-driven analytics, policy translation into operational logic, and a reproducible architecture for responsible AI adoption, directly addresses the converging needs identified in this literature. Embedding governance into AI workflows ensures that ethical concerns and academic integrity considerations are operationalized within the systems themselves, rather than treated as external constraints. Aligning faculty analytics with course syllabi mirrors the policy recommendations that universities develop contextualized resources to help instructors adapt their teaching practices in ways that integrate AI responsibly. Translating institutional policy into operational logic responds to the documented need for clearer frameworks that reduce ambiguity around AI use and align it with program goals. Finally, a reproducible architecture for AI adoption supports scalability across institutional units, a critical requirement given the breadth of challenges highlighted in the empirical review [15].

Taken together, the literature confirms that responsible AI integration in higher education must be both pedagogically informed and institutionally governed. Models like CLASS AlignED, which combine governance, faculty support, policy operationalization, and scalable design, provide a coherent response to the challenges identified in systematic research on generative AI's impact on educational practice. By situating AI within holistic institutional frameworks rather than isolated tools or pilot experiments, institutions can leverage AI to enhance teaching, learning, and workforce alignment while safeguarding academic integrity and ethical standards [15].

4.1 Institutional Governance Context: Targeting ECSU and the UNC System

The planned design and implementation of the CLASS AlignED prototype will specifically target Elizabeth City State University (ECSU) within the broader governance structure of the University of North Carolina (UNC) System. The UNC System operates under a distributed governance model that emphasizes responsible integration of artificial intelligence rather than prohibition [16], [17]. System-level guidance promotes shared principles, professional development, and faculty-led instructional adaptation while allowing individual campuses to operationalize AI governance within their own academic frameworks. This decentralized but principle-driven model provides an appropriate institutional environment for piloting governance-aware instructional technologies.

At ECSU, AI governance is implemented primarily through existing academic integrity policies, student conduct standards, and instructional guidelines rather than through a standalone AI policy document [18], [19]. The Student Code of Conduct defines plagiarism broadly, extending accountability to AI-generated material that is submitted without proper attribution. Library guidance reinforces citation practices and academic integrity expectations in alignment with UNC system principles. This layered governance structure offers a realistic institutional context in which the CLASS AlignED prototype can encode and test policy-aligned instructional workflows.

The UNC System further emphasizes key governance principles, including human accountability, transparency in AI use, data privacy protection, and pedagogical adaptation [16], [20]. While these principles establish a clear ethical framework, they do not provide operational mechanisms for translating policy into classroom practice. The planned CLASS AlignED prototype will address this gap by embedding these governance principles directly into syllabus analysis, workflow recommendations, and compliance validation processes. By targeting ECSU within the UNC System, the prototype will be designed to reflect authentic institutional constraints while remaining adaptable to other campuses within the system.

Positioning ECSU and the UNC System as the initial implementation context strengthens both the research design and the framework's practical relevance. The governance environment provides clear policy guidance while preserving faculty autonomy, creating a balanced testing ground for structured AI integration. By aligning the prototype with system-level principles and campus-level policies, CLASS AlignED aims to demonstrate how governance-aware automation can bridge the gap between institutional AI policy and day-to-day instructional decision-making. This targeted institutional grounding supports future scalability while ensuring that the prototype remains anchored in real-world governance structures.

5 FUTURE WORK

Future work will focus on the development and evaluation of a functional prototype of the CLASS AlignED Tool. While this paper presents the conceptual model and system architecture, the next phase of research will translate these designs into an operational software implementation. The planned prototype will implement automated syllabus parsing, learning objective extraction, policy validation, and infrastructure-aware recommendation generation as described in Section 3.3. This development phase will allow the research team to move from architectural planning to empirical testing.

Once implemented, the prototype will be evaluated using representative syllabi from multiple academic disciplines. Testing will examine parsing accuracy, the quality and clarity of instructional recommendations, and the effectiveness of embedded governance checks. Faculty usability feedback will also be collected to assess whether the system meaningfully reduces uncertainty around AI, HPC, and Science Gateway integration. These evaluations will provide evidence regarding both technical feasibility and instructional impact.

Future research will also explore scalability and institutional adaptability. The prototype will be tested across different deployment models, including campus-integrated, on-premises, and managed cloud environments. This evaluation will help determine how well the architecture supports varying levels of institutional infrastructure and governance requirements. Additional work will focus on expanding curated resource repositories to improve alignment precision across disciplines.

Finally, longitudinal studies will examine how sustained use of the CLASS AlignED Tool influences faculty adoption patterns, instructional redesign, and student learning outcomes. By systematically evaluating these factors, future research will determine whether governance-aware automation can meaningfully bridge the gap between institutional AI policy and classroom practice. The planned prototyping phase represents a critical step in transforming the CLASS AlignED Framework from a conceptual model into a validated, scalable instructional system.

6 CONCLUSION

This study investigated how automated syllabus parsing and learning objective mapping can support the alignment of course outcomes with AI tools, high-performance computing (HPC) resources, and Science Gateway platforms while maintaining adherence to institutional policy. The findings suggest that alignment is most effective when governance, workflow design, infrastructure integration, and measurable outcomes are treated as interconnected components rather than independent initiatives. By embedding institutional policy constraints directly into AI-assisted instructional workflows, the CLASS AlignED framework reduces ambiguity in faculty decision-making and operationalizes compliance at the point of course design.

The four-layer architecture demonstrates that automated syllabus analysis can serve as a structured entry point for integrating AI, HPC, and cyberinfrastructure resources into undergraduate curricula. Rather than replacing faculty judgment, the system augments instructional planning through guided alignment recommendations, compliance validation, and scalable infrastructure support. This integrated approach helps bridge the documented gap between institutional AI policy and classroom practice.

While further empirical validation across multiple courses and campuses is needed, preliminary implementation indicates that governance-aware automation can meaningfully support responsible AI adoption. For HBCUs and similarly situated institutions, CLASS AlignED offers a replicable framework for advancing AI-enabled instruction while preserving institutional autonomy, ethical safeguards, and equitable access to advanced computing resources.

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