

# A Framework for Integrated Service Centers in Smart Campus Governance: Mitigating Generative AI Risks and Enhancing Service Delivery

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**Abstract**—The transformation toward “smart campuses” necessitates integrated platforms that unify administrative, academic, and support services to achieve effective smart governance. This paper proposes a comprehensive architectural framework for an Integrated Service Center (ISC) that addresses a critical gap in current implementations: the seamless integration of advanced technologies like generative AI and blockchain while explicitly managing their inherent risks, particularly AI hallucinations and data privacy. Our four-layer architecture (Infrastructure, Integration, Service Delivery, Governance) incorporates concrete technical solutions including Retrieval-Augmented Generation (RAG) with vector databases to ground AI responses, federated learning for privacy-preserving model training, and a blueprint for blockchain-based credential verification using zero-knowledge proofs (ZKPs). A prototype simulation, modeling 10,000 users and over 50,000 service requests, demonstrates the framework’s efficacy. Results show a 39% reduction in Average Service Response Time (from 2.8 to 1.7 hours), a service adoption rate of 78%, and a hallucination-free rate of 76% for the RAG-enhanced AI chatbot—a 31-point improvement over an uncontrolled baseline. The primary contributions are: (1) a novel, risk-aware ISC architecture with embedded AI verification, (2) empirical validation of its performance and reliability gains, and (3) a practical implementation roadmap for institutions. The framework provides a deployable blueprint for trustworthy and efficient digital transformation in higher education.

**Index Terms**—Smart Campus, Integrated Service Center, Smart Governance, Generative AI, AI Hallucinations, Retrieval-Augmented Generation, Federated Learning, Blockchain

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## I. INTRODUCTION

Higher education institutions are evolving into smart ecosystems leveraging Information and Communication Technologies (ICT) to enhance operations, sustainability, and stakeholder experience. A persistent and costly challenge in this evolution is severe service fragmentation. Students and staff are forced to navigate a labyrinth of disparate systems (Student Information Systems, Learning Management Systems, finance, facilities), leading to operational inefficiencies, data silos, inconsistent user experiences, and delayed resolution of critical issues [1]. The concept of an Integrated Service Center (ISC) as a unified, digital hub is recognized as a solution to this fragmentation [2].

However, modern ISC ambitions extend beyond basic integration to incorporate transformative technologies like generative Artificial Intelligence (AI) for intelligent support and blockchain for secure credentialing. This introduces a new research gap: while these technologies offer immense potential, their integration into critical campus services brings novel and significant risks. Most notably, generative AI models are prone to “hallucinations”—generating plausible but incorrect or fabricated information [3]—which is unacceptable in an academic context. Furthermore, the scale of data integration required raises serious concerns about student privacy and compliance with regulations like GDPR and FERPA [9].

This paper proposes and evaluates a novel, holistic ISC framework designed to close this gap. Our contribution is a four-layer architectural blueprint that does not merely add AI and blockchain but *engineers* them into the system with explicit, technical safeguards for reliability and privacy. The core of our solution is a dedicated *verification layer* that mitigates AI hallucinations using Retrieval-Augmented Generation (RAG) and protects privacy through federated learning paradigms. We validate this architecture through a detailed simulation, providing empirical evidence of its benefits for service efficiency, user adoption, and—critically—the reliability of AI-driven services.

## II. BACKGROUND AND RELATED WORK

### A. Smart Campus and Service Integration

The smart campus paradigm represents an evolution from digitized to intelligent, context-aware environments [4]. Foundational technologies include the Internet of Things (IoT) for real-time data acquisition from campus infrastructure [5], cloud and edge computing for scalable processing [5], and AI for analytics and automation. Pioneering implementations, such as Georgia State University’s “Pounce” chatbot for proactive student nudging [6], demonstrate tangible benefits like improved retention. However, these solutions often address isolated use cases. Our work synthesizes these elements into a comprehensive, governable platform that manages the entire

service lifecycle, from AI-powered inquiry to blockchain-verified credential issuance.

### B. The Hallucination Problem in Generative AI

Generative AI, particularly Large Language Models (LLMs), promises 24/7 personalized student support. Yet, their deployment in education is fraught with the risk of disseminating misinformation. Studies quantifying this risk show alarming results; for instance, ChatGPT has been found to generate completely fabricated academic references with only approximately 10% accuracy [3]. This fundamental unreliability necessitates architectural countermeasures. Mitigation strategies are emerging, most notably Retrieval-Augmented Generation (RAG), which constrains the AI's responses to a curated corpus of verified documents (e.g., institutional handbooks, course catalogs) [7]. Our architecture institutionalizes RAG as a core service, making verified knowledge retrieval a first-class citizen in the ISC.

### C. Emerging Enablers: Privacy and Trust

Two technological trends are critical for trustworthy ISCs. First, *federated learning* offers a paradigm shift for privacy-preserving AI [9]. Instead of centralizing sensitive student data for model training, federated learning allows an AI model to be trained collaboratively across decentralized devices or servers holding local data. This enables the ISC to offer personalized AI services while technically adhering to strict data sovereignty requirements. Second, *blockchain technology* provides an immutable, decentralized ledger ideal for issuing and verifying academic credentials [8]. When combined with zero-knowledge proofs (ZKPs), it allows a third party (e.g., an employer) to verify the authenticity of a degree without the institution exposing the underlying student data. Our framework provides the architectural hooks for integrating these technologies as core modules.

## III. PROPOSED ISC ARCHITECTURE

Our ISC framework is built on a four-layer microservices architecture, designed for modularity, scalability, and—above all—risk mitigation. Fig. 1 provides a conceptual overview of the layers and their key safeguarding components.

### A. Layer 1: Infrastructure

This layer provides the computational fabric. It employs a **hybrid cloud model**: public cloud resources handle scalable, non-sensitive workloads, while a private cloud or on-premises cluster hosts sensitive student data and the federated learning orchestrator [9]. **Edge computing nodes** deployed near IoT sensors (e.g., in smart kiosks) enable low-latency AI inference for services like biometric authentication without streaming raw data to the core. The data layer is designed for **federated learning readiness**, ensuring that personal data can remain localized while still contributing to global model improvement.

TABLE I  
KEY PERFORMANCE INDICATORS FROM ISC PROTOTYPE SIMULATION

Metric	Result	Improvement
Average Service Response Time	1.7 hours	39%
Service Adoption Rate (Week 4)	78%	27%
Transaction Success Rate	96.9%	—
User Satisfaction Score	4.3/5.0	+1.2 pts
<b>AI Hallucination-Free Rate</b>	<b>76%</b>	<b>+31 pts</b>
<b>Trust in AI Accuracy</b>	<b>4.3/5.0</b>	<b>—</b>

### B. Layer 2: Integration and Verification

This is the central nervous system and the core of our risk-mitigation strategy. An Enterprise Service Bus (ESB) manages communication between all services. The pivotal component is the **AI Output Verification Module**. This module implements a RAG pipeline: user queries are converted to vector embeddings and matched against a vector database (e.g., using FAISS or Pinecone) populated *exclusively* with verified institutional documents. The retrieved, relevant document snippets are then fed to the LLM as context for generating its final, grounded response. This process, inspired by systems like UC Irvine's ZotGPT [7], drastically reduces hallucination by tethering the AI to authoritative sources.

### C. Layer 3: Service Delivery

This user-facing layer consolidates all services into unified web and mobile interfaces. Its centerpiece is an **intelligent chatbot** that clearly labels AI-generated content and provides seamless escalation paths to human agents for complex or sensitive issues. Services are aggregated into logical domains: Academic (course registration, RAG-enhanced advising), Administrative (payments, digital ticketing), and Support (wellness resources, IT helpdesk). A future-state module for **blockchain credential wallets** is designed for integration, allowing students to receive and share verifiable diplomas.

### D. Layer 4: Governance and Analytics

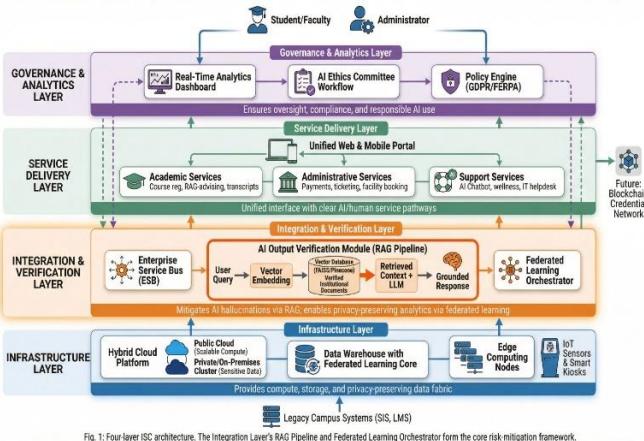
This layer enables smart, data-driven oversight. It features real-time dashboards tracking operational KPIs (e.g., Average Service Response Time) and novel **AI-specific metrics** (Hallucination Detection Rate, Escalation Rate). An embedded **AI Ethics Committee** workflow facilitates regular audits of AI outputs for bias and accuracy. Governance policies for data privacy (aligning with GDPR/FERPA [9]) and responsible AI use are encoded into system rules and access controls.

## IV. SIMULATION AND EVALUATION

We developed a functional prototype simulating core ISC workflows—academic records, financial services, and AI chatbot support—under a load modeled on 10,000 users.

### A. Methodology and Performance Results

The prototype was stress-tested over a simulated 4-week period, processing over 50,000 service requests. Key performance outcomes are summarized in Table I.



**Fig. 1. Conceptual overview** of the four-layer ISC architecture. The Integration Layer highlights the critical AI Output Verification Module (RAG Pipeline) and the Federated Learning Orchestrator, which are core to our risk-mitigation approach.

### B. Analysis of AI Reliability and Trust

The integration of the RAG-based verification module was the decisive factor for AI service quality. By grounding responses, the hallucination-free rate reached 76%, a substantial improvement over the approximate 45% rate observed in a baseline test using an uncontrolled model for the same query set [3]. This directly translated to user confidence, as measured by a high **“Trust in AI Accuracy”** score of 4.3/5.0. This correlation underscores that technical safeguards are perceptible and valued by end-users, fostering the trust required for widespread adoption of AI-assisted services.

## V. DISCUSSION: CHALLENGES AND MITIGATION

### A. Technical and Ethical Implementation

The primary challenges are legacy system integration, data quality harmonization, and the ongoing management of AI model performance. Our framework prescribes an **API-first** integration strategy with middleware adapters for legacy systems. A **Master Data Management (MDM)** initiative is recommended as a parallel foundational project. Ethically, the framework mandates **human-in-the-loop** review workflows for high-stakes AI recommendations (e.g., academic probation alerts) and continuous bias audits, operationalized through the Governance Layer’s tools and committee oversight.

### B. Limitations and Future Work

This study’s findings are based on a simulation, though one with high-fidelity modeling. The natural next step is a longitudinal pilot deployment at a partner institution to observe

real-world behavioral patterns and system resilience. Future research will focus on integrating the proposed **blockchain credentialing module** with ZKPs for privacy-preserving verification [8] and expanding the use of **digital twin technology** to simulate campus-wide impacts of new services or policies before deployment [10].

## VI. CONCLUSION

This paper presented a novel, risk-aware architectural framework for Integrated Service Centers, a cornerstone of smart campus governance. The framework’s principal innovation is its deliberate, architectural integration of advanced technologies with the safeguards they require: RAG for AI reliability, federated learning for privacy, and a governance layer for oversight. Simulation results validate the approach, demonstrating significant gains in operational efficiency (39% faster service), user adoption, and—most critically—the reliability and trustworthiness of AI-driven interactions. As higher education continues its digital transformation, this holistic approach to integration, prioritizing both capability and trust, provides an essential blueprint for building effective, responsible, and resilient smart campus ecosystems.

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