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The Application of Artificial Intelligence in Risk Management of University Procurement

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Abstract

Artificial intelligence (AI) is revolutionizing risk management in university procurement by enabling proactive, data-driven strategies to address complex challenges in supply chain resilience, compliance, and stakeholder demands. This study analyzes the application of AI across several critical domains: proactive risk identification through real-time data analysis, dynamic supplier profiling for enhanced selection and contract management, and workflow automation to significantly improve operational efficiency. The implementation of these technologies, however, presents significant challenges, including stringent data governance requirements, ethical considerations, and institutional resistance to change. This paper examines strategic solutions to these challenges, such as leveraging cooperative purchasing models and adopting tiered risk categorization frameworks. The findings demonstrate AI's potential to enhance supply chain resilience, optimize resource allocation, and align procurement activities with institutional sustainability goals. The conclusion emphasizes that successful, sustainable integration requires a risk-based approach to AI procurement itself, coupled with continuous model refinement and strategic capacity building.

Keywords: Ai-Driven Procurement, Risk Management, Higher Education, Supply Chain Resilience, Predictive Analytics

1 INTRODUCTION

University procurement operations face a complex risk landscape characterized by budget constraints, supply chain disruptions, compliance requirements, and the unique challenges of decentralized purchasing across academic departments, research labs, and administrative units [1]. The integration of artificial intelligence (AI) into procurement risk management represents a transformative opportunity for higher education institutions to enhance operational resilience, optimize resource allocation, and maintain strategic alignment with institutional goals. This research examines how AI technologies are being deployed to address the specific risk management challenges inherent in university procurement environments. The application speed of artificial intelligence in procurement has significantly accelerated, with most procurement managers now using generative artificial intelligence at least once a week, an increase of 44 percentage points from 2023 to 2024 [2]. This rapid integration reflects the growing recognition of AI's potential to automate complex tasks, provide predictive insights, and enhance decision-making capabilities. For universities, AI-powered solutions offer particular promise in addressing longstanding procurement challenges, including fragmented systems, limited visibility into supplier networks, and the need for more sophisticated risk assessment methodologies [3].AI applications in university procurement risk management span multiple domains, including supplier risk assessment, compliance monitoring, contract analysis, and supply chain disruption prediction. Machine learning algorithms can process vast datasets to identify patterns indicative of supplier financial instability, while natural language processing enables automated analysis of contract documents for compliance risks [4]. These capabilities are particularly valuable in higher education contexts, where procurement teams must navigate complex regulatory environments while supporting diverse stakeholder needs across campus operations [5].

The implementation of AI in university procurement also necessitates careful consideration of governance frameworks and risk-based approaches to technology adoption. As Casovan and Shankar (2022) emphasize, "Responsibly procuring and deploying AI systems requires organizations to develop capacity in the form of new contract requirements, assessments, and governance processes" [6]. This research explores how universities can

balance the transformative potential of AI with the ethical and operational considerations essential for sustainable implementation. As higher education institutions increasingly turn to AI solutions, understanding both the capabilities and limitations of these technologies becomes critical for effective risk management strategy development. This report provides a comprehensive analysis of current applications, implementation challenges, and future directions for AI in university procurement risk management, offering insights for institutional leaders seeking to leverage technological innovation while maintaining robust oversight mechanisms.

2 AI-DRIVEN PROACTIVE RISK IDENTIFICATION AND MONITORING

A foundational shift enabled by artificial intelligence in university procurement risk management is the transition from reactive, historical analysis to proactive, real-time identification of potential disruptions. Traditional methods, which often rely on periodic audits and self-reported supplier questionnaires, are ill-suited to the dynamic nature of modern supply chains. AI-powered systems address this gap by continuously ingesting and analyzing vast quantities of structured and unstructured data from diverse external sources. These systems monitor financial news wires for indicators of supplier instability, track global events for geopolitical or environmental disruptions, and scan regulatory databases for compliance changes [7]. This capability allows procurement teams at universities to receive automated alerts about emerging risks, such as a key supplier's credit rating downgrade or political unrest in a critical supplier's region, long before these issues manifest as supply shortages or contractual failures [8].

The predictive power of these systems is rooted in advanced pattern recognition. AI algorithms are trained to identify subtle correlations and anomalies within data that would be imperceptible to human analysts. For instance, a combination of minor delivery delays, negative sentiment in employee reviews on social media, and a slight increase in defect rates from a supplier could be synthesized by an AI to flag a high probability of a major operational breakdown in the near future. This provides university procurement officers with a crucial early-warning system, transforming their role from firefighters responding to crises to strategic planners preventing them. This is particularly critical for mitigating risks associated with lower-tier suppliers (Tier 2 and Tier 3), where visibility is traditionally lowest. A survey cited by GEP highlights that 70% of procurement leaders view insufficient visibility into Tier 3 suppliers as a primary cause of supply chain risks [7]. AI tools can map these complex, multi-tiered supply networks and apply the same real-time monitoring, thereby illuminating previously opaque risk areas.

Beyond mere monitoring, AI significantly deepens the quality of supplier risk assessments by creating dynamic, multi-dimensional risk profiles. Instead of relying on a static scorecard, AI systems amalgamate data from numerous criteria to generate a holistic view of a supplier's risk posture. This includes, but is not limited to, financial health, cyber-security resilience, operational capacity, historical performance metrics, and compliance history. By analyzing these factors in concert, the AI can assign a more nuanced and accurate risk score than any single metric could provide [9].

For university procurement, this is invaluable during the vendor selection process. AI can rapidly analyze and score a pool of potential suppliers for a major IT infrastructure project or a campus dining contract, highlighting those with the strongest overall risk profile. This data-driven approach supports more informed and defensible decision-making. Furthermore, these risk profiles are not static. AI systems continuously update them based on real-time data, ensuring that the university's understanding of a supplier's risk level evolves alongside the supplier's own circumstances. This ongoing assessment is crucial for managing long-term contracts, which are common in higher education for services like facilities management or bookstore operations. The system can proactively alert the procurement team if a long-standing supplier's risk profile begins to deteriorate, allowing for pre-emptive conversations or contingency planning. Table 1 presents the key data sources employed in the risk analysis of artificial intelligence suppliers.

TABLE 1 KEY DATA SOURCES FOR AI-POWERED SUPPLIER RISK PROFILING

Data Category	Specific Examples	Risk Insights Provided
Financial Data	Credit ratings, bankruptcy filings, stock performance, annual reports.	Indicators of financial stability and long-term viability.
Operational Data	On-time delivery rates, quality control metrics, production capacity data.	Assessment of reliability and ability to meet contractual obligations.

External & ESG Data	News alerts, geopolitical event feeds, sustainability reports, regulatory compliance databases.	Exposure to geopolitical, environmental, social, and governance risks.
Cyber Intelligence	Data breach reports, security certification status, dark web monitoring.	Evaluation of cybersecurity posture and data protection capabilities.

3 STRATEGIC IMPLEMENTATION AND INTEGRATION CHALLENGES

The successful deployment of AI for risk mitigation in a university setting necessitates a deliberate strategy that extends beyond mere software acquisition. A critical first step is the development of a strategic AI procurement plan that aligns with the institution's broader objectives. This requires close collaboration between the procurement office, IT departments, legal counsel, and academic stakeholders to define clear needs and identify areas where AI can deliver the greatest value, such as protecting research supply chains or ensuring the continuity of essential campus services [5].

A paramount consideration in this implementation is data governance and compliance. Universities are custodians of vast amounts of sensitive data, protected under regulations like the Family Educational Rights and Privacy Act (FERPA), Personal Information Protection Law of the People's Republic of China. Procurement teams must therefore conduct rigorous evaluations of AI vendors to ensure their tools adhere to strict data security and privacy protocols. This involves scrutinizing data handling practices, encryption standards, and data residency requirements during contract negotiations [5]. The foundation of any effective AI system is high-quality, unbiased data; if the input data is flawed, the risk predictions will be unreliable. As noted in industry analysis, strong data governance is vital to ensure AI has the precise data it needs for accurate predictions [7].

The integration of AI also presents significant change management challenges. Procurement staff must be trained not only to use the new tools but also to interpret their outputs and integrate data-driven insights into their established workflows. The technology's value is realized only when human expertise is augmented by AI-generated intelligence. Procurement professionals must learn to trust the system's alerts and analyses, shifting from intuition-based to evidence-based decision-making. This cultural shift is as important as the technological implementation itself. The fast-paced evolution of AI also demands a departure from traditional, multi-year procurement cycles for software. As one guide notes, "AI is evolving too fast for business-as-usual procurement and implementation," suggesting a need for more agile and iterative partnership models with vendors [10].

3.1 Leveraging Cooperative Models for AI Adoption

To navigate the complexities and costs of implementing advanced AI solutions, many universities are turning to cooperative purchasing organizations (CPOs). These cooperatives aggregate the purchasing power of thousands of educational institutions, allowing individual universities to access pre-negotiated contracts with AI technology vendors at significantly reduced costs [5]. This model is particularly advantageous for AI procurement because it reduces the time and resources required for lengthy supplier evaluations and contract negotiations. CPOs perform the initial vetting of vendors for financial stability, technical capability, and compliance with educational standards, providing a layer of risk mitigation in the procurement process itself.

For a university procurement team, leveraging a cooperative contract means they can tap into a pool of pre-vetted AI solutions that are already known to be compatible with the needs of the higher education sector. This is crucial given the unique requirements of university procurement, which often involves navigating complex regulatory environments and managing a diverse portfolio of purchases, from laboratory equipment to library resources. By using a cooperative, a university can more easily find "affordable solutions for your AI needs" and accelerate the adoption timeline, ensuring they do not fall behind in leveraging technology that is becoming critical for operational resilience [5].

3.2 Measuring ROI and Optimizing AI-Driven Risk Management

The ultimate validation of an AI investment in procurement risk management lies in demonstrating a tangible return on investment (ROI) and a measurable increase in supply chain resilience. Key performance indicators (KPIs) must

be established to track the effectiveness of the AI system over time. These metrics should move beyond simple cost savings to encompass broader measures of risk mitigation and operational stability. Table 2 lists the key performance indicators for risk mitigation driven by artificial intelligence. Optimization is an ongoing process. Post-implementation, procurement teams must continuously monitor the AI system's performance, using its own analytics capabilities to identify areas for improvement. Regular feedback from end-users—the procurement staff—is essential for refining alert thresholds, user interfaces, and reporting formats. This ensures the system evolves to meet the changing needs of the university and the dynamic nature of the risk landscape. The AI models themselves also require periodic retraining with new data to maintain their predictive accuracy and avoid model drift. This cycle of measurement, feedback, and optimization transforms the AI system from a static tool into a continuously learning asset that grows more valuable over time, solidifying the university's procurement function as a strategic, resilient, and data-driven operation.

TABLE 2 KEY PERFORMANCE INDICATORS FOR AI-DRIVEN RISK MITIGATION

KPI Category	Specific Metrics	Strategic Impact
Risk Reduction	Number of supply disruptions avoided; reduction in emergency purchases; decrease in costs associated with non-compliance.	Directly measures the system's success in preventing negative events.
Efficiency Gains	Time saved on manual risk assessment tasks; reduction in full-time equivalent (FTE) hours spent on supplier monitoring.	Quantifies the operational efficiency delivered by automation.
Strategic Impact	Improvement in supplier performance scores; increase in spend under management with low-risk suppliers; improvement in contract compliance rates.	Demonstrates the enhancement of overall procurement effectiveness and value.

4 AI-ENABLED WORKFLOW AUTOMATION IN PROCUREMENT OPERATIONS

The implementation of artificial intelligence in higher education procurement extends beyond risk assessment to fundamentally transform operational workflows through intelligent automation. While previous discussions have focused on risk identification and supplier profiling, this section examines how AI systems automate routine procurement tasks, thereby increasing efficiency and reallocating human expertise to strategic initiatives. Universities are leveraging AI to streamline processes ranging from purchase requisition to invoice processing, creating significant operational advantages.

Generative AI platforms specifically demonstrate transformative potential by handling complex administrative tasks that traditionally consumed substantial staff time. These systems can automatically process purchase requests, validate them against institutional policies and budget constraints, and even generate initial procurement documentation [11]. For instance, when a research department submits a request for specialized laboratory equipment, AI can instantly verify available funding, check compliance with research protocols, and identify preferred suppliers based on historical performance data. This automation reduces procurement cycle times from weeks to days while minimizing human error in administrative processing.

The integration of AI-powered virtual assistants represents another significant advancement in workflow automation. These systems handle routine stakeholder inquiries such as "What's the status of my purchase request?" or "Which suppliers are approved for this category?" without human intervention [12]. By providing immediate, consistent responses, these assistants reduce the administrative burden on procurement professionals while improving service levels for faculty and staff across campus. The technology's natural language processing capabilities enable it to understand context and provide accurate information drawn from institutional databases and policy documents.

4.1 Predictive Analytics for Strategic Resource Allocation

Unlike conventional procurement systems that operate on historical data, AI-driven predictive analytics enable universities to anticipate future needs and optimize resource allocation. This represents a shift from reactive purchasing to proactive supply chain management, particularly valuable in the context of academic calendars and research cycles. While risk management focuses on identifying potential disruptions, predictive analytics focuses on optimizing procurement timing, quantity, and sourcing strategies to achieve both efficiency and sustainability goals.

AI systems analyze patterns in consumption data across departments to forecast needs with remarkable accuracy. For example, by examining historical textbook adoption patterns, enrollment trends, and curriculum changes, AI can predict demand for specific titles semesters in advance [11]. This allows procurement teams to negotiate better pricing through early bulk purchasing while ensuring adequate availability. Similarly, for research institutions, AI can analyze grant cycles, research publication trends, and equipment utilization rates to forecast needs for laboratory supplies and specialized equipment, preventing research delays due to material shortages.

The predictive capabilities extend to budget optimization and spend analysis. AI systems can identify seasonal spending patterns, flag potential budget overruns before they occur, and suggest optimal timing for major purchases based on market price trends. This financial foresight is particularly valuable for universities operating with constrained budgets, as it enables more strategic allocation of resources across competing institutional priorities. By transitioning from cyclical budget reviews to continuous financial monitoring, procurement departments can provide real-time insights to institutional leadership regarding spending patterns and opportunities for optimization.

4.2 Sustainability Integration Through AI-Enabled Supply Chain Analysis

Artificial intelligence enables universities to advance sustainability goals through sophisticated supply chain analysis that extends beyond traditional environmental considerations. While sustainability was mentioned in previous discussions as a component of risk management, this section examines how AI specifically facilitates the integration of environmental, social, and governance (ESG) criteria into procurement decisions. Universities are leveraging AI's analytical capabilities to evaluate suppliers across multiple sustainability dimensions, aligning procurement practices with institutional commitments to environmental stewardship and social responsibility.

AI systems can analyze vast amounts of data to assess suppliers' environmental impact, evaluating factors such as carbon footprint, water usage, waste management practices, and compliance with environmental regulations [14]. This capability is particularly valuable for universities with ambitious sustainability targets, as it provides data-driven insights into how procurement decisions contribute to or detract from these goals. For example, when evaluating potential suppliers for campus dining services, AI can compare the environmental impact of different food sourcing strategies, factoring in transportation distances, packaging materials, and agricultural practices.

The social dimension of sustainability is similarly enhanced through AI implementation. Systems can screen suppliers for labor practices, diversity policies, community engagement, and ethical sourcing standards, providing a comprehensive view of a supplier's social responsibility profile. This analysis helps universities ensure that their procurement dollars support businesses that align with institutional values regarding fair labor practices and community benefit. AI's ability to process unstructured data from news sources, social media, and regulatory databases enables identification of potential red flags that might be missed in traditional supplier questionnaires.

4.3 Change Management Strategies for AI Adoption

Successful implementation of AI in university procurement requires deliberate change management strategies that address both technological and human dimensions of transformation. While previous sections have touched on integration challenges, this analysis focuses specifically on the organizational development aspects of AI adoption, including stakeholder engagement, capability building, and cultural adaptation. Universities must navigate significant shifts in roles, responsibilities, and workflows as AI assumes more routine tasks and enables more strategic focus for procurement professionals.

A critical component of change management is comprehensive training and development programs that equip procurement staff with the skills needed to work effectively with AI systems. This extends beyond technical training to include developing data literacy, critical thinking skills for evaluating AI recommendations, and strategic analysis capabilities [13]. Procurement professionals must transition from performing transactional tasks to interpreting AI-generated insights, managing exceptions, and focusing on relationship management and strategic sourcing. Universities that invest in this capability building ensure that their teams can maximize the value derived from AI investments rather than being displaced by them.

Stakeholder engagement across the university represents another crucial change management consideration. Faculty, researchers, and administrative staff who initiate procurement requests must understand how AI systems affect the procurement process and how to interact effectively with new digital interfaces. Clear communication about the benefits of AI implementation—such as faster processing times, improved compliance, and enhanced sustainability—helps build buy-in from across the institution. Additionally, establishing feedback mechanisms allows end-users to contribute to the continuous improvement of AI systems, creating a sense of shared ownership in the digital transformation journey.

The organizational structure of procurement functions may need to evolve to fully leverage AI capabilities. As routine tasks become automated, universities can reorganize teams to focus on strategic categories, supplier relationship management, and innovation. This might involve creating new roles such as AI procurement analysts, data stewards, and digital transformation specialists who bridge technical and operational domains. By proactively redesigning organizational structures alongside technology implementation, universities can ensure that their procurement functions evolve to meet changing institutional needs in an AI-enabled environment.

5 RISK CATEGORIZATION METHODOLOGIES FOR AI SYSTEMS IN PROCUREMENT

The implementation of a risk-based framework for AI procurement in universities requires sophisticated categorization methodologies that extend beyond binary classifications. While previous discussions have addressed supplier risk profiling, this section examines the systematic approaches for classifying AI systems themselves according to their potential impact on institutional operations. The National Institute of Standards and Technology's AI Risk Management Framework (NIST AI RMF) provides a foundational structure that universities can adapt to their specific contexts, though educational institutions face unique considerations not always addressed in government or corporate frameworks [15].

Universities must develop multi-dimensional risk categorization matrices that account for several intersecting factors: the sensitivity of data processed by the AI system, the criticality of the function being automated, the autonomy level of decision-making, and the potential impact on protected classes within the university community. For example, an AI system used for automated invoice processing would typically fall into a lower risk category than one used for admissions screening or research participant selection. The University of Alaska system exemplifies this approach through its "distributed risk-based approach to evaluating the adoption of AI tools," where system-wide vetting focuses on data privacy, compliance, and enterprise security risks [16].

The emerging consensus among policymakers suggests that risk categorization should determine the intensity of oversight and compliance requirements. As proposed in federal guidance, "the level of requirements verification [should be based] on the overall risk of the system" since "compliance audits are costly" [17]. For universities, this translates to a tiered approach where high-risk AI systems undergo rigorous assessment while lower-risk systems benefit from streamlined approval processes. This proportional approach acknowledges the resource constraints common in higher education while ensuring adequate safeguards where most needed.

5.1 Integration of Impact Assessment Protocols in Procurement Lifecycle

A critical component of risk-based AI procurement involves embedding impact assessment protocols throughout the acquisition lifecycle, from needs identification to contract management. Unlike traditional IT procurement, AI systems require continuous evaluation due to their adaptive nature and potential for unexpected behaviors. The Responsible AI Institute's framework emphasizes that "an organization should assign a risk level to an AI system—such as high, medium or low—based on the results of an organization's AI impact assessment during an early phase of the procurement process" [6].For university procurement offices, this necessitates the development of standardized impact assessment tools that evaluate AI systems across multiple dimensions. Table 3 lists the comparison of high-risk and low-risk indicators under each evaluation dimension.

These assessments should be conducted at multiple stages: during vendor selection, before contract signing, and at regular intervals throughout the system's lifecycle. The European Union's proposed Artificial Intelligence Act and

Canada's Artificial Intelligence and Data Act provide models for such staged assessments that universities can adapt to their procurement processes [6].

The challenge for universities lies in building institutional capacity to conduct these assessments effectively. This requires collaboration between procurement professionals, IT security, legal counsel, and subject matter experts from relevant academic departments. As noted in analysis of AI compliance challenges, "AI in application can extend across multiple organisational functions and solutions, making it nearly impossible to confine AI risk management and compliance to technology or procurement teams alone" [15].

TABLE 3 ASSESSMENT TOOLS

Assessment Dimension	High-Risk Indicators	Low-Risk Indicators
Data Sensitivity	Processes student records, health information, or proprietary research	Uses anonymized or publicly available data
Decision Autonomy	Makes final decisions affecting student admissions, hiring, or funding	Provides recommendations subject to human approval
Impact Scale	Affects large segments of campus community or core operations	Impacts limited departmental functions
Reversibility	Decisions are difficult to reverse or appeal	Outcomes easily corrected or overridden

5.2 Contractual Mechanisms for Risk-Adaptive AI Governance

Effective risk-based frameworks must translate assessment outcomes into specific contractual requirements that evolve with the technology's risk profile. While previous discussions have addressed general procurement planning, this section focuses on the particular contractual mechanisms that enable adaptive governance of AI systems throughout their lifecycle. These mechanisms must balance the need for vendor accountability with the flexibility required for AI systems that may learn and change over time.

A risk-based approach to AI procurement "allows an organization to incorporate contracting language that aligns with emerging laws, best practices and certification standards" [6]. For high-risk AI systems, universities should consider including clauses that mandate:

1. Continuous monitoring and reporting requirements that obligate vendors to disclose performance metrics, algorithm changes, and incident reports
2. Third-party audit rights that allow the university to verify compliance with agreed-upon standards
3. Explainability and interpretability requirements tailored to the specific context of use
4. Bias testing and mitigation protocols especially for systems affecting student or employee outcomes
5. Data governance provisions specifying ownership, usage rights, and protection measures

The implementation of these contractual mechanisms should be proportional to the assessed risk level. As observed in cybersecurity procurement, organizations face "difficulty balancing the level of risk management to the level of risk impact" and "difficulty balancing trust and verification in assessment requirements" [17]. Universities can address this challenge by developing standardized contract modules that correspond to different risk categories, allowing procurement teams to select appropriate provisions without reinventing contractual language for each acquisition.

An emerging best practice involves treating "providers like strategic partners, not software providers" and encouraging "co-development, workflow integration, and accountability for outcomes" [2]. This partnership approach is particularly valuable for AI systems, where ongoing collaboration between the university and vendor can enhance system performance and risk management. Contracts should facilitate this relationship while maintaining clear accountability structures.

5.3 Capacity Building for Risk-Based AI Procurement Implementation

The successful implementation of a risk-based AI procurement framework depends heavily on developing institutional expertise across multiple stakeholder groups. While previous discussions have addressed change

management strategies, this section examines the specific knowledge and skills required to operationalize risk-based approaches effectively. The USA government's experience suggests that "oversight and enforcement of supplier compliance with AI risk management standards will require a significant effort on behalf of the government" [17].

Universities must invest in specialized training programs that equip procurement professionals with the technical literacy to evaluate AI systems meaningfully. Research indicates that 94% of procurement executives now use generative AI at least weekly, reflecting the rapid integration of these technologies into procurement functions [2]. However, using AI tools differs significantly from procuring them responsibly. Universities can adapt this model by developing certification programs or required training modules for procurement staff involved in AI acquisitions. This training should be tiered according to responsibilities, with deeper technical content for those evaluating high-risk systems.

Beyond the procurement office, universities must also build awareness and capability among faculty and staff that will use AI systems. As the University of Alaska approach indicates, "issues surrounding pedagogy and appropriate use within an educational or research context are addressed at the individual university level" [16]. This distributed model requires clear communication channels between central procurement and decentralized users to ensure that risk-based frameworks are applied consistently across the institution.

6 CONCLUSION

This research demonstrates that artificial intelligence fundamentally transforms university procurement risk management by enabling a proactive, data-driven approach to identifying and mitigating supply chain vulnerabilities. The most significant finding is AI's capacity to shift procurement from reactive firefighting to strategic prevention through continuous monitoring of diverse data sources—from financial indicators and geopolitical events to supplier operational metrics—allowing for early warnings of potential disruptions (Furthermore, AI enhances risk assessment by creating dynamic, multi-dimensional supplier profiles that provide a more nuanced understanding of risk than traditional static scorecards, which is crucial for managing the complex, multi-tiered supply networks common in higher education .

The successful implementation of these AI systems, however, is contingent upon addressing significant strategic and operational challenges. A deliberate implementation strategy that includes robust data governance—ensuring compliance with regulations like FERPA—and comprehensive change management to foster a cultural shift towards data-driven decision-making is paramount. The adoption of cooperative purchasing models emerges as a critical enabler, allowing universities to access pre-vetted, cost-effective AI solutions while mitigating the risks associated with vendor selection.

The implications point toward a future where the university procurement function becomes a strategic, resilience-focused operation. Next steps for institutions involve developing a risk-based framework for AI procurement itself, incorporating ethical considerations like algorithmic fairness and transparency, and establishing key performance indicators to measure the return on investment in terms of risk reduction and operational efficiency. Ultimately, leveraging AI effectively will require universities to treat technology vendors as strategic partners and invest in continuous capacity building for procurement staff, ensuring that human expertise is augmented rather than replaced by intelligent systems.

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