

# ***Perceived Readiness for Artificial Intelligence Enabled Auditing in Power Equipment Procurement at Guangxi Electric Power Vocational and Technical College***

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**Abstract:** The research objectives were 1) to explore stakeholders' perceptions of the key enabling conditions associated with the applicability of AI-enabled auditing in power equipment procurement, and 2) to explore experts' perspectives on the applicability and expected governance contributions of AI-enabled auditing in power equipment procurement. The sample consisted of 255 respondents involved in equipment procurement, auditing, management, and utilization at Guangxi Electric Power Vocational and Technical College and three experts who participated in the focus group discussion. The instruments used were a structured questionnaire and a semi-structured focus group discussion guide. The quantitative data were analyzed using frequency, percentage, mean, and standard deviation, and the qualitative data were analyzed using content analysis. The findings revealed that 1) stakeholders perceived the five key enabling conditions at an overall high level ( $M = 3.70$ ,  $S.D. = 0.77$ ); Data Quality received the highest evaluation, while Auditor Competency received the lowest evaluation and was at a moderate level, indicating a particular need for AI-related professional development, and 2) the experts perceived AI-enabled auditing as applicable to transaction analysis, supplier evaluation, document review, risk identification, compliance monitoring, audit-efficiency improvement, education cost control, and asset-lifecycle management, provided that implementation is gradual, supported by reliable data and infrastructure, and subject to professional oversight and institutional governance.

**Keywords:** AI-enabled Auditing; Power Equipment Procurement; Institutional Readiness; Higher Education

## **1. Introduction**

### **1.1 Research Background and Significance**

Procurement auditing in a power-oriented vocational institution involves financial records, technical specifications, contracts, supplier information, acceptance documentation, and asset

records. As the volume and variety of these data increase, manual review and sample-based inspection may provide incomplete or delayed coverage. Guangxi Electric Power Vocational and Technical College therefore offers a relevant case for examining the organizational conditions needed before AI-supported audit tools are introduced.

Digital transformation has expanded the use of data analytics and automated tools in audit work, but implementation remains uneven. Studies report that technology can widen audit coverage and support more timely analysis, while outcomes depend on integrated information systems, appropriate methods, and staff capability<sup>[1,10,12]</sup>. These findings are relevant to procurement processes in which audit evidence is distributed across procurement, finance, asset management, and user departments.

Procurement analytics and continuous monitoring can help identify exceptions, compare transactions, and direct auditors toward records that require investigation<sup>[2,15]</sup>. These tools do not remove the need for professional judgment. Their value depends on the availability of reliable data, clear audit procedures, and an organizational process for reviewing and acting on analytical results.

AI can support document extraction, pattern recognition, anomaly detection, and risk screening. Research also identifies material constraints, including inconsistent data formats, weak system compatibility, limited technical skills, explainability, privacy, bias, and overreliance on automated output<sup>[3,4,7,13,14]</sup>. For that reason, this study examines perceived readiness and expected applications rather than assuming that AI will improve audit performance.

The study contributes evidence from a specialized vocational-education procurement setting. It combines stakeholder ratings of five institutional conditions with a small expert discussion about potential applications, barriers, and governance requirements. Because no AI auditing system was implemented, the results support planning and pilot design rather than claims about actual efficiency, cost savings, or audit quality.

## 1.2 Conceptual Framework

The framework organizes five perceived enabling conditions: Data Integration Capability, Technological Infrastructure, Auditor Competency, Organizational Support, and Data Quality. These conditions describe institutional readiness for prospective AI-enabled auditing. Expected governance contributions, including risk identification, compliance monitoring, audit efficiency, and education cost control, were explored only through the expert discussion and were not measured as dependent variables.

The study is descriptive and non-causal. It does not test relationships among the five conditions, and it does not treat expert expectations as observed implementation outcomes. Existing audit problems provide context for the study but were not measured as a separate construct.

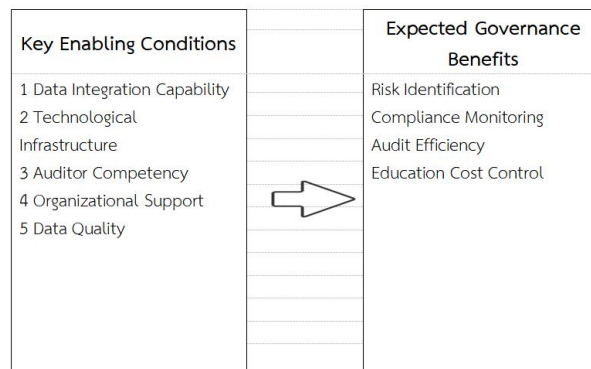


**Figure 1.** Conceptual Framework of Perceived Readiness and Expected Governance Contributions

Note: The framework organizes the study variables and qualitative themes; it does not represent a tested causal model.

### **1.3 Research Questions**

1. What key enabling conditions do stakeholders perceive as influencing the applicability of AI-enabled auditing in power equipment procurement within power-oriented vocational institutions?
2. How do stakeholders evaluate the applicability and expected governance benefits of AI-enabled auditing in power equipment procurement?

### **1.4 Research Objectives**

1. To explore stakeholders' perceptions of the key enabling conditions associated with the applicability of AI-enabled auditing in power equipment procurement.
2. To explore experts' perspectives on the applicability and expected governance contributions of AI-enabled auditing in power equipment procurement.

## **2. Literature Review**

### **2.1 Key Enabling Conditions for AI-enabled Auditing**

Research on AI and audit technology identifies data, infrastructure, professional capability, organizational commitment, and governance as recurring adoption conditions<sup>[3,4,9,13]</sup>. The present study uses five dimensions to organize these conditions in the context of power equipment procurement.

Data Integration Capability concerns access to and coordination of information held by procurement, finance, asset-management, audit, and user departments. Continuous audit and procurement-analytics research shows that analytical procedures depend on usable cross-system data and consistent identifiers<sup>[2,12,15]</sup>.

Technological Infrastructure includes digital platforms, computing and network capacity, software compatibility, maintenance, and technical support. Audit firms report that limited system maturity and compatibility can constrain the practical use of AI tools<sup>[3,4,13]</sup>.

Auditor Competency includes audit knowledge, digital literacy, data-analysis skills, and the ability to evaluate automated output. AI may assist with selected audit tasks, but auditors remain responsible for interpreting evidence and challenging results that are incomplete, opaque, or inconsistent with the audit context<sup>[3,7,8,13]</sup>.

Organizational Support includes leadership commitment, policies, resources, coordination, and accountability. Readiness research indicates that management commitment and organizational conditions affect whether AI tools can move from experimentation into routine work<sup>[9,13]</sup>.

Data Quality includes accuracy, completeness, consistency, accessibility, timeliness, security, and reliability. Poor data can weaken automated analysis, while privacy and governance controls affect whether information may be used responsibly<sup>[4,7,13,14]</sup>.

The Data Quality dimension requires cautious interpretation. Item 25 asks whether high-quality data provide reliable support for AI-enabled auditing. This item measures respondents' recognition of the importance of data quality rather than the factual quality of the college's current records. The dimension mean should therefore be read as a mixed perception of existing conditions and the importance of reliable data.

### **2.2 Artificial Intelligence, Digital Auditing, and Human Oversight**

AI-enabled audit tools range from document extraction and rule-based automation to machine-learning and foundation-model applications<sup>[5,8]</sup>. Their appropriate role is to support defined

audit tasks while leaving final evaluation and accountability with professional auditors.

Potential procurement-audit uses include extracting contract terms, comparing specifications, screening transactions, identifying unusual patterns, and prioritizing records for review. Such uses require controls for data access, model validation, documentation, explainability, and human review [4,7,13,14].

Accordingly, the study treats AI as a prospective audit-support mechanism. It evaluates perceived institutional readiness and expert expectations before implementation, not the performance of an existing system.

## **2.3 Power Equipment Procurement Auditing in Vocational Institutions**

Power equipment procurement combines substantial expenditure with specialized specifications, installation requirements, acceptance criteria, and long asset lives. Audit work may cover demand justification, budgets, bidding documents, supplier qualifications, technical parameters, contracts, acceptance records, asset registration, and payment. Procurement analytics and continuous monitoring can support this work by comparing data and identifying exceptions for further investigation [2,15].

The case institution illustrates these characteristics. Procurement activities involve multiple departments and equipment for teaching, training, research, operation, and maintenance. Audit evidence is distributed among procurement, finance, asset management, user departments, and technical staff. A technology-enabled approach can connect information from different stages, but complexity also creates implementation challenges.

Education cost control is discussed only as a potential governance contribution identified by experts. The study did not collect financial outcome data and therefore cannot conclude that AI reduces procurement or education costs.

## **2.4 Related Research and Research Gap**

Prior research documents the gradual digitalization of auditing, limited but expanding use of audit data analytics, emerging AI applications, and organizational barriers to adoption [1,3,4,6,10-13]. Procurement research also describes the role of data and cognitive analytics in sourcing and transaction analysis [15].

Three gaps motivate this study. First, evidence about readiness for AI-enabled auditing in specialized equipment procurement is limited. Second, power-oriented vocational institutions combine public procurement requirements with technical equipment evaluation, a context not directly addressed in the cited audit literature. Third, pre-implementation studies rarely combine stakeholder ratings of institutional conditions with context-specific expert views on potential uses and governance requirements.

This study addresses these gaps through a single-institution, perception-based assessment. Its contribution is limited to perceived readiness and an expert-informed implementation agenda; it does not validate a technical model or establish causal effects.

## **3. Research Methodology**

### **3.1 Research Design**

This study used a non-experimental, descriptive mixed-method design. A structured questionnaire measured stakeholders' perceptions of five readiness conditions. A subsequent group discussion with three experts explored potential applications, implementation barriers, governance requirements, and practical recommendations. Quantitative results were descriptive, and the qualitative component supplemented rather than validated the survey findings.

### 3.2 Population and Sample

The target population consisted of 700 staff members at Guangxi Electric Power Vocational and Technical College: 140 administrative staff associated with procurement, finance, asset management, or internal audit; 490 faculty and staff users of power equipment; and 70 teaching and technical staff involved in equipment operation and management.

The target sample size was calculated with Yamane's finite-population formula,  $n = N/[1 + N(e^2)]$ , using  $N = 700$  and  $e = 0.05$ , which produced approximately 255 respondents [16]. Because respondents were selected purposively within proportionally allocated stakeholder groups, the formula served as a sample-size guide rather than proof of probability-based representativeness.

Proportional allocation produced target groups of 51 administrative staff, 179 faculty and staff users, and 25 teaching and technical staff. Respondents within each group were selected purposively based on their involvement in equipment procurement, auditing, management, operation, or use. The resulting sample supports description of the participating staff but does not permit probability-based generalization to the entire population.

**Table 1.** Population and Sample Distribution

| Stakeholder Group          | Population | Sample | Sample Share (%) |
|----------------------------|------------|--------|------------------|
| Administrative Staff       | 140        | 51     | 20.00            |
| Faculty & Staff Users      | 490        | 179    | 70.20            |
| Teaching & Technical Staff | 70         | 25     | 9.80             |
| Total                      | 700        | 255    | 100.00           |

### 3.3 Research Instrument

The questionnaire contained 25 positively worded statements, with five items for each readiness dimension: Data Integration Capability, Technological Infrastructure, Auditor Competency, Organizational Support, and Data Quality. Responses used a five-point agreement scale from 1 (strongly disagree) to 5 (strongly agree). The instrument measured perceptions of institutional conditions, not actual AI-system performance.

A pilot test was conducted with 30 respondents from the target population who were excluded from the final sample. The pilot was used to review item clarity and preliminary internal consistency before the main survey.

The overall questionnaire obtained a Cronbach's alpha coefficient of 0.89 in the pilot test, indicating good internal consistency for the full 25-item instrument. Because separate reliability coefficients were not reported for the five dimensions, reliability should not be claimed independently for each subscale.

Content validity was assessed using the Index of Item-Objective Congruence (IOC). Three experts evaluated the alignment of each questionnaire item with the research objectives. Item-level IOC values ranged from 0.67 to 1.00, and all 25 items met the stated acceptance threshold of  $IOC \geq 0.67$ .

A semi-structured guide supported the supplementary expert group discussion. The three purposively selected participants represented internal auditing, procurement management, and asset management. The discussion covered potential AI applications, enabling conditions, barriers, improvement measures, and future directions. Given the small number of participants, the findings are presented as expert perspectives rather than evidence of thematic saturation.

### 3.4 Data Collection Process

The college granted permission before data collection. The questionnaire was distributed to selected participants through institutional communication channels. Participation was voluntary, and completed questionnaires were checked before analysis. The expert discussion took place after the questionnaire analysis so that participants could comment on the main patterns and implementation issues.

### 3.5 Data Analysis Methods and Interpretation

Frequency and percentage summarized demographic characteristics. Mean and standard deviation summarized responses to the five readiness dimensions. Mean scores were interpreted as follows: 4.51-5.00 = highest, 3.51-4.50 = high, 2.51-3.50 = moderate, 1.51-2.50 = low, and 1.00-1.50 = lowest. Content analysis was used to organize the expert discussion into themes. No inferential tests or causal analyses were conducted.

## 4. Research Results

### 4.1 Demographic Characteristics of Respondents

The 255 participants represented the three predefined stakeholder groups. Female respondents accounted for 53.73% and male respondents for 46.27%. The largest age group was 31-40 years (38.04%). Most respondents held a master's degree (59.22%), and faculty and staff users of power equipment formed the largest stakeholder group (70.20%). These characteristics describe the sample but do not establish population representativeness because selection within groups was purposive.

**Table 2.** Demographic Profile of Respondents (N = 255)

| Characteristic    | Category                   | Frequency | Percentage (%) |
|-------------------|----------------------------|-----------|----------------|
| Gender            | Male                       | 118       | 46.27          |
|                   | Female                     | 137       | 53.73          |
| Age               | Under 30 years             | 48        | 18.82          |
|                   | 31–40 years                | 97        | 38.04          |
|                   | 41–50 years                | 73        | 28.63          |
|                   | Above 50 years             | 37        | 14.51          |
|                   |                            |           |                |
| Education         | Bachelor's Degree          | 43        | 16.86          |
|                   | Master's Degree            | 151       | 59.22          |
|                   | Doctoral Degree            | 61        | 23.92          |
| Stakeholder Group | Administrative Staff       | 51        | 20.00          |
|                   | Faculty & Staff Users      | 179       | 70.20          |
|                   | Teaching & Technical Staff | 25        | 9.80           |
| Work Experience   | Less than 5 years          | 58        | 22.75          |
|                   | 5–10 years                 | 77        | 30.20          |
|                   | 11–15 years                | 65        | 25.49          |
|                   | More than 15 years         | 55        | 21.56          |

### 4.2 Key Enabling Conditions for AI-enabled Procurement Auditing

The overall mean across the five dimensions was 3.70 (S.D. = 0.77), interpreted as high. Data Quality had the highest dimension mean (M = 3.88, S.D. = 0.70), followed by Technological Infrastructure (M = 3.76, S.D. = 0.75), Data Integration Capability (M = 3.74, S.D. = 0.77), and

Organizational Support (M = 3.61, S.D. = 0.79). Auditor Competency had the lowest mean and was moderate (M = 3.49, S.D. = 0.84). The ranking reflects respondent perceptions; it is not an objective audit of institutional systems, staff competence, or data quality.

**Table 3.** Summary of Key Enabling Conditions

| Rank | Readiness Dimension          | Mean | S.D. | Interpretation |
|------|------------------------------|------|------|----------------|
| 1    | Data Quality                 | 3.88 | 0.70 | Agree (High)   |
| 2    | Technological Infrastructure | 3.76 | 0.75 | Agree (High)   |
| 3    | Data Integration Capability  | 3.74 | 0.77 | Agree (High)   |
| 4    | Organizational Support       | 3.61 | 0.79 | Agree (High)   |
| 5    | Auditor Competency           | 3.49 | 0.84 | Moderate       |
|      | Overall                      | 3.70 | 0.77 | High           |

Table 4 shows the highest- and lowest-scoring items in each dimension. The lowest scores concerned data accessibility, network support, AI-related training, financial resources, and data security and privacy. Item 25, the highest-scoring Data Quality item, states that high-quality data provide reliable support for AI-enabled auditing. Because this is a normative statement, its score should not be treated as direct evidence that current procurement data are high quality.

**Table 4.** Highest and Lowest Questionnaire Items by Dimension

| Dimension                    | Highest-scoring Item                                               | Mean | Lowest-scoring Item                                       | Mean |
|------------------------------|--------------------------------------------------------------------|------|-----------------------------------------------------------|------|
| Data Integration             | Data from different departments can be effectively integrated      | 3.94 | Data are accurate, complete, and accessible               | 3.49 |
| Technological Infrastructure | Adequate digital infrastructure for AI-enabled auditing            | 3.92 | Network facilities adequately support AI-enabled auditing | 3.47 |
| Auditor Competency           | Auditors are willing to adopt AI-assisted methods                  | 3.61 | Adequate AI-related professional training                 | 3.34 |
| Organizational Support       | Institution supports implementation of AI-enabled auditing         | 3.78 | Adequate financial resources are available                | 3.43 |
| Data Quality                 | High-quality data provide reliable support for AI-enabled auditing | 4.05 | Data security and privacy are effectively protected       | 3.47 |

### 4.3 Focus Group Discussion

The discussion with three experts provided supplementary views on potential uses and implementation requirements. The participants represented internal auditing, procurement management, and asset management. Their comments were organized into five themes: potential applications, facilitating conditions, barriers, improvement measures, and future directions. The themes summarize the views of these three participants and are not presented as saturated or broadly generalizable qualitative findings.

**Table 5.** Summary of Focus Group Themes

| Theme                  | Main Findings                                                                                                                    | Implication                                                         |
|------------------------|----------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------|
| Potential applications | Transaction analysis, monitoring, supplier evaluation, document/contract review, asset lifecycle management, risk identification | These are proposed uses, not tested outcomes.                       |
| Facilitators           | Standardized procedures, complete digital records, quality data, infrastructure, governance, leadership, funding                 | Readiness depends on coordinated institutional conditions.          |
| Barriers               | Competency gaps, fragmented data, incomplete records, technical constraints, privacy, funding, resistance to change              | Human, data, technical, and organizational risks must be addressed. |
| Improvement measures   | Training, data governance, infrastructure upgrades, AI policies, security safeguards, cross-departmental collaboration, pilots   | Adoption should be phased and governed.                             |
| Future directions      | Continuous auditing, integrated digital platforms, lifecycle management, advanced AI, long-term digital transformation           | Pilot evidence should precede broader scaling.                      |

## 4.4 Integrated Findings and Proposed Recommendations

The combined findings support five recommendation areas: professional development, procurement-data governance, digital infrastructure, AI governance and institutional support, and cross-departmental coordination with phased evaluation. These recommendations respond to perceived gaps and expert expectations. They should be tested through a limited pilot before wider adoption.

**Table 6.** Proposed Recommendations for Enhancing AI-enabled Procurement Auditing

| Recommendation Area                                                      | Key Recommendations                                                                                                                                                                                                                    |
|--------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1. Strengthening AI Professional Competency                              | Provide continuous training on artificial intelligence, digital auditing, data analytics, and intelligent decision-making for auditors, procurement personnel, and administrative staff.                                               |
| 2. Improving Procurement Data Management                                 | Standardize procurement data management, improve data quality, strengthen integration across departments, and develop more centralized and usable data resources.                                                                      |
| 3. Enhancing Digital Infrastructure                                      | Upgrade information systems and network facilities, improve interoperability, and strengthen technical support for future AI-assisted audit tasks.                                                                                     |
| 4. Strengthening AI Governance and Institutional Support                 | Develop AI governance policies, enhance data security and privacy protection, clarify ethical and professional oversight requirements, and provide sustainable leadership and financial support.                                       |
| 5. Promoting Cross-Departmental Collaboration and Continuous Improvement | Strengthen collaboration among procurement, finance, auditing, asset management, and information technology functions; conduct pilot AI auditing projects; and establish monitoring and evaluation mechanisms before broader adoption. |

## 5. Conclusion

This study assessed perceived readiness for prospective AI-enabled power equipment procurement auditing at Guangxi Electric Power Vocational and Technical College. Questionnaire responses from 255 participants produced an overall high rating across five readiness dimensions. Data Quality had the highest dimension mean, but its interpretation is limited by item wording.

Auditor Competency had the lowest mean and was moderate, identifying professional development as the clearest perceived gap.

Three experts identified possible applications in transaction screening, supplier evaluation, document review, risk identification, compliance monitoring, and asset-lifecycle management. They also identified requirements involving data integration, infrastructure, staff capability, security, funding, and institutional governance.

The evidence supports a phased approach. The college should first assess data and process quality, clarify governance and accountability, strengthen staff capability, and test one bounded application with measurable criteria. Expansion should depend on documented pilot performance and professional review.

The study establishes perceived readiness and an expert-informed implementation agenda. It does not establish that AI-enabled auditing is already effective at the college or that it will reduce costs, improve compliance, or increase audit quality without further testing.

## **6. Discussion**

The Data Quality dimension had the highest mean, but the result should not be read as objective evidence that existing procurement data are accurate and complete. The lowest item in this dimension concerned security and privacy, while the highest item expressed the importance of high-quality data. Prior research confirms that data reliability, privacy, explainability, and governance are central to responsible AI use in auditing [4,7,13,14]. A data-quality assessment should therefore precede any pilot.

Technological Infrastructure and Data Integration Capability were perceived at high levels, yet lower item scores for network support and data accessibility identify operational constraints. Research on digital auditing and procurement analytics similarly shows that analytical tools depend on integrated systems and usable data rather than the mere presence of software [1,3,12,15].

Auditor Competency was the only dimension rated moderate. This finding is consistent with studies that identify digital skills, AI literacy, and the ability to interpret automated output as adoption requirements [3,4,8,9,13]. Training should therefore cover data interpretation, model limitations, explainability, ethical judgment, and procedures for challenging AI-generated results.

Organizational Support was rated high overall, although financial resources received a lower item score. Adoption studies indicate that management commitment, resources, compatible workflows, and governance arrangements affect whether AI tools progress beyond experimentation [9,13].

The experts identified potential uses in supplier review, contract and document analysis, transaction monitoring, risk screening, and asset-lifecycle tracking. These uses are consistent with continuous-audit and procurement-analytics research [2,12,15]. They remain proposed applications in this setting because the study did not deploy or test an AI system.

AI should therefore be introduced as a controlled support tool. Initial pilots should use well-defined tasks, documented data sources, human review, and predetermined evaluation criteria. Explainability, audit documentation, privacy, and professional accountability should be addressed before outputs inform audit conclusions [7,8,14].

## **7. Recommendations**

### **7.1 Practical Recommendations**

The college should begin with a data and process audit covering data ownership, field definitions, identifiers, access rights, completeness, security, and interfaces among procurement, finance, asset management, and audit systems. It should then provide role-specific training and

select a narrow pilot, such as document extraction or transaction screening. The pilot should define accuracy, false-positive rates, review time, exception resolution, data-protection controls, and reviewer responsibility before implementation. Wider use should depend on documented pilot results rather than favorable perceptions alone.

## 7.2 Suggestions for Future Research

Future research should include multiple institutions and use probability-based sampling where feasible. The questionnaire should be refined so that every item measures current institutional conditions rather than mixing current conditions with statements about importance. Separate reliability evidence should be reported for each dimension. Larger and more diverse qualitative samples could examine differences among auditors, procurement staff, technical users, and managers. Most importantly, pilot studies should measure actual outcomes such as detection accuracy, false positives, review time, documentation quality, and user reliance.

## 7.3 Limitations

This study has five limitations. First, it examines one institution and uses purposive selection within stakeholder groups, so the findings cannot be generalized statistically to the full population or other colleges. Second, respondents had different roles and may not have had equal knowledge of audit systems, auditor competence, or data quality. Third, the questionnaire used self-reported perceptions and included at least one normative item, which limits interpretation of the Data Quality dimension. Fourth, only the overall questionnaire reliability coefficient was reported; the reliability of each five-item dimension was not established separately. Fifth, the qualitative component involved three experts and did not test thematic saturation. The study did not implement an AI system, so it provides no evidence of actual effectiveness, cost savings, or audit-quality improvement.

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