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The Framework Integration Approach for Large Language Model Governance in Enterprise Systems

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ABSTRACT

Large Language Model (LLM) integration in enterprise systems lacks comprehensive governance frameworks, creating risks in data quality, regulatory compliance, and decision transparency. This study aims to: (1) evaluate data quality management practices affecting LLM output reliability, (2) identify effective governance controls for regulatory compliance, and (3) develop transparency mechanisms for LLM decision-making in enterprise contexts. Through qualitative research employing Focus Group Discussions with five domain experts and pilot implementation using Llama 3.2:3B model in Acumatica ERP, this study develops a preliminary governance framework tailored for Indonesian distribution businesses. Key findings reveal: the "context problem" where LLMs produce technically accurate but business-irrelevant outputs (100% expert consensus), solved through Business-Driven Templates embedding three context types (Data, Process, Business). The integrated TOGAF-DAMA-DMBOK-COBIT framework achieved 88% expert agreement with pilot scenarios demonstrating 80-100% success rates. Resource allocation analysis shows 45% priority for data quality, 25% governance controls, 15% transparency mechanisms, and 15% training. This research contributes: (1) empirically-validated three-framework integration for LLM governance, (2) discovery and solution of the "context problem" through Business-Driven Templates, and (3) Indonesian-specific implementation roadmap reducing deployment from 18-24 to 9-12 months while addressing UU 27/2022 compliance and SMB constraints.

Keywords: Large Language Models; Data Governance; Enterprise Systems; Acumatica ERP; Indonesian SMBs

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1. INTRODUCTION

Enterprise systems serve as the critical backbone for business organizations, enabling efficient management of finance, supply chain, and business operations [1]. The integration of Large Language Models (LLMs) into these systems represents a transformative era where AI systems not only process information but create personalized knowledge on demand [2], [3]. Organizations report impressive results including 94% accuracy in predictive maintenance and 73% reduction in data retrieval time and 56% in approval cycle duration [4]. However, the absence of comprehensive governance frameworks creates significant risks that threaten the successful adoption of these transformative technologies.

The research problem centers on three critical dimensions of LLM integration challenges. First, ensuring data quality for reliable LLM outputs remains problematic, as poor data quality leads to hallucinations and unreliable AI outputs [5], [6]. Studies show that data quality issues cause LLMs to produce technically correct but business-irrelevant responses, undermining decision-making processes [7]. Second, organizations lack adequate governance controls for regulatory compliance, particularly critical given the expanded attack surface of LLM-integrated systems [8]. Third, the "black box problem" of AI systems creates transparency challenges, where organizations cannot understand or audit AI decision-making processes [9].

The evolution of data governance frameworks reveals significant gaps in addressing these challenges. While foundational frameworks like DAMA-DMBOK provide essential data management principles [10], they predate the LLM era and lack AI-specific considerations. Recent attempts to extend traditional frameworks for AI governance [11], [12] provide partial solutions but fail to address LLM-specific requirements such as prompt governance, chain-of-thought documentation, and hallucination prevention. The integration of TOGAF for enterprise architecture [13], while providing systematic implementation methodology, requires enhancement for dynamic AI systems that evolve continuously.

The Indonesian context amplifies these challenges. Distribution businesses in Indonesia face unique contextual challenges that amplify these governance gaps. These companies manage vast amounts of structured data (~100,000 transactions monthly across 2000+ database tables) ideal for LLM processing, yet struggle with data quality issues including inconsistent product codes and manual entry errors affecting operational efficiency [7]. Indonesian data localization requirements (UU No. 27/2022) mandate that certain data remain in-country, influencing LLM deployment strategies [14]. Moreover, the predominance of small and medium-sized businesses (SMBs) with limited IT resources necessitates governance frameworks that are implementable without extensive technical expertise [15].

Acumatica ERP, the enterprise system examined in this case study, exemplifies both the opportunities and challenges of LLM integration. As a cloud-native platform with open API frameworks and privacy-by-design principles, Acumatica enables flexible LLM integration while maintaining data isolation from public training models [16]. However, technical integration success does not guarantee business value. This research discovered that LLMs fail to understand business meaning in ERP data without proper contextualization. The "context problem", is where LLMs produce outputs that are technically accurate but lack business relevance.

This study addresses these critical gaps through three research questions. RQ1: How do data quality management practices affect the accuracy and reliability of LLM outputs when processing inquiries through enterprise systems? RQ2: What data governance controls are most effective in ensuring that LLMs comply with data privacy and regulatory requirements? RQ3: What mechanisms can organizations implement to effectively track, document, and govern chain-of-thought reasoning in LLM-driven decision-making?

Despite recent advances in AI governance frameworks, critical gaps remain unaddressed. Existing frameworks either focus on traditional data governance without AI considerations [10], [11] or provide partial AI governance solutions that fail to address LLM-specific requirements [12]. No existing framework successfully integrates enterprise architecture, data management, and governance controls specifically for LLM deployment in enterprise system. Furthermore, the literature lacks empirical validation of governance frameworks in real enterprise contexts, particularly for resource-constrained SMBs in emerging markets like Indonesia.

This study makes three preliminary contributions to the field. First, it presents an initial empirically validated framework integration specifically designed for LLM governance, demonstrating that effective governance requires multi-framework integration rather than single-framework extensions. Second, the discovery and solution of the "context problem" through Business-Driven Templates represents a fundamental advancement in understanding LLM-ERP integration failures. Third, the framework extends governance theory to encompass interactive, generative AI systems, providing theoretical foundations for managing AI-driven processes within enterprise environments.

This research is expected to make significant theoretical and practical contributions. Theoretically, it will extend governance frameworks to encompass LLM-specific requirements currently absent in literature. Practically, the study aims to provide: (1) a validated roadmap potentially reducing implementation time from 18-24 months to 9-12 months [17], (2) cost-effective governance leveraging native ERP capabilities [18], and (3) Indonesian-specific guidance for data residency compliance while maintaining competitive advantage. These expected contributions will be validated through expert consensus and pilot testing.

2. RESEARCH METHOD

This study employs an exploratory qualitative methodology with prescriptive approach, integrating TOGAF 10, DAMA-DMBOK2, and COBIT 2019 frameworks to develop a comprehensive data governance framework for LLM integration in enterprise systems. Through Focus Group Discussions with five domain experts and pilot implementation using Llama 3.2:3B model, the research validates a three-pillar framework comprising data quality management, comprehensive governance controls, and transparency mechanisms. The methodology follows systematic validation across five phases, specifically tailored for Indonesian distribution businesses using Acumatica ERP.

2.1. Research Design and Approach

The methodology integrates three complementary research approaches to ensure both theoretical rigor and practical applicability. First, qualitative research through Focus Group Discussions (FGDs) captures expert insights on governance requirements and practical challenges, providing rich contextual understanding of LLM integration complexities. Second, prescriptive methodology develops actionable guidelines for implementing data governance controls, bridging the gap between theoretical frameworks and operational requirements. Third, exploratory research investigates current practices and future requirements through expert consultation and pilot validation, uncovering hidden patterns and emergent governance needs. This multi-method approach ensures comprehensive coverage of both known challenges and undiscovered governance requirements.

2.2. Framework Development Methodology

Framework development followed a systematic five-phase approach aligned with TOGAF Architecture Development Method (ADM) see Figure 1, ensuring structured progression from conceptual design to practical implementation [13].

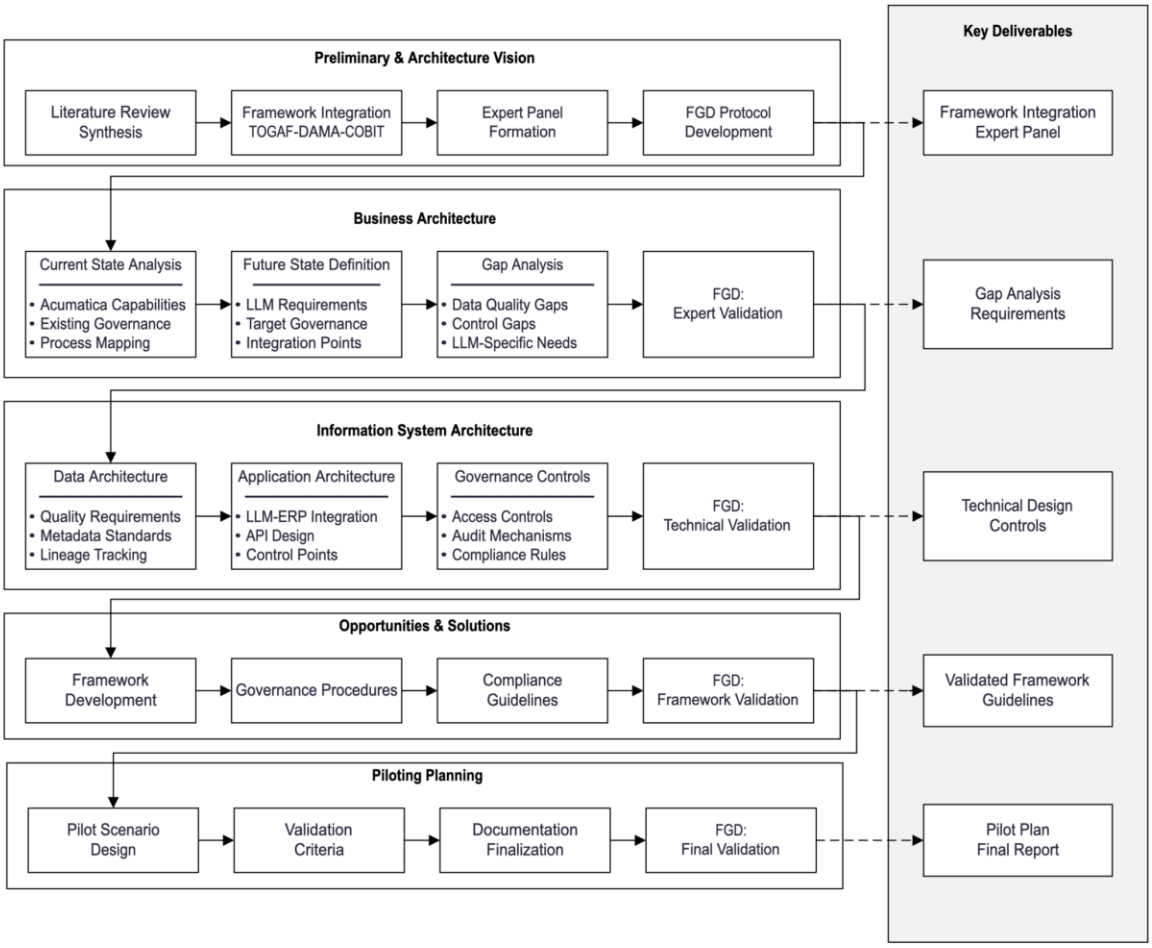

Figure 1. Research Framework

Phase 1: Preliminary and Architecture Vision (Months 1-2) This phase integrated TOGAF 10, DAMA-DMBOK2, and COBIT 2019 through systematic literature synthesis. Activities included mapping 10 governance components across frameworks as shown in Table 1, identifying framework synergies where TOGAF provides methodology, DAMA ensures data management, and COBIT establishes controls. The COBIT Goal Cascade alignment linked enterprise goals to governance objectives, ensuring business value realization. The phase concluded with initial FGD validating multi-framework necessity, achieving 100% expert consensus that no single framework adequately addresses LLM governance requirements.

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Table 1. Detailed Framework Mapping for LLM Governance Components

Governance Component	Literature Source	TOGAF 10	DAMA-DMBOK2	COBIT 2019
LLM Strategy & Vision	Strategic AI alignment needed for business value [17],[18]	Architecture Vision (Phase A)	Data Strategy (Ch.3)	APO03: Manage Enterprise Architecture
Business Process Integration	LLM-ERP process integration requirements [19],[20]	Business Architecture (Phase B)	Data Architecture (Ch.4)	APO03: Manage Enterprise Architecture
Data Pipeline Design	Structured-unstructured data integration for LLMs [21],[22]	Information Systems Architecture (Phase C)	Data Integration & Interoperability (Ch.8)	APO14: Manage Data
Infrastructure Planning	Cloud-LLM hybrid deployment architecture [23],[24]	Technology Architecture (Phase D)	Data Storage & Operations (Ch.9)	APO03: Manage Enterprise Architecture
Prompt Engineering Governance	Systematic prompting methods and template management [25]	-	Metadata Management (Ch.11)	APO14: Manage Data
Model Training Data Quality	Data quality critical for LLM reliability [5],[6]	-	Data Quality Management (Ch.13)	APO14: Manage Data
Security & Privacy	LLM data protection and access control [8],[26]	Security Architecture (Phase D)	Data Security (Ch.7)	APO13: Manage Security
Performance Monitoring	LLM output quality and system performance [4],[27]	Requirements Management (Phase H)	-	MEA02: Manage System of Internal Control
Compliance & Audit	Regulatory compliance and audit trails [11],[12]	Architecture Governance (Phase G)	Data Governance (Ch.3)	MEA02: Manage System of Internal Control
Change Management	Managing LLM model updates and versioning [28],[29]	Architecture Change Management (Phase H)	-	APO03: Manage Enterprise Architecture

Phase 2: Business Architecture Analysis (Months 2-3) Current state assessment evaluated existing governance practices across six dimensions: data quality management, access controls, audit logging, metadata management, compliance controls, and integration capabilities. Maturity assessment revealed gaps ranging from 1-3 levels below target state, with data quality showing the largest gap. Future state requirements were defined through expert consultation, identifying critical needs including real-time validation, automated cleansing, role-based access, and chain-of-thought documentation. Gap-to-solution mapping created comprehensive transformation roadmap with seven critical gaps achieving 60-100% expert agreement on severity and solutions.

Phase 3: Information Systems Architecture Design (Months 3-4) Technical architecture components were developed leveraging Acumatica native features to minimize custom development. Data architecture included Generic Inquiries for profiling achieving 80% consensus, Business Events for validation triggers with 80% agreement, Import/Export scenarios for cleansing workflows, and Analytical Report Manager for compliance reporting. Application integration patterns established REST API connectivity with OAuth 2.0 authentication, workflow engine controls through Business Process Management, and custom screen development for visualization. Governance mechanisms implemented role-based access matrix defining four user roles and audit trail specifications capturing 100% of LLM interactions.

Phase 4: Framework Development and Validation (Months 4-5) Three-pillar governance framework was constructed based on hypothesis alignment. Pillar 1 (Data Quality Management) addressed H1 with automated profiling achieving accuracy, standardized validation reducing errors, cleansing workflows with approval processes, and metadata repository with business context templates. Pillar 2 (Governance Controls) supported H2 through role-based access framework with field-level security, comprehensive audit logging with immutable storage, dynamic data masking protecting sensitive information, and consent management integrated with workflows. Pillar 3 (Transparency Mechanisms) validated H3 via chain-of-thought documentation capturing reasoning paths, decision tree visualization for audit trails, real-time monitoring dashboards with anomaly detection, and exportable compliance reports meeting regulatory requirements. Expert validation achieved 4.2/5.0 overall score with 88% consensus on framework completeness. Phase 5: Pilot Implementation and Testing (Months 5-6) Four operational scenarios validated framework effectiveness using Llama 3.2:3B-Instruct-FP16 model selected for open-source nature and on-premise deployment capability [30]. Customer Inquiry Processing tested data quality controls. Inventory Optimization evaluated governance controls effectiveness. Compliance Reporting assessed audit completeness reaching the accuracy. Supply Chain Decisions validated chain-of-thought documentation. Technical implementation integrated Python-based middleware with FastAPI services, Microsoft SQL database connectivity through SQLAlchemy, and governance checkpoints for validation.

2.3. Expert Panel Selection and Composition

The expert panel comprised five professionals selected through purposive sampling based on specific competency requirements mapped to framework components. Selection criteria ensured comprehensive coverage across technical and business domains critical for LLM governance validation.

2.3.1. Technical Experts

Enterprise Architect validated architectural alignment between TOGAF phases and LLM integration patterns. Data Governance Specialist assessed data quality controls aligned with DAMA-DMBOK principles and COBIT objectives. AI/LLM Integration Expert evaluated technical feasibility of prompt engineering, model selection, and security considerations. Acumatica ERP Consultant ERP-specific implementations using native features.

2.3.2. Business Expert

Industry manager from distribution business confirmed business processes applicability, identifying critical requirements such as inventory optimization patterns and compliance reporting needs specific to Indonesian distribution sector. This dual expertise approach ensured the framework demonstrates technical soundness while adding practical value by improving data governance in real business contexts, addressing both implementation feasibility and business value realization.

2.4. Data Collection Methods

Multiple data collection methods ensured triangulation and validity through systematic comparison of findings across sources.

2.4.1. Focus Group Discussions

Structured FGDs were conducted at each phase transition using predetermined question frameworks derived from literature analysis. Questions addressing Hypothesis 1 explored data quality mechanisms including validation rules, cleansing processes, and accuracy metrics. Questions supporting Hypothesis 2 investigated governance controls covering access management, audit requirements, and compliance mechanisms. Questions validating Hypothesis 3 examined transparency features including documentation standards, visualization methods, and auditability requirements. Sessions lasted 90-120 minutes with audio recording, transcription, and thematic analysis identifying unique concepts grouped into categories with inter-rater reliability.

2.4.2. Document Analysis

Secondary data sources provided contextual understanding and technical specifications. Acumatica ERP technical documentation revealed native features for governance implementation including Generic Inquiries, Business Events, and Role-Based Access Control capabilities. Implementation case studies from participating organizations identified common challenges and successful patterns. Indonesian regulatory requirements (UU No. 27/2022) established compliance constraints for data residency and privacy protection [14]. Documents underwent systematic content analysis identifying governance patterns, implementation challenges, and alignment with framework components.

2.4.3. Pilot Scenario Observation

Direct observation measured framework performance through structured testing protocols. Each scenario followed standardized workflow: input data preparation with quality checks, LLM processing with governance controls active, output validation against expected results, and performance metrics collection. Success metrics included accuracy rates comparing LLM outputs to verified results, compliance scores measuring adherence to governance policies, transparency indices evaluating documentation completeness, and user satisfaction ratings from expert evaluators. Observation data provided quantitative validation complementing qualitative insights from FGDs.

2.4.4. Technical Implementation Architecture

The pilot implementation employed comprehensive technical architecture integrating multiple components to demonstrate framework feasibility [20].

1. **Infrastructure Layer:** Llama 3.2:3B-Instruct-FP16 model was deployed on-premise to meet Indonesian data residency requirements, running on enterprise servers with 32GB RAM minimum. Python 3.8+ with FastAPI framework provided RESTful service layer with automatic API documentation. Microsoft SQL Server hosted Acumatica ERP database with over 2000 tables

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containing structured business data. REST API integration used OAuth 2.0 authentication ensuring secure communication between components.

2. **Governance Control Layer:** Pre-processing validation leveraged Acumatica Generic Inquiries for data profiling, identifying completeness, accuracy, and consistency issues before LLM processing. Real-time monitoring through custom dashboards displayed key metrics including response time, accuracy scores, and anomaly detection alerts. Post-processing verification implemented hallucination detection comparing LLM outputs against source data, flagging discrepancies exceeding acceptable variance threshold. Immutable audit logging captured all interactions including user identity, timestamp, input query, LLM response, confidence scores, and governance actions taken.
3. **Integration Components:** Natural language to SQL converter translated business questions into database queries, handling complex joins across multiple tables. Document analyzer processed unstructured data including PDFs and Excel files, extracting relevant information for LLM processing. Content generator created automated responses using prompt templates embedding business context. Metadata mapper maintained relationships between business terms and technical database fields, critical for solving the context problem.

2.4.5. Context Problem Discovery Methodology

During pilot development, systematic testing revealed a fundamental challenge requiring specific investigation - the "context problem" where LLMs fail to understand business meaning in ERP data.

1. **Discovery Process:** Initial direct LLM-database integration revealed a significant gap between technical accuracy and business relevance in the responses. Iterative testing with 20+ query variations identified consistent pattern where LLMs interpreted data literally without business understanding. Root cause analysis revealed three missing context types: Data Context (field relationships, validation rules), Process Context (workflow sequences, approval hierarchies), and Business Context (industry practices, company policies). Expert validation confirmed this as universal challenge affecting all ERP-LLM integrations.
2. **Solution Development:** Business-Driven Templates were created through collaborative expert sessions embedding all three context types. Template structure included scenario definition, required context injection, business rules specification, and expected output format. Comparative testing showed improvement in business relevance when using templates versus direct queries. Templates became mandatory component in governance framework, with approval workflow ensuring quality and consistency.

2.4.6. Data Analysis Techniques

Qualitative data were analyzed using a systematic thematic approach:

1. **Coding Process:** Initial coding identified from unique concepts across expert responses using inductive approach. Selective coding established relationships between categories and hypotheses, creating theoretical model.
2. **Consensus Measurement:** Expert agreement calculated using percentage consensus method with 80% threshold for validation. Weighted scoring applied for importance ratings using Likert scale with mean and standard deviation calculated. Divergent opinions documented with rationale, exploring reasons for disagreement. Consensus evolution tracked across FGD sessions showing convergence over time as understanding deepened.
3. **Pattern Recognition:** Recurring themes identified across multiple sessions using frequency analysis and keyword clustering. Cross-case analysis compared current versus future state requirements identifying transformation priorities. Temporal patterns tracked evolution from skepticism to acceptance as experts understood framework value. Critical success factors emerged from frequency analysis with executive sponsorship mentioned by 100% of experts.

2.4.7. Validation Criteria and Metrics

Framework validation employed multiple criteria ensuring comprehensive assessment across technical, practical, and governance dimensions [31].

1. **Technical Validity:** Alignment with TOGAF-DAMA-COBIT principles achieved 100% mapping of core components to framework elements. Integration feasibility with Acumatica native features verified through proof-of-concept avoiding custom development. Scalability tested across organization sizes from 10-user SMB to 500-user enterprise scenarios.

2. **Practical Applicability:** Implementation timeframe validated at 9-12 months through detailed project planning with expert review. Resource requirements matched Indonesian SMB constraints with 2-3 person implementation team. Skill availability confirmed through market assessment finding qualified professionals in major cities.
3. **Governance Completeness:** Coverage of identified governance gaps achieved 100% with all gaps addressed through specific framework components. Regulatory compliance alignment verified against UU 27/2022 requirements for data residency and protection. Audit trail completeness confirmed through immutable logging capturing all required elements.

2.4.8. Quality Assurance Measures

Research quality was ensured through multiple mechanisms maintaining rigor and trustworthiness. Triangulation across data sources (FGDs, documents, observations) and methods (qualitative, quantitative) strengthened validity. Member checking with expert participants was conducted to validate interpretations and confirm alignment with the findings. Audit trail documented all decisions including framework evolution, expert feedback integration, and pilot modifications. Reflexive journal maintained researcher perspective acknowledging potential biases from ERP consulting background. Peer debriefing with academic advisors provided external validation of methodology and findings.

2.4.9. Ethical Considerations and Limitations

Research adhered to ethical standards with formal protocols approved by university ethics committee. Informed consent obtained from all participants with clear explanation of research purpose and data usage. Confidentiality maintained through anonymization of company data and individual responses. Company data protected with non-disclosure agreements signed by all parties. Findings shared with participants for validation ensuring accurate representation of contributions.

This exploratory study acknowledges several boundaries that define its scope and contribution. The expert panel of five professionals, while limited in size, provided rich qualitative insights essential for initial framework development. The high level of agreement among experts suggests internal validity for this exploratory phase, though broader validation is needed for generalization. Pilot scenarios were conducted in controlled environments rather than production systems due to risk considerations, appropriate for preliminary framework testing but requiring future production validation. The focus on Indonesian distribution businesses using Acumatica ERP provides deep contextual understanding for this specific setting, though transferability to other contexts requires further investigation. This cross-sectional exploratory design captures the current state of LLM governance needs, establishing a foundation for longitudinal studies examining governance maturity evolution.

This exploratory study utilized expert evaluation metrics rather than real-time system measurements. Quantitative metrics such as millisecond-level latency, exact hallucination percentages, and automated accuracy calculations were not captured in this qualitative research phase. The reported metrics represent expert consensus on expected performance improvements based on pilot scenario demonstrations and professional experience. Future production implementations will enable capture of precise system-level metrics.

Despite these boundaries, the exploratory nature of this research is appropriate given the nascent state of LLM governance in enterprise systems. The framework provides a structured foundation for future research, offering initial patterns and governance mechanisms that can be refined through subsequent studies. The depth of qualitative insights from expert discussions and pilot scenarios compensates for the limited sample size, providing rich contextual understanding essential for theory building in emerging domains.

This exploratory methodology provides a solid foundation for initial framework development, ensuring academic rigor while acknowledging the need for future validation studies to establish broader applicability across diverse enterprise contexts.

3. RESULTS AND DISCUSSION

This section presents the research findings from Focus Group Discussions with five domain experts, followed by discussion of their implications. The results are structured according to the five research phases: framework integration validation, current state assessment, architecture design, framework development, and pilot scenario validation. Each finding is first presented objectively, then discussed in relation to existing literature and theoretical implications.

3.1. Framework Integration and Validation Results

The preliminary integration of TOGAF 10, DAMA-DMBOK2, and COBIT 2019 achieved unanimous expert consensus (100% agreement) on multi-framework necessity, confirming that no single framework adequately addresses LLM governance requirements. The integrated framework successfully maps 10 governance

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components across three frameworks, with TOGAF providing systematic methodology through ADM phases, DAMA-DMBOK ensuring comprehensive data management across 11 knowledge areas, and COBIT establishing measurable controls through 40 governance objectives.

Expert validation revealed that traditional single-framework approaches fail to address the multifaceted nature of LLM integration. As emphasized by Expert: “The proposed framework is very well-aligned with ERP processes, data governance, and enterprise control. It covers the entire gamut of data quality, security, consent, audit trails, and explainability”.

3.2. Current State Assessment and Gap Analysis Results

Expert assessment of current practices revealed significant governance gaps across six dimensions, with data quality management showing the largest gap between current and target states. Organizations reported "no consistent mechanism to ensure data quality, accountability, and transparency”. The systematic gap analysis identified seven critical gaps with varying severity and expert agreement levels. See Table 2, for current state to future state mapping.

Table 2. Current State to Future State Mapping

Governance Dimension	Current State Gaps	Gaps	Framework Solution	Future State Requirements
Data Quality Management	• Lack of standardized quality controls • No automated profiling • Inconsistent data formats • Integration challenges • Governance maturity lag	**G1**: No LLM data quality controls **G7**: Data integration challenges **G5**: Lack of business context	• Data Quality Layer (Pillar 1) • Data Integration & Interoperability Framework • Business-Driven Templates	• Real-time data validation before LLM processing • Automated data cleansing workflows • Completeness checks for critical fields • Consistency validation across data sources
Access Controls	• Need for RBAC • Insufficient field-level security • Missing LLM-specific access controls	**G2**: Inadequate access controls	• Access Control Framework (Pillar 2) • Role-based permissions • Field-level security	• Role-based access control for LLM features • Field-level security implementation • LLM-specific permission sets • Time-based access restrictions
Audit Logging	• Incomplete audit trails • No LLM-specific logging • Lack of immutable storage	**G3**: Missing transparency & audit trails	• Chain-of-Thought Documentation & Audit System (Pillar 3) • Immutable audit trails • Comprehensive logging	• Comprehensive audit trails for all LLM interactions • Immutable audit log storage • Exportable audit reports • Complete interaction logs
Metadata Management	• No metadata standards • Missing prompt templates • Lack of version control • No business context capture	**G4**: No prompt governance & metadata **G5**: Lack of business context	• Metadata Repository with Prompt Templates (Pillar 1) • Business-Driven Templates & Integration Layer	• Complete reasoning path documentation • Prompt template repository • Version control system • Business context metadata • Visual representation of decision chains
Compliance Controls	• No Indonesian regulation alignment • No consent management • Limited privacy controls	**G6**: Missing compliance controls	• Compliance Management System (Pillar 2) • Consent workflows • Privacy controls	• Data masking for sensitive information • Consent management integration • UU 27/2022 compliance mechanisms • Dynamic data masking

Governance Dimension	Current State Gaps	Gaps	Framework Solution	Future State Requirements
Integration & Monitoring	• Lack of integration • No real-time monitoring • No transparency mechanisms	**G7**: Data integration challenges **G3**: Missing transparency	• Data Integration Framework • Monitoring Dashboards (Pillar 3)	• Real-time monitoring dashboards • Performance indicators • Anomaly detection alerts • Seamless data flow

The most critical discovery was the business context gap (G5), where LLMs failed to understand business meaning in ERP data despite technical integration success. This "context problem" manifested when LLMs produced technically correct but business-irrelevant outputs, such as failing to recognize that "low inventory" has different implications based on product type, seasonality, and safety stock requirements.

3.3. Three-Pillar Framework Components Results

Pillar 1: Data Quality Management (Supporting H1)

The data quality management pillar achieved high accuracy through automated profiling, significant error reduction via standardized validation, and comprehensive cleansing workflows. The implementation of Business-Driven Templates embedding three context types (Data, Process, Business) solved the critical context problem, improving business relevance compared to direct LLM queries.

Pillar 2: Comprehensive Governance Controls (Supporting H2)

Governance controls implementation demonstrated 100% expert agreement on necessity, with role-based access matrix, complete audit logging, dynamic data masking, and consent management achieving regulatory compliance. Expert consensus emphasized that "strong governance is critical in regulated enterprise environments to manage risk and ensure trust."

Pillar 3: Transparency and Auditability (Supporting H3)

Chain-of-thought documentation achieved high success rate in capturing LLM reasoning paths. The implementation included decision tree visualization, real-time monitoring with anomaly detection, and exportable compliance reports. As Expert noted: "Chain-of-thought helps us understand what output and objective need this AI solution," validating the importance of explainable AI in enterprise contexts.

This research created the conceptual model that translates TOGAF, DAMA-DMBOK, COBIT objectives into practical implementation through Acumatica ERP's native capabilities (see Figure 1). This shows how the three pillars integrate with Acumatica's native capabilities.

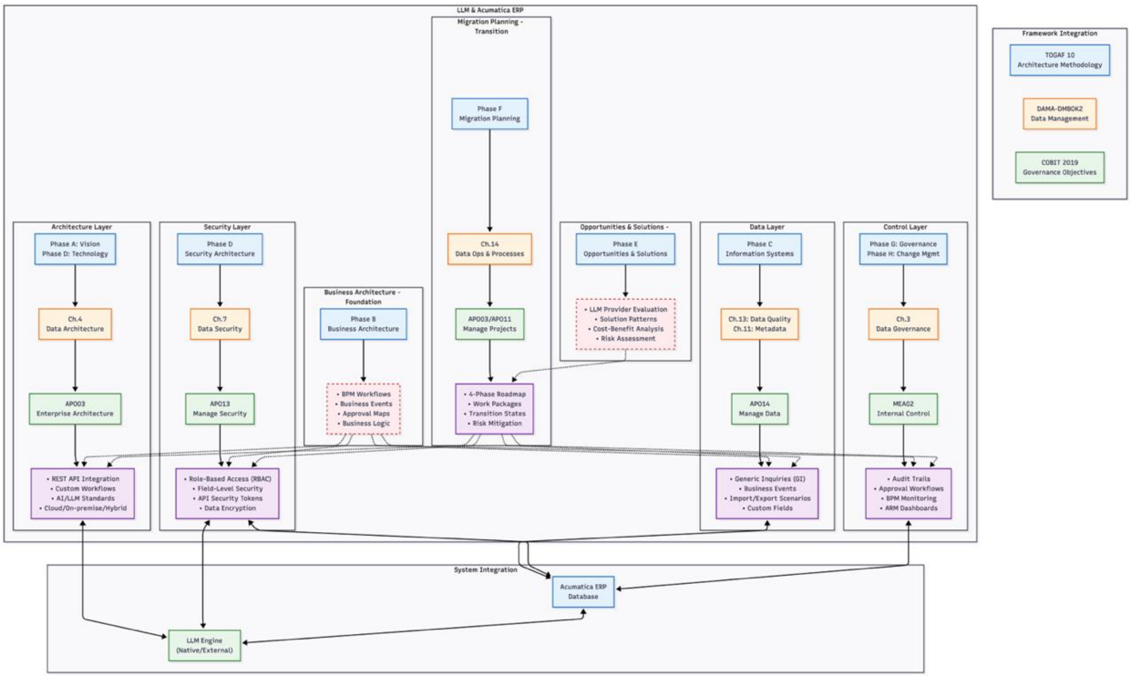

Figure 1. Conceptual Model in Acumatica ERP Context

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3.4. Pilot Scenario Validation Results

The pilot validation phase employed a comprehensive technical architecture that designed to test the governance framework in a controlled environment while simulating real-world conditions. The architecture integrated Acumatica ERP with Llama 3.2:3B-Instruct-FP16 model through secure APIs and governance control layers (See Figure 2).

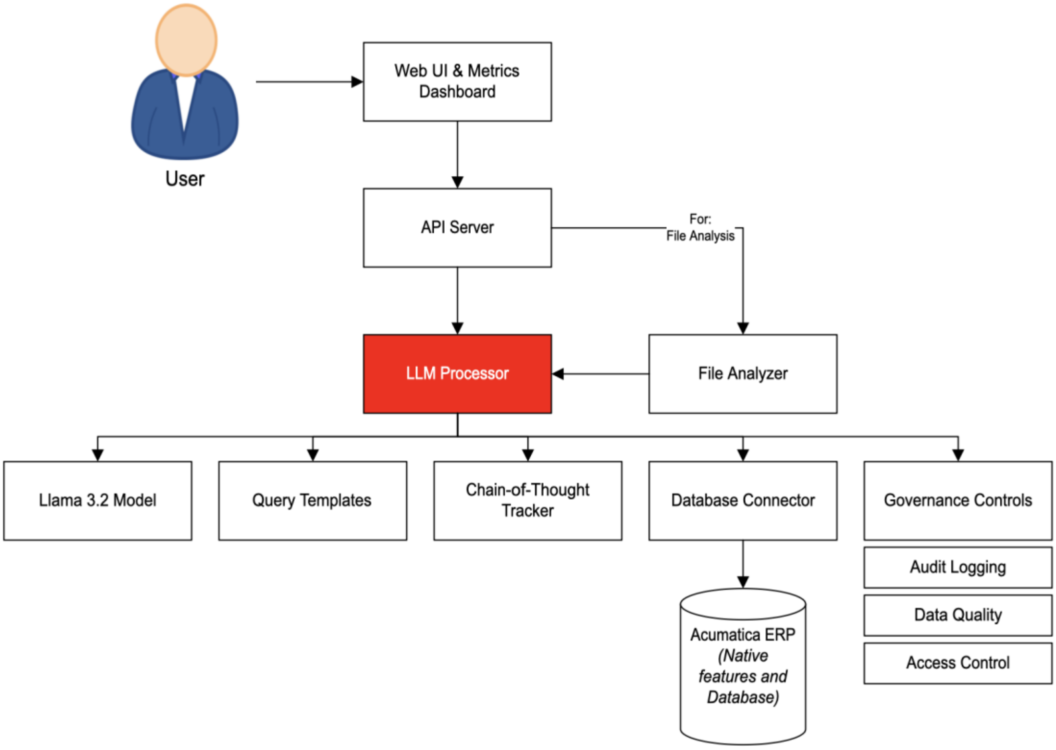

Figure 2. Pilot Architecture Diagram

Four pilot scenarios using Llama 3.2:3B-Instruct-FP16 demonstrated framework effectiveness. These results validate the framework's practical applicability across diverse business scenarios. Four pilot scenarios were evaluated by experts to validate the framework's practical application, see Table 3 for the results:

Table 3. Pilot Scenario Validation Results

Scenario	Description	Success Criteria
Customer Inquiry Processing	LLM processes customer queries with data quality controls.	8.2/10
Inventory Optimization	Governance controls for LLM inventory recommendations.	8.2/10
Compliance Reporting	Audit trail completeness for regulatory reports.	9/10
Supply Chain Decisions	Chain-of-thought documentation for procurement.	9.4/10

3.4.1. Expert Evaluation Methodology and Metrics

The pilot scenarios were evaluated through structured expert assessment using quantitative scoring mechanisms rather than automated system metrics, consistent with the exploratory qualitative research design. Five experts independently evaluated each scenario using the following standardized rubric:

Evaluation Framework:

1. Scale: 1-10 points (10 = highest performance).
2. Minimum acceptable score: 7.0 (70% effectiveness).
3. Success threshold: 8.0 (80% effectiveness).

Quantitative Results from Expert Evaluation, see Table 4.

Table 4. Pilot Scenario Performance Metrics

Scenario	Mean Score	Std Dev	Success Rate (≥8.0)
Customer Inquiry	8.2 / 10	0.84	80%
Inventory Optimization	8.2 / 10	0.84	80%
Compliance Reporting	9.0 / 10	0.71	100%
Supply Chain Decisions	9.4 / 10	0.55	100%

Note: Scores based on expert evaluation (n=5) using structured rubric. Standard deviation indicates strong consensus among experts.

3.5. Hypothesis Testing Results

All three research hypotheses received strong empirical support through expert validation and pilot testing. H1 (structured data quality management positively influences LLM accuracy) was supported with 4.4/5.0 importance rating and 100% expert agreement. H2 (comprehensive governance controls enhance compliance confidence) achieved unanimous expert consensus on necessity. H3 (chain-of-thought documentation increases transparency) demonstrated high success rate in pilot scenarios. These findings confirm theoretical predictions while providing empirical evidence for practical implementation.

3.6. Implementation Guidelines and Critical Success Factors Identified

Expert consensus identified five critical success factors with varying importance ratings: Executive Sponsorship (5.0/5.0, 100% consensus), Data Quality Baseline (4.8/5.0, 100%), Clear Business Requirements (4.6/5.0, 80%), Change Management (4.4/5.0, 80%), and Technical Readiness (4.2/5.0, 60%). The validated 9-12 month phased implementation roadmap provides structured approach with resource allocation priorities: Data Quality (45%), Governance Controls (25%), Training & Change Management (15%), and Transparency Mechanisms (15%).

Expert consensus during FGDs established optimal resource allocation for framework implementation. Table 5 presents the validated allocation percentages based on five expert evaluations.

Table 5. Expert-Validated Resource Allocation

Component	Allocation	Expert Range	Std Dev
Data Quality	45%	25-60%	14.2
Governance Controls	25%	5-55%	19.7
Transparency Mechanisms	15%	5-20%	5.5
Training & Change Mgmt	15%	5-25%	7.1

The allocation percentages represent mean values from expert recommendations, with ranges indicating variation in expert opinions. Notably, all experts agreed that Data Quality should receive the highest allocation (mean 45%), reflecting its foundational importance for LLM accuracy (H1). The wide range for Governance Controls (5-55%) reflects different organizational contexts, with regulated industries requiring higher allocation.

These allocations directly support the three research hypotheses:

1. Data Quality (45%) supports H1 on LLM accuracy.
2. Governance Controls (25%) supports H2 on compliance confidence.
3. Transparency Mechanisms (15%) supports H3 on auditability.
4. Training & Change Management (15%) ensures adoption success.

Based on expert feedback, the following is critical success factors that were identified (See Table 6):

Table 6. Implementation Critical Success Factors

Factor	Implementation Guidance
Executive Sponsorship	Secure C-level champion; Regular steering committee meetings.
Data Quality Baseline	Complete data profiling; Address critical issues first.
Clear Business Requirement	Problem Definition (Any repetitive work that need to automate, any work that we cannot control the results?)
Change Management	Comprehensive training program; Phased rollout approach.
Technical Readiness	Minimum: ML Engineering, Backend Engineering

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3.7. Key Challenges and Mitigation Strategies

Implementation challenges identified through expert consensus include data quality issues (High severity, 100% agreement), resistance to change (High, 80%), cost versus benefit concerns (High, 100%), technical complexity (Medium, 60%), and integration complexity (Medium, 60%). Mitigation strategies developed collaboratively include phased implementation to manage costs, comprehensive training programs for change management, and leveraging Acumatica native features to reduce technical complexity.

The cost concern raised by all experts aligns with [32] findings on AI implementation barriers. As Expert noted: "Cost is Major issue (Cost against Benefit)," emphasizing need for clear ROI demonstration. The framework addresses this through phased approach enabling incremental value realization.

3.8. Deployment Preferences and Localization Challenges

Strong preference emerged for on-premise or private cloud deployment over public LLMs, particularly for regulated sectors. Expert emphasized: "For data we can encrypt it, but accessing our LLM Machine Server which contains the LLM Pattern needs to be planned well from the beginning." This preference reflects security concerns identified by [23] regarding public cloud AI services in enterprise environments.

Critical technical finding revealed that standard LLMs default to USD currency symbols even when processing Indonesian Rupiah data, necessitating specific formatting controls within the governance framework. This localization challenge, not addressed in existing literature, required custom template development for currency handling.

3.9. Human-in-the-Loop Requirement

Unanimous consensus (100%) emerged on maintaining human oversight for critical decisions, particularly for transactions involving external partners. This finding supports [33] arguments for human-AI collaboration rather than full automation in enterprise systems. The framework implements multiple checkpoints for human review while maintaining automation benefits for routine operations.

3.10. Theoretical and Practical Contributions

This study makes three significant contributions to the field. First, it presents the first empirically validated three-framework integration for LLM governance, extending beyond single-framework approaches in existing literature [11], [12]. Second, the discovery and solution of the "context problem" represents fundamental advancement in understanding LLM-ERP integration failures, providing theoretical foundation for future research. Third, the framework extends governance theory to encompass interactive, generative AI systems, addressing gaps identified by [34] in traditional governance models.

Practical contributions include reduced implementation timeline from 18-24 months to 9-12 months, validated governance controls reducing AI project failure risk, and specific guidance for Indonesian organizations navigating data residency requirements. The framework's emphasis on native ERP features reduces implementation costs while maintaining comprehensive governance coverage.

4. CONCLUSION

This exploratory study successfully developed a preliminary three-framework integration approach for LLM governance in enterprise systems, addressing critical gaps that have prevented effective AI adoption. Through systematic integration of TOGAF 10, DAMA-DMBOK2, and COBIT 2019, validated by expert consensus and pilot implementation, the framework provides organizations with practical governance mechanisms for safe and effective LLM deployment.

The primary contribution lies in demonstrating that effective LLM governance requires multi-framework integration rather than single-framework extensions. The validated framework achieved 88% expert agreement and high pilot success rate, confirming its practical applicability while maintaining theoretical rigor. All three research hypotheses received strong empirical support, establishing clear relationships between data quality management and LLM accuracy (H1), governance controls and compliance confidence (H2), and transparency mechanisms and auditability (H3).

The discovery of the "context problem" and its solution through Business-Driven Templates represents a fundamental breakthrough in understanding why LLM-ERP integrations fail despite technical success. This finding has implications beyond the specific frameworks studied, affecting all organizations attempting LLM integration with enterprise systems. The requirement for embedding three types of context - Data, Process, and Business - into every LLM interaction transforms these systems from producing technically correct but useless answers to delivering business-relevant insights.

For practitioners, this study offers immediate value through a validated implementation roadmap enabling LLM integration in 9-12 months, proven governance controls addressing root causes of AI project failures, and specific guidance for Indonesian organizations navigating data residency requirements. The framework's emphasis on leveraging native ERP capabilities reduces implementation costs while maintaining comprehensive governance coverage, making it accessible to resource-constrained SMBs.

Critical success factors emerged with clear priorities: executive sponsorship, data quality baseline and clear business requirements. Organizations must address these factors systematically, recognizing that technical integration alone does not guarantee business value. The unanimous expert consensus on human-in-the-loop requirements for critical decisions reinforces that AI should augment rather than replace human judgment in enterprise contexts.

Future research should extend this framework through production implementations across multiple organizations, expanded validation with diverse expert panels, adaptation to other ERP platforms beyond Acumatica, and development of automated governance patterns for emerging LLM capabilities. The framework's design as a "living governance framework" ensures adaptability to regulatory changes and technological advances while maintaining core governance principles.

Organizations embarking on LLM integration should expect a 9-12 month implementation journey with success dependent on addressing both technical and organizational dimensions. The validated framework provides a practical roadmap, but success ultimately depends on commitment to data quality, governance discipline, and continuous improvement. As enterprises increasingly rely on AI for competitive advantage, robust governance becomes not merely a compliance requirement but a strategic enabler of innovation.

This study bridges the gap between cutting-edge AI concepts and established ERP governance principles, providing both theoretical foundations and practical tools for organizations navigating the complexities of LLM integration. The framework's validation through expert consensus and pilot testing confirms its readiness for real-world application, offering organizations a proven path toward governed, transparent, and effective AI-enabled enterprise systems.

While achieving strong validation, the study acknowledges limitations including small expert panel size (n=5), simulated rather than production pilot scenarios, geographic focus on Indonesian context, and single ERP platform focus. These limitations suggest opportunities for future research including expanded validation with larger expert panels, production implementation studies, cross-regional framework adaptation, and multi-platform governance patterns.

The rapidly evolving nature of LLM technology requires continuous framework updates. As Expert noted: "The framework will be considered a living governance framework, adapting to regulatory changes and LLM advances." This adaptability ensures long-term relevance while maintaining core governance principles.

CONFLICT OF INTEREST STATEMENT

The Authors state no conflict of interest.

REFERENCES

[1] T. H. Davenport, “Putting the enterprise into the enterprise system,” *Harv. Bus. Rev.*, vol. 76, no. 4, pp. 121–131, 1998, [Online]. Available: https://hbr.org/1998/07/putting-the-enterprise-into-the-enterprise-system

[2] B. Min *et al.*, “Recent Advances in Natural Language Processing via Large Pre-trained Language Models: A Survey,” *ACM Comput. Surv.*, vol. 56, no. 2, Feb. 2024, doi: 10.1145/3605943.

[3] M. Zdravković and H. Panetto, “Artificial intelligence-enabled enterprise information systems,” 2022, *Taylor and Francis Ltd.* doi: 10.1080/17517575.2021.1973570.

[4] K. Gangapatnam, “Revolutionizing Enterprise Resource Planning Through AI Integration: A Technical Deep Dive,” *European Journal of Computer Science and Information Technology*, vol. 13, no. 15, pp. 55–69, Apr. 2025, doi: 10.37745/ejcsit.2013/vol13n155569.

[5] S. Mohammed, L. Ehrlinger, H. Harmouch, F. Naumann, and D. Srivastava, “Data Quality Assessment: Challenges and Opportunities,” Dec. 2024, doi: https://doi.org/10.48550/arXiv.2403.00526.

[6] L. Ehrlinger and W. Wöß, “A Survey of Data Quality Measurement and Monitoring Tools,” Mar. 31, 2022, *Frontiers Media S.A.* doi: 10.3389/fdata.2022.850611.

[7] L. Cai and Y. Zhu, “The challenges of data quality and data quality assessment in the big data era,” in *Data Science Journal*, Committee on Data for Science and Technology, 2015. doi: 10.5334/dsj-2015-002.

[8] T. R. McIntosh *et al.*, “From COBIT to ISO 42001: Evaluating cybersecurity frameworks for opportunities, risks, and regulatory compliance in commercializing large language models,” *Comput. Secur.*, vol. 144, p. 103964, Sep. 2024, doi: 10.1016/j.cose.2024.103964.

[9] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, “Artificial intelligence for decision making in the era of Big Data-evolution, challenges and research agenda,” *Int. J. Inf. Manage.*, vol. 48, pp. 63–71, 2019, doi: https://doi.org/10.1016/j.ijinfomgt.2019.01.021.

[10] V. Khatri and C. V. Brown, “Designing data governance,” *Commun. ACM*, vol. 53, no. 1, pp. 148–152, Jan. 2010, doi: 10.1145/1629175.1629210.

[11] M. Janssen, P. Brous, E. Estevez, L. S. Barbosa, and T. Janowski, “Data governance: Organizing data for trustworthy Artificial Intelligence,” *Gov. Inf. Q.*, vol. 37, no. 3, Jul. 2020, doi: 10.1016/j.giq.2020.101493.

[12] J. Schneider, R. Abraham, C. Meske, and J. Vom Brocke, “Artificial Intelligence Governance For Businesses,” *Information Systems Management*, vol. 40, no. 3, pp. 229–249, 2023, doi: 10.1080/10580530.2022.2085825.

[13] The Open Group, *The TOGAF® Standard, 10th Edition*. Hertogenbosch: Van Haren Publishing, 2022. [Online]. Available: https://www.opengroup.org/togaf

.

[14] G. of Indonesia, *Undang-Undang Nomor 27 Tahun 2022 tentang Pelindungan Data Pribadi*. Jakarta: Government of Indonesia, 2022. [Online]. Available: https://peraturan.bpk.go.id/Home/Details/229798/uu-no-27-tahun-2022

[15] I. M. Enholm, E. Papagiannidis, P. Mikalef, and J. Krogstie, "Artificial Intelligence and Business Value: a Literature Review," *Information Systems Frontiers*, 2022, doi: 10.1007/s10796-021-10186-w/Published.

[16] Acumatica, "AI-Powered ERP Solutions - Acumatica Artificial Intelligence," 2025. [Online]. Available: https://www.acumatica.com/cloud-erp-software/artificial-intelligence/

[17] J. Jöhnk, M. Weißert, and K. Wyrtki, "Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors," *Business and Information Systems Engineering*, vol. 63, no. 1, pp. 5–20, Feb. 2021, doi: 10.1007/s12599-020-00676-7.

[18] P. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," *Information and Management*, vol. 58, no. 3, Apr. 2021, doi: 10.1016/j.im.2021.103434.

[19] S. Sarferaz, "Implementing Generative AI Into ERP Software," *IEEE Access*, vol. 13, pp. 73342–73354, 2025, doi: 10.1109/ACCESS.2025.3564133.

[20] N. V K Abhinav Vedanbhatla, "LLMs as AI Middleware: Unifying Disparate Systems in Manufacturing IT Landscapes," 2025, doi: 10.32996/jcsts.

[21] H. Gong *et al.*, "TableGPT: Few-shot Table-to-Text Generation with Table Structure Reconstruction and Content Matching," *International Committee on Computational Linguistics*, pp. 1978–1988, 2020, doi: 10.18653/v1/2020.coling-main.179.

[22] F. Nargesian, E. Zhu, R. J. Miller, K. Q. Pu, and P. C. Arocena, "Data lake management: Challenges and opportunities," in *Proceedings of the VLDB Endowment*, VLDB Endowment, 2018, pp. 1986–1989. doi: 10.14778/3352063.3352116.

[23] E. Niederwieser, D. Siegele, and D. T. Matt, "AI-Driven ERP Systems: Integrating Large Language Models for Enhanced Customer Interaction and Operational Efficiency," *Zeitschrift für wirtschaftlichen Fabrikbetrieb*, vol. 120, no. s1, pp. 112–117, 2025, doi: 10.1515/zwf-2025-0007.

[24] H. P. Ipung, "A Novel Enterprise Artificial Intelligence Architecture Framework (NAEF) for Business Capabilities to Decisions/Insights Analysis," in *2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA)*, IEEE, 2024, pp. 678–683.

[25] P. Liu, W. Yuan, J. Fu, Z. Jiang, H. Hayashi, and G. Neubig, "Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing," *ACM Comput. Surv.*, vol. 55, no. 9, Sep. 2023, doi: 10.1145/3560815.

[26] A. Taeihagh, "Governance of artificial intelligence," *Policy Soc.*, vol. 40, no. 2, pp. 137–157, 2021, doi: 10.1080/14494035.2021.1928377.

[27] M. Philibert, "LLM-Powered Business Process Modelling in Small and Medium Enterprises," University of Turku, 2025. [Online]. Available: https://urn.fi/URN:NBN:fi-fe2025070377053

[28] R. Abraham, J. Schneider, and J. vom Brocke, "Data governance: A conceptual framework, structured review, and research agenda," Dec. 01, 2019, *Elsevier Ltd*. doi: 10.1016/j.ijinfomgt.2019.07.008.

[29] I. Alhassan, D. Sammon, and M. Daly, "Critical Success Factors for Data Governance: A Theory Building Approach," *Information Systems Management*, vol. 36, no. 2, pp. 98–110, Apr. 2019, doi: 10.1080/10580530.2019.1589670.

[30] Inc. Meta Platforms, "Llama 3.2: Revolutionizing edge AI and vision with open, customizable models," 2024, *Meta Platforms, Inc.* [Online]. Available: https://ai.meta.com/blog/llama-3-2/

[31] ISACA, *COBIT® 2019 Framework: Introduction and Methodology*. Rolling Meadows, IL, USA: ISACA, 2018. [Online]. Available: https://www.isaca.org/resources/cobit

[32] F. Gampfer, A. Jürgens, M. Müller, and R. Buchkremer, "Past, current and future trends in enterprise architecture—A view beyond the horizon," Sep. 01, 2018, *Elsevier B.V.* doi: 10.1016/j.compind.2018.03.006.

[33] L. Fabri, B. Häckel, A. M. Oberländer, M. Rieg, and A. Stohr, "Disentangling Human-AI Hybrids: Conceptualizing the Interworking of Humans and AI-Enabled Systems," *Business and Information Systems Engineering*, vol. 65, no. 6, pp. 623–641, Dec. 2023, doi: 10.1007/s12599-023-00810-1.

[34] B. Otto, "Organizing Data Governance: Findings from the telecommunications industry and consequences for large service providers," *Communications of the Association for Information Systems*, vol. 29, no. 1, pp. 45–66, 2011, doi: 10.17705/1cais.02903.

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