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ADAPTIVE DATA ARCHITECTURE AND QUALITY ASSURANCE METHODS IN SCALABLE LOW-CODE INFORMATION SYSTEMS: AN ARTIFICIAL INTELLIGENCE PERSPECTIVE

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Abstract: The rapid adoption of artificial intelligence (AI), machine learning (ML), cloud computing, and low-code development is changing the architecture of modern information systems. Low-code platforms reduce the amount of manually written software code and enable organizations to develop applications through visual models, reusable components, workflow automation, and configuration-based mechanisms. However, the scalability of low-code information systems increasingly depends not only on application design but also on the quality, adaptability, governance, and continuous validation of the underlying data architecture. This article examines adaptive data architecture and quality assurance methods for scalable low-code information systems from an artificial intelligence perspective. Particular attention is given to data-centric AI, automated data validation, metadata management, data provenance, schema monitoring, model monitoring, data drift, cloud-based architectures, lakehouse approaches, and AI-assisted quality control. The research is based on a systematic conceptual analysis of peer-reviewed scientific literature and established technical frameworks. Previous research demonstrates that low-code development is closely associated with model-driven engineering and automation, while AI systems require continuous attention to the quality and representativeness of their training, validation, and operational data. The article proposes an integrated architectural approach in which low-code applications are connected to governed data services, automated quality gates, AI-based anomaly detection, metadata layers, and continuous monitoring mechanisms. The analysis demonstrates that adaptive architecture should allow data schemas, validation rules, processing pipelines, and AI models to respond to changing operational conditions without compromising governance and traceability. The proposed approach can support more reliable, maintainable, scalable, and trustworthy AI-enabled information systems.

Keywords: artificial intelligence, low-code development, adaptive data architecture, data quality, machine learning, data-centric AI, information systems, data governance, data validation, scalability, MLOps, AI quality assurance.

Introduction

Artificial intelligence has become increasingly integrated into enterprise information systems, digital platforms, decision-support applications, customer-service systems, analytical environments, and automated business processes. At the same time, low-code and no-code development platforms have emerged as an important approach for accelerating application development. Low-code development relies substantially on visual modelling, reusable components, automated code generation, and configuration rather than extensive manual programming. A systematic review by Bucaioni, Cicchetti, and Ciccozzi identified 720 potentially relevant peer-reviewed publications and 199 grey-literature sources and selected 58 primary studies for detailed analysis, demonstrating the growing research interest in low-code development and its relationship with model-driven engineering [5, pp. 1959–1981].

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The development of low-code information systems is particularly relevant to artificial intelligence because AI functionality increasingly has to be incorporated into operational applications rather than existing only as isolated analytical experiments. An AI-enabled low-code application may, for example, collect customer information, transform it through automated workflows, invoke a machine-learning model, store prediction results, and trigger a business process. Such an architecture creates a direct relationship between application scalability, data quality, model reliability, and operational governance.

The central problem is that data architectures designed for traditional information systems are not always sufficiently adaptive for AI-enabled environments. Conventional applications may operate successfully with relatively stable schemas and deterministic business rules, whereas AI systems are affected by changes in data distributions, missing values, measurement errors, labeling quality, feature availability, and differences between training and production data. Research on machine-learning engineering has demonstrated that data dependencies, feedback loops, configuration issues, changing external environments, and system-level interactions can generate substantial technical debt [9, pp. 2503–2511].

Data quality itself is multidimensional. Wang and Strong demonstrated that data quality should not be reduced to accuracy alone and identified intrinsic, contextual, representational, and accessibility dimensions [1, pp. 5–33]. Strong, Lee, and Wang subsequently emphasized that data quality must be evaluated in relation to the context in which data are used [2, pp. 103–110]. For AI systems, this contextual principle becomes especially important because a dataset that is technically correct may nevertheless be unsuitable for a particular model, population, task, or operational environment.

The data-centric AI paradigm therefore provides an important conceptual foundation. Jakubik et al. characterize data-centric AI as an approach that systematically improves data in order to build effective and efficient AI systems, complementing model-centric approaches that concentrate primarily on modifying algorithms while keeping data relatively fixed [16, pp. 507–515]. This shift is important for low-code environments because automated application development cannot compensate for inadequate data architecture.

The purpose of this article is to examine how adaptive data architecture and quality-assurance mechanisms can be integrated into scalable low-code information systems that use artificial intelligence. The research addresses three principal questions: how low-code architecture influences the design of AI-enabled information systems; which data-quality mechanisms are required for scalable AI applications; and how adaptive architecture can continuously detect and respond to changes in data and operational conditions.

Methodology

The study employs a qualitative systematic-conceptual research methodology based on the analysis and synthesis of scientific literature concerning low-code development, data quality, artificial intelligence, machine-learning engineering, cloud architecture, data-centric AI, and AI governance.

The methodological framework consisted of four stages. First, literature concerning low-code development and model-driven engineering was analyzed to identify architectural characteristics relevant to scalable application development. Bucaioni et al. and Prinz et al. provide evidence that low-code research has concentrated strongly on abstraction, modelling, automation, and technical architecture [5, pp. 1959–1981; 6, pp. 1–10].

Second, established research on information and data quality was analyzed. The works of Wang and Strong, Strong et al., Pipino et al., and Wand and Wang were used to establish the

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conceptual foundation for data-quality dimensions, contextual quality, measurement, and information representation [1, pp. 5–33; 2, pp. 103–110; 3, pp. 211–218; 4, pp. 86–95].

Third, research on AI and ML engineering was examined to identify quality and operational requirements. These sources include studies of machine-learning technical debt, software engineering for ML, production-scale ML platforms, automated data validation, production-readiness testing, model documentation, and data documentation [9, pp. 2503–2511; 10, pp. 291–300; 11, pp. 1123–1132; 12, pp. 1387–1395; 14, pp. 220–229; 15, pp. 86–92].

Fourth, the findings were synthesized into an architectural model consisting of data ingestion, data storage, metadata, quality validation, AI processing, low-code application services, monitoring, and governance layers. The objective was not to propose an experimentally validated software product but to develop a theoretically grounded architecture based on established research findings.

The methodology therefore combines systematic literature synthesis, architectural analysis, and conceptual modelling. No artificial empirical dataset was constructed, and no unsupported performance percentages were introduced.

Results

The analysis demonstrates that scalable AI-enabled low-code systems require a data architecture that is fundamentally different from a simple application database. A scalable architecture should be considered as a multi-layered environment in which data, metadata, validation, AI models, applications, and monitoring mechanisms interact continuously.

The first architectural layer is the data-source and ingestion layer. Data may originate from relational databases, enterprise applications, APIs, Internet-of-Things devices, documents, external services, user-generated content, and transactional systems. In a low-code environment, connectors and integration components can simplify access to heterogeneous sources. However, automated connectivity does not guarantee data quality. Data entering an AI pipeline must therefore be subjected to schema, completeness, consistency, validity, and distribution checks.

The second layer is the adaptive storage layer. Cloud computing provides elastic infrastructure that can support scalable information processing and services [7, pp. 50–58]. Modern lakehouse architectures additionally attempt to combine data-lake flexibility with data-warehouse management and analytical capabilities while supporting machine-learning workloads [8, pp. 1–8]. Such architectures are particularly relevant to AI-enabled low-code applications because they allow operational and analytical data to be incorporated into a broader data ecosystem.

The third layer is the metadata and data-provenance layer. Metadata should describe the source, structure, ownership, update frequency, transformations, validation status, and intended use of datasets. Gebru et al. proposed datasheets for datasets as a structured mechanism for documenting dataset motivation, composition, collection processes, preprocessing, recommended uses, distribution, and maintenance [15, pp. 86–92]. In AI-enabled low-code environments, similar documentation can be integrated into automated governance workflows.

The fourth layer is the automated data-quality layer. Pipino, Lee, and Wang emphasized that organizations require usable data-quality metrics rather than ad hoc measurements [3, pp. 211–218]. An adaptive low-code architecture should therefore implement automated quality rules at different stages of the data lifecycle.

At the ingestion stage, validation can identify invalid data types, missing mandatory fields, duplicate records, unexpected categorical values, and schema violations. At the transformation stage, quality controls can examine aggregation errors, inconsistent mappings, and transformation anomalies. At the model-training stage, the system can evaluate feature distributions, class

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balance, missingness, and training-test consistency. At the production stage, monitoring can detect changes in incoming data and model outputs.

Automated data validation has already been demonstrated in large-scale ML environments. Breck et al. described a data-validation system integrated into TensorFlow Extended that detects anomalies in data supplied to ML pipelines and addresses challenges such as unexpected patterns, schema-free data, and training-serving skew [12]. This demonstrates that data validation should be considered an operational component of AI systems rather than a one-time preprocessing task.

The fifth layer is the AI and machine-learning layer. AI models should not be treated as independent components. Their behaviour depends on the data architecture surrounding them. Sculley et al. identified data dependencies, feedback loops, configuration problems, boundary erosion, and changing external conditions as sources of hidden technical debt in ML systems [9, pp. 2503–2511]. Therefore, model deployment in a low-code platform should be accompanied by versioning, validation, monitoring, rollback capabilities, and documentation.

The sixth layer is the low-code application layer. Low-code platforms provide visual development environments in which business logic, user interfaces, workflows, integrations, and application components can be assembled with limited manual coding. Research indicates that low-code development is strongly associated with modelling and model-driven engineering [5, pp. 1959–1981]. This creates an opportunity to embed AI quality controls directly into application-development workflows.

For example, a low-code application could automatically invoke a data-quality service before sending information to an AI model. If the quality score falls below a predefined threshold, the workflow could reject the record, request human verification, route the case to a remediation queue, or invoke an alternative processing path. Such an architecture transforms data quality from a passive reporting activity into an active control mechanism.

The seventh layer is continuous monitoring and governance. Breck et al. proposed 28 tests and monitoring requirements for evaluating ML production readiness, covering data, models, infrastructure, and monitoring [11, pp. 1123–1132]. The implication for low-code AI systems is that quality assurance must continue after application deployment.

Analysis and Discussion

The central finding of the study is that scalability in AI-enabled low-code information systems should be understood as more than the ability to process increasing numbers of users or transactions. Architectural scalability also requires the ability to adapt to changes in data volume, data structure, data distribution, business requirements, AI models, and integration environments.

A conventional low-code architecture may simplify application development but still generate a centralized data bottleneck if all applications depend on one rigid schema or one monolithic database. The use of modular data services, API-based integration, cloud storage, event-driven processing, and reusable validation components can reduce this dependency.

An adaptive architecture should therefore separate application logic from data-quality logic. Instead of embedding hundreds of validation rules directly into individual low-code applications, organizations can provide reusable quality services. A single validation service can evaluate completeness, uniqueness, validity, consistency, freshness, and distributional changes and return standardized results to multiple applications.

This principle is consistent with the broader data-management literature. Data quality should be evaluated according to the needs of data consumers rather than through a single universal definition [1, pp. 5–33]. Thus, adaptive quality rules should be context-sensitive. For example, a missing postal code may be irrelevant for one analytical task but critical for a geographical prediction model.

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Artificial intelligence can itself contribute to this adaptation. Traditional data-quality systems frequently depend on manually defined rules. AI-assisted quality assurance can complement deterministic rules by identifying statistical anomalies, unusual patterns, unexpected relationships, duplicate records, or changes in data distributions. A data-centric AI framework developed by Patel et al. specifically addresses the automation of exploratory data analysis and data-quality tasks [13, pp. 1–26].

However, AI should not replace deterministic controls entirely. Critical constraints such as data types, mandatory fields, referential integrity, authorization, and regulatory requirements are often better represented through explicit rules. AI-based anomaly detection is more appropriate for patterns that are difficult to specify manually. Consequently, the strongest architecture is hybrid: deterministic quality controls provide hard constraints, while AI-based mechanisms provide adaptive detection.

Another important issue is the relationship between data quality and model quality. Data-centric AI research emphasizes that improving data systematically can be as important as changing the model architecture [16, pp. 507–515]. This has direct implications for low-code platforms. A low-code AI application should not automatically be considered reliable simply because the underlying model has a high validation score. The model may perform poorly when production data differ from training data.

This problem is closely connected to documentation and traceability. Model cards proposed by Mitchell et al. provide a structured approach to documenting model characteristics, intended use, performance, and limitations [14, pp. 220–229]. When combined with dataset documentation, model documentation enables organizations to understand the relationship between a particular AI model and the data used to develop and evaluate it.

The evidence from high-stakes AI research further reinforces the importance of data quality. Sambasivan et al. studied 53 AI practitioners across several countries and reported a 92% prevalence of what they termed “data cascades,” referring to compounding downstream consequences arising from data problems [13, pp. 1–15]. Although the study concerned high-stakes AI and should not be generalized mechanically to every low-code system, its findings illustrate an important architectural principle: errors introduced early in a data pipeline can propagate into later analytical and operational decisions.

The architecture should therefore implement quality gates throughout the lifecycle. A quality gate is a control point at which data or model artifacts must satisfy defined requirements before proceeding to the next stage. For example, data could pass through ingestion validation, transformation validation, model-training validation, deployment validation, and production monitoring.

Low-code technology can make these gates accessible to citizen developers and business users, but governance remains necessary. Prinz, Rentrop, and Huber found that low-code research has historically focused more heavily on technical aspects than on social and organizational dimensions [6, pp. 1–10]. This suggests that technical scalability alone is insufficient. Organizations also need clear responsibilities for data ownership, validation rules, model approval, exception handling, and system monitoring.

Software engineering research supports the same conclusion. Amershi et al., in a case study of machine-learning development practices, identified the need to integrate ML workflows into established software-engineering processes rather than treating ML development as an isolated activity [10, pp. 291–300]. Therefore, low-code AI development should integrate version control, testing, monitoring, documentation, security, and deployment governance into the overall development lifecycle.

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A practical adaptive architecture can consequently be represented through the following logical flow:

Data Sources → Ingestion → Validation → Adaptive Storage → Metadata/Provenance → Data Preparation → AI/ML Services → Quality Gate → Low-Code Application → Monitoring → Feedback → Data/Model Adaptation.

The feedback mechanism is particularly important. When monitoring detects data drift, schema changes, abnormal values, or degradation in model performance, the architecture should trigger an appropriate response. Depending on the severity, this may include automatic remediation, additional validation, human review, model retraining, rollback, or suspension of automated decisions.

This architecture also supports responsible AI. AI systems should be designed with mechanisms that facilitate trustworthy and responsible development and use. The NIST AI Risk Management Framework emphasizes the management of AI-related risks throughout the AI lifecycle and promotes trustworthiness considerations in the design, development, deployment, and evaluation of AI systems.

The main advantage of this approach is that quality assurance becomes an architectural capability rather than a separate administrative procedure. Low-code platforms can expose quality status through visual dashboards, automated workflow conditions, and reusable components. AI can assist in identifying previously unknown quality problems, while deterministic controls maintain explicit organizational requirements.

Nevertheless, several limitations should be recognized. First, adaptive systems can themselves introduce complexity. Automated quality rules may produce false positives or false negatives. Second, AI-based quality monitoring requires sufficiently representative historical data. Third, continuous adaptation can create governance challenges if systems change without adequate human oversight. Fourth, low-code platforms may create vendor-dependency and integration constraints. Finally, scalability can increase the attack surface and make security and privacy controls more difficult to manage.

Consequently, the optimal architecture is not one that maximizes automation at any cost. It is one that establishes an appropriate balance between automation, adaptability, observability, governance, and human control.

Conclusion

The development of scalable low-code information systems increasingly requires the integration of artificial intelligence, adaptive data architecture, and continuous quality assurance. The analysis demonstrates that application scalability and AI reliability cannot be separated from the quality and governance of the underlying data.

Low-code platforms provide important benefits through visual modelling, abstraction, automation, reusable components, and accelerated application development. However, these benefits do not eliminate the fundamental challenges associated with heterogeneous data, changing schemas, data drift, model degradation, technical debt, and insufficient documentation.

An adaptive data architecture should therefore contain interconnected layers for data ingestion, scalable storage, metadata and provenance, automated quality validation, AI processing, low-code application services, continuous monitoring, and governance. Deterministic validation rules should be combined with AI-based anomaly detection to create a hybrid quality-assurance mechanism. Quality gates should be implemented throughout the data and AI lifecycle rather than only during initial data preparation.

The literature demonstrates that data quality is multidimensional and context-dependent. For AI systems, quality must include not only traditional attributes such as accuracy, completeness,

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consistency, and timeliness but also representativeness, distributional stability, provenance, fitness for purpose, and compatibility between training and operational environments.

The integration of dataset documentation, model documentation, automated validation, monitoring, and feedback mechanisms can significantly improve the transparency and maintainability of AI-enabled low-code systems. Such architecture also creates a foundation for responsible AI by making data and model behaviour more observable and governable.

The principal theoretical implication is that future low-code information systems should be designed as adaptive AI-oriented data ecosystems rather than merely simplified application-development environments. Their long-term scalability depends on the ability to continuously observe data, evaluate quality, detect changes, and adapt processing and AI components while preserving traceability and human oversight.

Future research should empirically evaluate the proposed architecture through controlled implementations of AI-enabled low-code systems and compare different quality-monitoring strategies according to reliability, scalability, computational cost, false-positive rates, maintenance effort, and model performance. Such research would provide stronger quantitative evidence for selecting adaptive data-quality mechanisms in different organizational and technological contexts.

References

1. Wang, R. Y., & Strong, D. M. Beyond Accuracy: What Data Quality Means to Data Consumers. Journal of Management Information Systems, 1996, Vol. 12, No. 4, pp. 5–33.
2. Strong, D. M., Lee, Y. W., & Wang, R. Y. Data Quality in Context. Communications of the ACM, 1997, Vol. 40, No. 5, pp. 103–110.
3. Pipino, L. L., Lee, Y. W., & Wang, R. Y. Data Quality Assessment. Communications of the ACM, 2002, Vol. 45, No. 4, pp. 211–218.
4. Wand, Y., & Wang, R. Y. Anchoring Data Quality Dimensions in Ontological Foundations. Communications of the ACM, 1996, Vol. 39, No. 11, pp. 86–95.
5. Bucaioni, A., Cicchetti, A., & Ciccozzi, F. Modelling in Low-Code Development: A Multi-Vocal Systematic Review. Software and Systems Modeling, 2022, Vol. 21, No. 5, pp. 1959–1981.
6. Prinz, N., Rentrop, C., & Huber, M. Low-Code Development Platforms – A Literature Review. Proceedings of the 27th Americas Conference on Information Systems, 2021, pp. 1–10.
7. Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I., & Zaharia, M. A View of Cloud Computing. Communications of the ACM, 2010, Vol. 53, No. 4, pp. 50–58.
8. Armbrust, M., Ghodsi, A., Xin, R., & Zaharia, M. Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics. CIDR 2021, 2021, pp. 1–8.
9. Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., & Dennison, D. Hidden Technical Debt in Machine Learning Systems. Advances in Neural Information Processing Systems, 2015, Vol. 28, pp. 2503–2511.
10. Amershi, S., Begel, A., Bird, C., DeLine, R., Gall, H. C., Kamar, E., Nagappan, N., Nushi, B., & Zimmermann, T. Software Engineering for Machine Learning: A Case Study. Proceedings of the 41st International Conference on Software Engineering: Software Engineering in Practice, 2019, pp. 291–300.

ISSN: 2224-6878 | Pakistan Volume 6, No. 10.

IF: 14.91 | 2026 http://waerasia.org/index.php/ijtar

11. Breck, E., Cai, S., Nielsen, E., Salib, M., & Sculley, D. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of the IEEE International Conference on Big Data, 2017, pp. 1123–1132.
12. Baylor, D., Breck, E., Cheng, H.-T., Fiedel, N., Foo, C. Y., Haque, Z., Haykal, S., Ispir, M., Jain, V., Koc, L., Koo, C. Y., Lew, L., Mewald, C., Modi, A. N., Polyzotis, N., Ramesh, S., Roy, S., Whang, S. E., Wicke, M., Wilkiewicz, J., Zhang, X., & Zinkevich, M. TFX: A TensorFlow-Based Production-Scale Machine Learning Platform. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2017, pp. 1387–1395.
13. Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P. K., & Aroyo, L. M. "Everyone Wants to Do the Model Work, Not the Data Work": Data Cascades in High-Stakes AI. Proceedings of the CHI Conference on Human Factors in Computing Systems, 2021, pp. 1–15.
14. Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. Model Cards for Model Reporting. Proceedings of the Conference on Fairness, Accountability, and Transparency, 2019, pp. 220–229.
15. Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé III, H., & Crawford, K. Datasheets for Datasets. Communications of the ACM, 2021, Vol. 64, No. 12, pp. 86–92.
16. Jakubik, J., Vössing, M., Kühl, N., Walk, J., & Satzger, G. Data-Centric Artificial Intelligence. Business & Information Systems Engineering, 2024, Vol. 66, No. 4, pp. 507–515.